THE TERM STRUCTURE OF INTEREST RATES AND THE REAL ECONOMY

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ABSTRACT

The Term Structure of Interest Rates and the Real Economy

Philippe Mueller

In the first chapter of this dissertation, joint with Mikhail Chernov, we use evidence from the term structure of inflation expectations implicit in the nominal yields and survey forecasts of inflation to address the question of whether or not monetary policy is effective. We construct a model that accommodates forecasts over multiple horizons from multiple surveys and Treasury yields by allowing for differences between risk-neutral, subjective, and objective probability measures. We extract private sector expectations of inflation from this model and establish that they are driven by inflation, real activity and one latent factor, which is correlated with survey forecasts. We show that the interest rate responds to this “survey” factor. The inflation premium and out-of-sample estimates of the inflation long-run mean and persistence suggest that monetary policy became effective over time. As an implication, our model outperforms a standard macro-finance model in inflation and yield forecasting.

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

1 The Term Structure of Inflation Expectations .......................... 1
   1.1 Introduction .................................................. 1
   1.2 Selective Empirical Literature Review .......................... 5
   1.3 The Model ....................................................... 7
      1.3.1 The Setup ............................................... 8
      1.3.2 Monetary Policy and Inflation Expectations .......... 12
   1.4 Empirical Approach ............................................ 15
      1.4.1 Data ...................................................... 15
      1.4.2 Observation Equations .................................. 16
      1.4.3 Additional Considerations .............................. 17
   1.5 Findings ....................................................... 19
      1.5.1 Measuring Inflation Expectations ....................... 20
      1.5.2 The Determinants of the Inflation Expectations ...... 26
      1.5.3 Monetary Policy Effectiveness .......................... 31
      1.5.4 The Implication of Stable Expectations .............. 38
   1.6 Conclusion ................................................... 40

2 Credit Spreads and Real Activity ....................................... 59
   2.1 Introduction .................................................. 59
   2.2 The External Finance Premium and Real Activity ............ 63
      2.2.1 The Financial Accelerator Mechanism .................. 63
List of Tables

1.1 Mean Absolute Errors .............................................. 41
1.2 In-Sample Inflation Forecast RMSE Ratios ....................... 42
1.3 Simplified Filters .................................................. 43
1.4 Theoretical $R^2$ for Expected Inflation and Yields .......... 44
1.5 Sample Statistics for Nominal Yields Decomposition ........... 45
1.6 Out-of-Sample Inflation Forecast RMSE Ratios ................. 46
1.7 Out-of-Sample Yield Forecast RMSE Ratios .................... 47

2.1 Credit Spread Regressions ....................................... 94
2.2 Summary of $R^2$'s ................................................ 95
2.3 Model Fit: $R^2$'s for Implied Yields and Spreads ............. 96
2.4 Implied Credit Spread Regressions ............................. 97
2.5 Implied Credit Spread Regressions: Term Premia and Spreads Under $\mathbb{P}$-Measure ................................. 98
2.6 The Forecasting Power of Determinants of Credit Spreads ... 99
2.7 Implied Credit Spread Regressions: Full Decomposition ...... 100
2.8 Term Spread and Short Rate Regressions ....................... 102
2.9 Credit Spread Regressions: Lehman and Merrill Lynch Bond Indices . 103
List of Figures

1.1 The Term Structure of Survey Forecasts .................................. 48
1.2 Term Bias ................................................................................. 49
1.3 Inflation Expectations ................................................................. 50
1.4 The Term Structure of Inflation Expectations .............................. 51
1.5 Factor Loadings for Inflation Expectations ................................. 52
1.6 Expectations and Yields Decomposition ..................................... 53
1.7 The Fisher Equation .................................................................... 54
1.8 Out-of-Sample Parameters ......................................................... 55
1.9 Out-of-Sample Impulse Responses ............................................. 56
1.10 Out-of-Sample Inflation Expectations ....................................... 57
1.11 Out-of-Sample Average Term Structure of Inflation Expectations . . 58

2.1 Treasury Yields: Actual and Implied Slope and Curvature .............. 104
2.2 Credit Spreads: Actual and Implied Levels .................................. 105
2.3 Implied Spreads and Treasury Yields, and Term Premia ................. 106
2.4 Normalized Factor Loadings ....................................................... 107
2.5 Factor $f_1$, B Spreads and Index of Tighter Loan Standards .......... 108
2.6 Factor $f_2$, Treasury Yields and Federal Funds Target Rate .......... 109
2.7 Decomposition of Implied Spreads ............................................. 110
2.8 Treasury Yields and Credit Spreads ............................................ 111
2.9 Impulse Response Functions for Bivariate VARs ......................... 112
2.10 Impulse Response Functions for VARs ....................................... 113
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To my parents, Christine, Emma and Theo
Chapter 1

The Term Structure of Inflation Expectations

1.1 Introduction

One of the most important conclusions in recent research in macroeconomics is that monetary policy matters for the development of the real economy. The main purpose of the paper is to provide yield-curve- and survey-based empirical evidence on how effective the US monetary policy is in handling the economy.

We approach the task by evaluating whether inflation expectations are anchored. The motivation for this line of thinking is Friedman's (1968) American Economic Association address. He emphasizes that "...[the] economic system will work best when producers and consumers, employers and employees, can proceed with full confidence that the average level of prices will behave in a known way in the future – preferably that it will be highly stable." Friedman further argues that in the US, the effective monetary policy has to be conducted by targeting the price level.

In the rational expectations equilibrium (REE), a monetary policy that reacts to current inflation and output shocks is optimal (see, for example, Clarida, Gali, and Gertler (1998) for a review). However, if private sector expectations deviate from
rational expectations due to imperfect knowledge of the economy's structure, the REE monetary policy will lead to an unstable economy. The main implication is that monetary policy should respond to either private expectations or their determinants in order to anchor these expectations (e.g., Evans and Honkapohja (2003), Howitt (1992), Preston (2006), among others).

These theoretical developments suggest that the US monetary policy should be evaluated in two stages. First, it should be established whether there is any evidence that the monetary policy responds to the expectations of the private sector. Second, if this is the case, it should be determined whether expectations regarding inflation are anchored or became anchored over time.

There are two principal sources of observations of private sector expectations in the US. First, the expectations might be extracted from the nominal yield curve. However, one needs to disentangle the expectations from the inflation premium and from real yields. ¹ Second, surveys, which represent direct estimates of future inflation by individuals, should be useful for learning about the expectations of a marginal economic agent.

However, it is not clear whether information that is derived from yields is identical to or, perhaps, conflicting with that derived from surveys. Indeed, the mechanisms that generate the expectations are different. In contrast to consensus survey forecasts, which average opinions of up to 50 participants, the expectations embedded in the bond prices are formed by thousands of traders who put hundreds of millions of dollars on the line. To date, the literature has been interested in comparing different methods of inflation forecasting, but, to the best of our knowledge, no one has reported whether observed yields and survey forecasts could be rationalized within one model. A joint model of surveys and yields would help in establishing whether the two sources of inflation expectations are compatible by detecting whether there is a common set of

¹ Inflation-linked bonds offer direct observation of real yields, but, until recently, they were not available in the US. However, inflation-linked bonds, even if available, are still contaminated by the inflation premium.
factors that explain both.

With these motivations and considerations in mind, we proceed with our task in six steps. First, we build a model that is sufficiently flexible to allow for REE-based and private-expectations-based interest rate rules. Second, we measure the private sector expectations of inflation using this model by simultaneously incorporating information from survey-based inflation forecasts and nominal yields. Third, we establish the determinants of inflation expectations. Fourth, we check whether the interest rate rule implicit in our model responds to these determinants. Fifth, we investigate whether monetary policy is effective, that is, whether inflation expectations are anchored. Sixth, we evaluate the implications of anchoring for out-of-sample forecasting.

Inflation forecasts are available from various surveys and at various horizons (see Figure 1.6). However, each survey is different in terms of the composition of forecasters, frequency of observations, and forecast horizons. We propose a model of the term structure of inflation forecasts that incorporates these characteristics. The key feature of this model is that forecasts from different surveys and at different horizons enter the model in an internally consistent fashion, taking into account, in a reduced form, potentially different sets of information or the forecasting objective functions of the surveys. We integrate our model of inflation forecasts together with a no-arbitrage macro-finance term structure model.

In our model, the yields and forecasts are driven by two observed macro variables (real activity and inflation) and by two latent variables. The joint dynamics of these four variables determine inflation expectations at any horizon under the objective probability measure. The yields reflect expectations of inflation under the risk-neutral probability measure. Because forecast surveys may differ from each other systematically, we model the respective expectations as those of heterogeneous agents. This implies that for each survey, the forecasts are computed under a subjective measure that is potentially different from both objective and risk-neutral measures. This flexibility in the modeling allows for state-dependent deviations of the survey
forecasts from the optimal objective-measure-based expectations.

For our empirical analysis, we use a panel of eight yields ranging from three months to ten years, with inflation and GDP observed at a quarterly frequency from 1970 to 2004. We combine these with a total of twenty inflation forecasts from the four surveys depicted in Figure 1.6. The forecasts from these surveys are available for various horizons and at various frequencies.

Allowing for the difference between survey-specific subjective and objective probability measures, we document a rich pattern of survey biases. The surveys overpredict inflation the most and disagree the least at the end of recessions. A model that restricts subjective measures to coincide with the objective one cannot be distinguished statistically from a richer model. Further, the restricted version of the model produces more reasonable inflation expectations than the standard version of a macro-finance model that uses yields only. Thus, we conclude that private sector expectations have to be extracted from both yields and surveys.

Inflation expectations that are computed from our leading model use inflation and real activity, and load similarly on one of the two latent factors across all forecasting horizons. The second latent factor is barely used in the construction of these expectations. Further, the first latent factor can be explained by a linear combination of contemporaneous real activity, inflation, and one-year inflation forecasts. These properties justify the interpretation of this factor as a "survey" factor. This factor affects the spot interest rate, which suggests that implicit monetary policy responds to the information reflected in this factor.

We use the estimated inflation expectations to infer inflation premia from nominal yields via the Fisher equation. The ten-year inflation premium declines from six to zero per cent during the post-monetary-experiment period. This decline suggests that long-run inflation expectations became more stable over time. Further, we reestimate our model every quarter and find that the long-run expectations have declined over time from 6% to 2%. The inflation persistence declined and the term structure of
inflation expectations became flat over time. This evidence suggests that monetary policy became better anchored.

One implication of anchored inflation expectations is that it should be easier to forecast inflation and yields. Consistent with this prediction, we find that the model that incorporates both yields and surveys dominates in out-of-sample forecasting of both inflation and yields. These results lead us to conclude that information in surveys is extremely important for establishing the links between inflation expectations and yields.

1.2 Selective Empirical Literature Review

Scores of empirical papers have been dedicated to studying the interactions between inflation and interest rates. It is not possible to discuss all of them in this brief survey. Two main strands of the literature that study the subject are those on term structure and macro forecasting.

The empirical side of the literature on no-arbitrage term structure explores the behaviour of state variables and risk premia in the context of no-arbitrage models. The main focus is to explain and summarize parsimoniously the relationships that are of interest and, therefore, most of the analysis is conducted in-sample. In addition to the data on yields, various authors utilize either inflation itself (the no-arbitrage macro literature beginning with Ang and Piazzesi (2003)), or the data that reflects inflation expectations, such as inflation-indexed bonds (Evans and Honkapohja (2003)), or survey forecasts of inflation (Chun (2005), Pennacchi (1991)).

The typical research questions that arise are: (i) Does inflation help to explain the yields? (Ang and Piazzesi (2003), Bikbov and Chernov (2006), Duffee (2005)); (ii) Does inflation help to explain the risk premia? (Ang, Dong, and Piazzesi (2004), Bikbov and Chernov

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2 A recent work by Kim and Orphanides (2005) is related to this literature in methodology, but not in research questions. These authors study the traditional latent factor models and use survey forecasts of yields in addition to contemporaneous yields.

Part of the literature on macroeconomic forecasting focuses on predicting inflation from the prices of financial assets, notably the short rate and the term spread, in the regression framework (see Stock and Watson (2003a) for a comprehensive survey). The natural motivation for such an approach is that, because of their forward-looking nature, yields should serve as good predictors of macroeconomic activity. In contrast to the literature on term structure, a lot of work focuses on out-of-sample performance. Conceptually, the approach suffers from the following drawback. As any no-arbitrage model would imply, yields simultaneously reflect the market's expectations of the state variables, such as inflation and risk premia. There is formidable evidence that the risk premia are time-varying. As a result, it is virtually impossible to disentangle the yield components in a regression framework. Depending on the variability of the risk premia, yields might introduce a lot of noise, which would make the inference unreliable.

A separate strand of the literature on forecasting investigates the predictive ability of survey forecasts. As with yields, the analysis is performed in a regression framework. The analysis focuses on the forecasts' rationality and efficiency and typically concentrates on a one-year horizon. The key finding, based on considering roughly pre- and post-Volcker subsamples, is that inflation is underestimated when it is high and vice versa (see, Thomas (1999), among many others). However, a more refined conditional analysis is not feasible because of the inherently unconditional nature of the regression-based analysis.

Finally, Ang, Bekaert, and Wei (2007) combine the views contained in the reviewed literature by running a horse-race between the different ways of forecasting one-year
inflation. They use the different forecasts separately and also combine them via various weighted-averaging schemes. The authors find that surveys forecast inflation better than other models and approaches.

Our work, while having a different focus, is related to the following four concurrent studies. Kozicki and Tinsley (2006) use a descriptive time-series model of inflation to construct the term structure of inflation expectations using inflation forecasts from the Livingston survey. D'Amico, Kim, and Wei (2007) build a no-arbitrage model and estimate it using the nominal yield curve, TIPS, Blue Chip forecasts of one-quarter yields, and one-year and ten-year SPF forecasts of inflation from 1999 to 2007. They document the importance of using TIPS for accurate predictions of inflation. In a similar spirit, Joyce, Lildholdt, and Sørensen (2007) exploit information from the UK real and nominal bonds along with Consensus forecasters’ expectations of average inflation from five to 10 years ahead from 1992 to 2007 to construct inflation forecasts and inflation risk premia. Piazzesi and Schneider (2008) focus on using an affine term-structure model to construct a measure of subjective bond risk premia, which they derive from survey data, and specifying a structural model that can explain these premia.

1.3 The Model

In this section, we develop the theoretical underpinnings of our approach. In section 1.3.1, we describe our assumptions. Section 1.3.2 discusses the advantages of our approach and contrasts it with previous methodologies.

They also consider the Phillips curve and pure time-series models. However, discussion of these lies beyond the scope of our paper.
1.3.1 The Setup

State Variables

Following Ang and Piazzesi (2003) (AP henceforth), we assume that the state of the economy is captured by the vector $z_t = (m_t', x_t')'$. In particular, the vector of macroeconomic variables $m_t$ is equal to $(g_t, \pi_t)', \text{where } g_t \text{ and } \pi_t \text{ are quarterly GDP and the inflation rate, respectively.}$ We define the inflation rate $\pi_t$ as

$$\pi_t = \log \left( \frac{P_t}{P_{t-1}} \right), \quad (1.3.1)$$

where $P_t$ is the price level. The remaining factors $x_t$ are latent. The latent factors may represent the lags of $m_t$, other macro variables, or other unknown variables. Importantly, the vector $z_t$ fully reflects all available information at time $t$, so, for instance, one need not consider lags of $x_t$.

We assume that the state vector $z_t$ follows a VAR(1) process under the objective probability measure $\mathbb{P}$:

$$z_t = \mu + \Phi z_{t-1} + \Sigma \epsilon_t \quad (1.3.2)$$
$$= \begin{bmatrix} \mu^m \\ \mu^x \end{bmatrix} + \begin{bmatrix} \Phi^{mm} & \Phi^{mx} \\ \Phi^{xm} & \Phi^{xx} \end{bmatrix} \begin{bmatrix} m_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \Sigma^{mm} & \Sigma^{mx} \\ \Sigma^{xm} & \Sigma^{xx} \end{bmatrix} \begin{bmatrix} \epsilon_t^m \\ \epsilon_t^x \end{bmatrix}, \quad (1.3.3)$$

where $\epsilon_t \sim N(0, I)$. We denote the vector of parameters controlling the dynamics of state by $\Theta = (\mu, \Phi, \Sigma)$. The block representation will be useful for later discussions.

In particular, the state dynamics imply that the objective expectation, or $\mathbb{P}$-expectation, of the future state variables is a linear function of the current state variables:\footnote{In this paper, we use the terms $\mathbb{P}$-expectation, marginal expectation, optimal expectation, objective expectation, and private sector expectation interchangeably.}

$$E_t(z_{t+\tau}) = \Psi^r \mu + \Phi^r z_t, \quad (1.3.4)$$
where

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

(1.3.5)

**Spot Interest Rate and Yields**

It is customary in the literature on term structure to specify the interest rate as a linear function of the state variables (e.g., Dai and Singleton (2000), or AP):

\[ r_t = \delta_0 + \delta'_z z_t = \delta_0 + \delta'_m m_t + \delta'_x x_t. \]  

(1.3.6)

The specification of the state variables (1.3.2), combined with the interest rate specification in (1.3.6), allows us to complete the usual affine no-arbitrage framework by specifying the stochastic discount factor \( \xi_t \), or, equivalently, the transformation to the risk-neutral probability \( Q \):

\[ \log \xi_t = -r_t - \frac{1}{2} \Lambda_{t-1}' \Lambda_{t-1} - \Lambda_{t-1}' \epsilon_t, \]  

(1.3.7)

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

\[ \Lambda_t = \Lambda_0 + \Lambda_z z_t. \]  

(1.3.8)

Therefore, yields on zero-coupon bonds are linear in the state variables,

\[ y_t(\tau) = -\frac{1}{\tau} \log E_t \left( \prod_{s=t+1}^{t+\tau} \xi_s \right) = a^Q(\tau) + b^Q(\tau)' z_t \]

\[ \Delta \]

Short rate expectations Term premium

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

(1.3.9)

where \( \tau \) is the respective maturity, and \( a^Q \) and \( b^Q \) solve recursive equations with boundary conditions \( a^Q(1) = \delta_0 \), and \( b^Q(1) = \delta_z \) (see, e.g., Backus, Foresi, and Telmer
(1999)). In particular, the one-quarter yield coincides with the short rate, \( y_t(1) = r_t \).
The last line breaks down the yields into the expectations of the future short rates and the term premium. The former component is equal to the usual factor loadings computed under the assumption of zero market prices of risk.

**Heterogeneous Forecasters**

We assume that the world is populated by agents who have heterogenous inflation expectations. The heterogeneity might arise from the differential information, or different loss functions used in the forecasts. We treat a consensus forecast from each survey as a forecast of one such agent. A reduced-form representation of this assumption is an equivalent subjective probability measure \( \mathbb{P}^i \), that corresponds to beliefs of an agent \( i \).

5 We parameterize the transformation of measure \( \mathbb{P} \) to measure \( \mathbb{P}^i \) similarly to the way it is done with the risk-neutral measure (1.3.8):

\[
\log \xi_i^t = -\frac{1}{2} \Lambda_{t-1}^i \Lambda_{t-1}^i - \Lambda_{t-1}^i \xi_t,
\]

where \( \Lambda_t^i \) follows the essentially-affine specification

\[
\Lambda_t^i = \Lambda_0^i + \Lambda_z^i z_t.
\]

We assume that the agents diverge only with respect to their beliefs about inflation. Therefore, \( \Lambda_t^i \) should be restricted. We assume that only the second element of the vector \( \Lambda_0^i \), \( \lambda_0^i \), and the second line of the matrix \( \Lambda_z^i \), \( \lambda_z^i \), are not equal to zero.6

5 This modelling approach could be justified in the framework of such models as Detemple and Murthy (1994), Dumas, Kurshev, and Uppal (2008), Harrison and Kreps (1978), Scheinkman and Xiong (2003), among others. See Basak (2005) for a review. Appendix A provides a simple model that motivates our assumptions. Alternatively, Patton and Timmermann (2007) show that asymmetric and different loss functions of forecasters imply unbiased forecasts with iid errors under subjective probability measures.

6 We do not need to assume that beliefs differ in inflation only. However, because we will be using forecasts of inflation only, most of the parameters controlling \( \Lambda_t^i \) will not be identified. Therefore, the described restrictions would have to be imposed in any case.
Because $\mathbb{P}^i$ is not a pricing measure, $\Lambda^i_t$ do not represent prices of risk. These quantities reflect the deviations of individual expectations from the $\mathbb{P}$—expectations. For this reason, we will refer to $\Lambda^i_t$ as biases. The resulting dynamics of the state variables corresponding to the individual probability measure $\mathbb{P}^i$ will be denoted by

$$z_t = \mu_t + \Phi_t z_{t-1} + \varepsilon^i_t, \quad (1.3.12)$$

Survey Forecasts

A forecaster from group $i$ (a participant of a forecast survey) has the following estimate of the expected state:

$$E^i_t(z_{t+r}) = \Psi^i_t \mu_t + \Phi^i_t z_t, \quad (1.3.13)$$

where, by analogy with (1.3.5),

$$\Psi^i_t = (I - \Phi^i_t)^{-1} (I - \Phi^i_t). \quad (1.3.14)$$

Because we assumed heterogeneity in expectations only with respect to inflation, the expression (1.3.4) will differ from the $\mathbb{P}$—expectation of state only in

$$E^i_t(z_{t+r}) = E^i_t(\pi_{t+s}) + (1 - \frac{1}{r}) \sum_{j=1}^{r} \pi_{t+s+j}, \quad (1.3.15)$$

where $e_2$ is a vector of zeros with a one in the second position.

In practice, most forecasts represent estimates of inflation over some period (a quarter or a year) beginning at a future date. This amounts to forecasts of averages of quarterly inflation. The forecasts of averages will be denoted and computed as follows:

$$\bar{\pi}^{i}_{t,s}(\tau) = E^i_t(\pi_{t+s \cdot \tau}) = E^i_t \left( \frac{1}{\tau} \sum_{j=1}^{\tau} \pi_{t+s+j} \right). \quad (1.3.16)$$
Therefore,

$$\bar{p}_{t,s}^i(\tau) = \frac{1}{\tau} \sum_{j=1}^{\tau} E_t^i \left( E_{t+s}^i (\pi_{t+s+j}) \right) = \frac{1}{\tau} \sum_{j=1}^{\tau} E_t^i \left( c_2^j \left( \Psi_i^j \mu_i + \Phi_i z_{t+s} \right) \right)$$

$$= \frac{c_2^0}{\tau} \sum_{j=1}^{\tau} \Psi_i^j + \Psi_i^j \Phi_i^{s+1} z_t \triangleq a^P(s,\tau) + b^TBI(s,\tau)^t z_t.$$

(1.3.17) Term bias

The last line decomposes the forecasts into the $P$-expectations of the future inflation and the survey-specific term biases. The former component is equal to the usual factor loadings computed under the assumption of zero biases $\Lambda^i_t$.

### 1.3.2 Monetary Policy and Inflation Expectations

Following the insight of Ang, Dong, and Piazzesi (ADP henceforth), one can use (1.3.4) or (1.3.13) to rewrite the interest rate rule (1.3.6) as a linear function of objective or subjective inflation expectations. In a reduced-form model, such as ours, one generally cannot identify whether subjective or objective expectations and which expectations horizon should be used because of this equivalence between the different representations. Using the direct observations of subjective expectations in conjunction with yields, which reflect objective expectations, should help in solving the identification problem.

To aid the interpretation of our empirical results, we rewrite the spot interest rate in a form that is similar to the theoretical work on optimal monetary policy (e.g., Evans and Honkapohja (2003)). First, we use the ADP approach to express the spot interest rate as a function of one-period inflation expectations from survey $i$ (omitted $i$ corresponds to objective expectations):

$$r_t = \gamma_0^i + \gamma_g^i g_t + \gamma_{\pi}^i E_t^i (\pi_{t+1}) + \gamma_{\pi x}^i x_t,$$

(1.3.18)
where the coefficients $\gamma$ are related to the coefficients $\delta$ in the original rule (1.3.6) via

$$
\begin{align*}
\delta_0 &= \gamma_0^i + \gamma_{a}^i e_{\mu_i}, \\
\delta_2 &= \gamma_2^i e_1 + \Phi_2^i \gamma_{a}^i e_2 + \gamma_{a,1}^i e_3 + \gamma_{a,2}^i e_4,
\end{align*}
$$

(1.3.19) (1.3.20)

where $e_i$ is a vector of zeros with a one in position $i$. A similar representation can be obtained for any forecasting horizon $r$ (see ADP for details).

Further, following Bikbov and Chernov (2006), we break down each latent variable $x$ into a component explained by inflation and real activity, and into a residual $f$ that is orthogonal to the entire history $M_t = \{m_t, m_{t-1}, \ldots, m_0\}$ of the two macro variables:

$$
x_t = \hat{x}(M_t) + f_t,
$$

(1.3.21)

$$
\hat{x}(M_t) = c(0) + \sum_{j=0}^{t} c_{t-j}(\Theta) m_{t-j} \equiv c(\Theta) + c(\Theta)m_t + c(\Theta,L)m_{t-1},
$$

(1.3.22)

where the matrices $c$ are functions of parameters $\Theta$ that control the dynamics of the state variables and $c(\cdot, L)$ emphasizes the lag-polynomial structure of the expression. In particular, the results in Bikbov and Chernov imply that under the standard identification assumptions, the joint dynamics of $m_t$ and $f_t$ can be described as

$$
\begin{bmatrix}
m_t \\
f_t
\end{bmatrix} =
\begin{bmatrix}
\mu^m \\
0
\end{bmatrix} +
\begin{bmatrix}
\Phi^{mm}(L) & \Phi^{mx} \\
0 & \Phi^{ff}
\end{bmatrix}
\begin{bmatrix}
m_{t-1} \\
f_{t-1}
\end{bmatrix} +
\begin{bmatrix}
\Sigma^{mm} & 0 \\
\Sigma^{fm} & \Sigma^{xx}
\end{bmatrix}
\begin{bmatrix}
e^m_t \\
e^x_t
\end{bmatrix},
$$

(1.3.23)

This is a stylized representation. In order to focus on the most important issues, we do not reproduce full expressions for some matrices (e.g., for the lag-polynomial matrix $\Phi^{mm}(L)$ or the covariance matrix $\Sigma^{fm}$). Therefore, we can think of an economy that is driven by output, inflation, and persistent shocks. This is consistent with typical New-Keynesian models of the private sector (see Clarida, Gali, and Gertler (1998))

---

7 Appendix B provides the details of the procedure.
for details).

Substituting (1.3.21) and (1.3.22) into (1.3.18) we obtain

$$r_t = \hat{\gamma}_0 + \hat{\gamma}_y y_t + \hat{\gamma}_{\pi} \pi_t + \gamma^F_t E_t^r(\pi_{t+1}) + \hat{\gamma}_r(L)m_{t-1} + \gamma^F f_t,$$

(1.3.24)

where coefficients $\hat{\gamma}$ represent a convolution of the coefficients $\gamma$ in (1.3.18) and $c(\Theta)$ in (1.3.22). The combination of this particular form of the interest rate rule and state dynamics in (1.3.23) is interesting because it nests, in a reduced form, the private sector dynamics and optimal rule prescription in a world in which the private sector deviates from rational expectations and the policy maker is learning about parameters that describe the economy (see, e.g. Evans and Honkapohja (2003), or Primiceri (2006)). In this world, monetary policy should respond to the private sector expectations of inflation or to their determinants.

As the expression (1.3.24) demonstrates, our framework is sufficiently flexible to allow for this possibility. Moreover, by taking the model to the data, we can establish whether we should be using a specific survey (the value of $i$) in this expression or some combination of surveys to compute the private sector expectations. Furthermore, by focusing on expectations $E_t^r(\pi_{t+1})$ in (1.3.24), we can evaluate how the various data sources (macro variables, yields, or survey forecasts) contribute to the determination of these expectations.

Having established the appropriate way to determine inflation expectations, we can use our model to determine the effects of monetary policy. Our framework offers three main ways of addressing this topic. First, the macroeconomic literature on optimal monetary policy suggests that if the policy responds correctly to the expectations of the private sector, expectations about long-term inflation will be anchored. Therefore, we can investigate the properties of long-term forecasts and whether these properties have changed over time. Second, another aspect of the anchoring of expectations is how fast long-term inflation expectations adjust to transient inflation shocks. In other words, expectations are anchored better when inflation is less per-
sistent and reverts back to its long-run mean soon after a shock. Third, we can use
the finance side of our model to extract inflation risk premia. If long-term inflation
expectations are anchored, the long-term inflation premium should be small.

The inflation premium (ignoring convexity terms) can be extracted from a gener­
alized version of the Fisher equation:

\[ y_t(\tau) = y_t^R(\tau) + \bar{p}_{t,0}(\tau) + IP_t(\tau), \quad (1.3.25) \]

where \( y^R \) refers to real yield, expected inflation \( \bar{p} \) under the \( \mathbb{P} \) measure is defined in
(1.3.16), and \( IP \) denotes the inflation premium. Because inflation is one of the ob­
served factors, we can use our model to identify the real yields and inflation premium
by observing inflation and nominal yields (see, e.g., Ang, Bekaert, and Wei (2008)).
Specifically, the real discount factor is

\[ \log \xi_t^R = -r_{t-1} + \pi_t - \frac{1}{2} \Lambda'_t \Lambda_{t-1} - \Lambda'_t \epsilon_t, \quad (1.3.26) \]

This allows us to compute real yields, \( y_t^R(\tau) \), by analogy with the nominal yields
(1.3.9). Before that, we establish the appropriate measure of \( \mathbb{P} \)–expectations. As a
result, we will be able to obtain an accurate estimate of the inflation premium.

Finally, if inflation expectations are stable, we should be able to forecast inflation
more accurately. We check this by conducting an out-of-sample forecasting analysis.

1.4 Empirical Approach

1.4.1 Data

We use three types of data in this paper. Direct measures of macro variables (inflation
and GDP) represent two observable state variables in our model. Treasury yields
and survey forecasts are the observable data that help us to learn about the model
parameters and latent state variables. Using these data, we construct a quarterly
panel from 1970 to 2004. We describe the data details in appendix D.

### 1.4.2 Observation Equations

We estimate our term structure model via maximum likelihood with the Kalman filter, following Duffee and Stanton (2004) and de Jong (2000), among others.\(^8\) We place estimation errors on all yields and survey forecasts so that the latent factors are not associated with pre-specified observables. We assume that the macro variables are observed without error.

As a result, we have the following set of measurement equations:

\[
y_t(\tau) = a^Q(\tau) + b^Q(\tau)'z_t + \omega_t, \quad (1.4.1)
\]

\[
\bar{p}_{t,s}^i(\tau) = a^i(s, \tau) + b^i(s, \tau)'z_t + \chi_{t,s}^i(\tau). \quad (1.4.2)
\]

where \(y\) represents the yields of maturities from one month to ten years, and \(\bar{p}_t^i\) represents all the forecasts made in all the surveys (as described above).

The errors in measurement of the yields are denoted by \(\omega\). We assume the simplest possible structure of the errors; that they are independent and normally distributed with zero mean and standard deviation \(\sigma_{\omega}\) (for each individual element of the vector \(\omega\)). We need not specify a more flexible error structure because these variables are introduced in addition to the VAR shocks that we considered earlier.

Within each survey, we introduce two types of forecast error. The forecasts with shorter horizons, \(\tau \leq 6\) quarters, have many observations and are allowed to have an unrestricted error \(\chi\). The longer term forecasts have few observations. We do not want these observations to influence the estimation results unduly, yet we do not want to ignore them completely, because long-term forecasts could be important for addressing

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\(^8\) Other important estimation strategies applied to term structure models include, but are not limited to, the exact inversion likelihood of Chen and Scott (1993), the closed-form approximate likelihood of Aït-Sahalia and Kimmel (2002), the simulated maximum likelihood of Brandt and He (2002), and the Bayesian MCMC of Collin-Dufresne, Goldstein, and Jones (2003).
our questions. Therefore, for each survey, we restrict the errors in the measurement of long-term forecasts to be no less than those of short-term forecasts and those of yields. While such a flexible specification runs the risk of overparameterization, we decided to use it because of diverging properties of forecasts. As we can see from the description above, the forecasts within one survey but at different horizons might be available for different data spans, different quarters, and different frequencies.

1.4.3 Additional Considerations

In this section, we review briefly additional matters that we took into account when estimating.

**Missing Observations**

We determine the main span of our dataset by the availability of the yield data. Thus, we end up with 140 quarters from 1970 to 2004. However, as noted above, the result of this choice if that many forecast observations are missing. There are two reasons for this: (i) some surveys were only available from a date later than 1970, and some are available less frequently than quarterly. Regardless, missing observations are not problematic. They can be handled easily in the Kalman filter framework. We simply do not update, or partially update, the state vector when the observations are missing. This procedure is automatic when one uses a new forecast vector $\bar{p}$ that is an old forecast vector $\bar{p}$ scaled by a matrix that has zeros in place of missing observations, and ones in place of the available ones (see Harvey (1989a)).

---

9 Long-term forecasts are available for LS and SPF only.

10 This approach was also used by Kim and Orphanides (2005), Kozicki and Tinsley (2006), Lu and Wu (2005), and Pennacchi (1991).
Number of Factors and Identification

We largely follow the setup of Bikbov and Chernov (2006) in selecting the number of latent factors and the scheme for identifying parameters. We decided to use a four-factor model (two latent factors) because it is the smallest model that can reasonably fit the yield curve. We were hesitant to increase the number of states because we wanted to make sure that the same latent variables drive both yields and forecasts, so that we could learn about these latent states from a rich set of observations.

Risk Premia and Survey-Specific Biases

The elaborate risk-premia specification combined with forecast-specific biases leaves one with a concern about overfitting. We follow Bikbov and Chernov (2006) and augment the standard log-likelihood function, $\mathcal{L}$, with a penalization term that is proportional to the variation of the term premium in (1.3.9):

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

$$
- \frac{1}{2\sigma_p^2} \sum_{i,s,\tau} \left( a^{TBI}(s, \tau) \right)^2 + b^{TBI}(s, \tau)' \cdot \text{Diag}(\text{var}(z_t)) \cdot b^{TBI}(s, \tau),
$$

(1.4.3)

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 and biases are equal to zero, the term premium and term biases will be equal to zero as well. Therefore, $\mathcal{L}_p$ imposes an extra burden on the model to use the risk premia and survey biases as a last resort in fitting the yields. In practice, we take $\sigma_p = 300$, which introduces a modest modification to the original log likelihood. Nonetheless, it helps to stabilize the likelihood and simplifies the search for the global optimum. In particular, this setup helps us to avoid very large values of risk premia.
Optimization

We need to estimate 77 parameters in our model. We have a large cross-section of observations, which should help in pinning these parameters down. However, with a time-series of 140 observations there remains a concern as to whether or not a global optimum can be found. We use a large and efficient set of starting values to search for the global optimum. The grid search is extremely costly in a multi-dimensional space, and, in practice, limits the extent of the global search. We reduce the computational costs by using Sobol' quasi-random sequences to generate the starting points (see, e.g., Press, Teukovsky, Vetterling, and Flannery (1992)). We evaluate the likelihood in two billion Sobol' points and then optimize the likelihood using the best twenty thousand points as starting values. We optimize alternating between simplex and SQP algorithms and eliminating half of the likelihoods at each stage.

1.5 Findings

We estimate six versions of our model. The full model that uses the survey and yield data is labelled AS (All data, Subjective expectations). A model that uses all the data, but restricts subjective measures to coincide with objective measure, is labelled AO (All data, Objective expectations). A model that uses only yields for estimation is referred to as NF (No Forecasts). In this implementation, the subjective measures cannot be estimated because they are not identified. We also estimate a model that uses only forecasts and label it OF (Only Forecasts). In this implementation, the risk-neutral measure cannot be estimated. In order to implement various robustness checks we have estimated two more models. ASR (All data, Subjective expectations, Restricted) restricts the values of $\mathbb{P}$-measure parameters to the values estimated in AO and allows other parameters ($\mathbb{P}^i$ and $Q$) to be free. OFO (Only Forecasts, Objective expectations) is a version of OF that restricts subjective measures to coincide
with objective measure.\textsuperscript{11}

We do not report the technical details of the estimation results, such as parameter values, tests of their statistical significance, and measures of fit. There are too many parameters to discuss and most of them are difficult to interpret. We will comment on the relevant aspects of the fit as we discuss the model implications.

\subsection*{1.5.1 Measuring Inflation Expectations}

First, we wish to establish a measure of private sector expectations about inflation. Specifically, in the context of our model, we want to understand whether a subjective forecast from a specific survey \(i\), or objective forecast, or some combination thereof, could represent such expectations. We compare forecasts from the different surveys to the \(\mathbb{P}\)-measure expectations. Then we evaluate the importance of the heterogeneous agent framework for forecasting purposes.

\textbf{The Term Structure of Forecast Biases}

In Figure 1.6 we plot the term structure of term biases – the deviations of the survey forecasts from the optimal forecasts by maturity (see formula (1.3.17)). We consider term biases of survey forecasts made today over the horizon matching the maturity of the bonds in our sample, that is:

\begin{equation}
TB_i^t(\tau) = E_t^i(\pi_{t+r}) - E_t(\pi_{t+r}), \ \tau = 1, 4, 8, 12, 20, 28, 40 \text{ qtr} \quad (1.5.1)
\end{equation}

We use the AS model for the computations. We report the unconditional term structure, which measures the average bias for each horizon, and the time-series of conditional biases for the horizons of one (\(\tau = 4\)) and 10 (\(\tau = 40\)) years.

The first panel shows the unconditional term structure of the survey biases. All the surveys exhibit a bias that increases as the horizon lengthens. This is to be

\textsuperscript{11}In spirit, OFO is similar to the time-series model of Kozicki and Tinsley (2006).
expected, because most of the forecasts are concentrated at the short horizons and longer-term horizons are available for a shorter time span. BCEI is uniformly worse and varies from -0.7% at the three-month horizon to -1.9% at the 10-year horizon.

Turning to the conditional biases in Figure 1.6, we see that there is virtually no difference between the different surveys. If anything, MCS seems to be more in line with the optimal forecast at longer horizons. The shaded regions represent the NBER dated recessions and help to identify the reasons for the biases. The peak of inflation overestimation generally coincides with the end of a recession. This property of biases is consistent with the view that monetary policy tends to be accommodative during recessions, thereby increasing fears of inflation.

The extant analysis (e.g., Thomas (1999)) finds, on the basis of the split-sample regressions, that surveys overestimate inflation when it is low and vice versa. Our conditional framework allows us to perform a more refined analysis period by period instead of comparing the pre- and post-Volcker samples. We check the conclusion from the regression-based work by plotting the one-year term bias against the demeaned inflation. Indeed, we observe a general pattern that suggests that inflation is underpredicted during periods of high inflation. This impression is particularly strong because the two subperiods previously considered in the literature (pre- and post-Volcker) could be characterized as the periods of “great inflation” and “disinflation,” respectively. Nonetheless, this relationship between underprediction and inflation can be traced even during the disinflation period.

Business cycles and inflation are, of course, related. Thus, it is not surprising that we find links from the overestimation of inflation to both. Which link is more informative about the behaviour of forecasters? It appears that the business cycle indicator is more robust: the end of a recession always coincides with a local maximum of the bias, while the end of an expansion always coincides with a local minimum of the bias. In contrast, inflation could peak after or before the bias’ minimum was reached. Sometimes, inflation does not move much, as in the mid-1990s, but biases
have very strong patterns.

We characterize the disagreement between the various surveys by computing the difference between the largest and the smallest bias:

\[ D_t(\tau) = \max_i (TB_i^t(\tau)) - \min_i (TB_i^t(\tau)) \]  

(1.5.2)

The time series of the one- and 10-year disagreement are presented in Figure 1.6 as well.

There is greater disagreement between the surveys at the one-year horizon than at the 10-year horizon. The ranges are from 0 to 2 percent and from 0.2 to 3.5 percent, respectively. While overprediction is countercyclical, the disagreement is procyclical. Consistent with our reasoning about the overprediction of inflation, it appears that, at the end of a recession, all forecasters tend to agree that future inflation will be high.

**Subjective and Objective Expectations**

We have demonstrated that our model is sufficiently rich to describe the evolution of subjective and objective inflation expectations. However, it is not clear which type should be used as a measure of the private sector expectations. To address this question, we use information from the other three models that we have estimated (AO, NF, and OF). These versions of our main model differ in the restrictions that they place on parameters and the data used for estimation. These differences should help us to understand the primary sources of expectations.

We start by evaluating the model-implied mean absolute errors (MAE), which are reported in Table 1.6. Overall, the models match the data well; depending on the model, the average MAE ranges from 10 to 20 basis points for surveys and from 10 to 30 basis points for yields. As one would expect, the model clearly trades off the fit of surveys and yields. OF and NF provide a lower bound on the errors. The survey MAE in AS are comparable to those in OF. The biggest difference between the two
models is for the BCEI longer maturity forecasts. Clearly, AS sacrifices the yield fit in favour of the survey fit, because the differences between the NF and AS yield errors are larger than those between the OF and AS survey errors.

AO should have more difficulty fitting the surveys than AS because we restrict 20 parameters that control the subjective probability measures of the four surveys to the values of their objective measure counterparts. However, in practice, we see small differences.

The largest discrepancy between AO and AS is in how they fit the MCS forecast. In addition, regardless of the model, the MCS error is noticeably large. The type of bias implicit in MCS is likely to be different from other surveys, either because consumers do not predict CPI explicitly or because an average consumer forms expectations differently from an average professional. It appears that MCS does contain useful information. However, some features of the survey either have to be ignored via the error term, while some could be accommodated via the subjective probability measure. Our model can be extended to fit MCS better, but this improvement is not likely to affect any other surveys or yields.

Because AO is so similar to the larger AS in terms of MAE, it is natural to wonder whether the richness provided by the subjective probability measures is required, either (i) for a good model fit or (ii) inflation forecasting. The first issue can be addressed via the likelihood ratio (LR) test because AO (the null hypothesis) is nested in AS (the alternative hypothesis). The likelihood-ratio test statistic is equal to 1.5, which is insignificant. Clearly, there is no statistical difference between the two models.

Our analysis of the term biases suggests that, despite the lack of statistical significance, there could be economic differences between the two models. We evaluate economic differences using a metric that is important for our study: objective infla-

\[12\] Ang, Bekaert, and Wei (2007) provide a detailed numerical analysis of the biases in LS, MCS, and SPF.

\[13\] The five percent critical value of the chi-squared distribution with 20 degrees of freedom is 31.4.
tion expectations. Figure 1.6 plots the time series of inflation expectations that are computed from AO, OF, and NF. The AS-based expectations are similar to those from NF and are omitted to avoid clutter.\textsuperscript{14} We also plot, as a benchmark, the time series of realized inflation and the 10-year inflation expectations that are implied by TIPS.\textsuperscript{15}

Despite the similarity in the survey fit, the model-implied expectations diverge quite dramatically, especially at the 10-year horizon. The NF expectations float around 5\% in the 1970s, during the great inflation and in the 1990s, during the disinflation. The AO expectations increase to 9\% in 1980 and decline to 2\% in 2004. In addition, the 10-year expectations implied by AO fall right on top of the TIPS-based expectations. This provides informal evidence that AO-based forecasts have a reasonable level. In addition, using the visual inspection of the realized inflation as a basis, AO fares better than NF and AS after 1985.

We provide more formal evidence regarding the differences between AO and NF by displaying the in-sample inflation forecast RMSE in Table 1.6. In the full sample, the RMSE ratios are very close to one, which suggests that there is not much difference between the two models. We attempt to reconcile these numbers with Figure 1.6, where AO appears to be dominant, by splitting the sample at the first quarter of 1983. This is when most surveys started to report their forecasts on a regular basis. Therefore, we should be able to generate useful results by using the surveys in the post-1983 subsample. Indeed, NF dominates AO by 5\% to 20\%, depending on the forecasting horizon, prior to 1983, while AO dominates NF by 15\% to 45\% afterwards.\textsuperscript{16}

\textsuperscript{14} Our interpretation is that the extra flexibility allowed for by the AS specification leads to objective expectations that are unaffected by the information from the survey data.

\textsuperscript{15} We use TIPS-based expectations that have been adjusted for risk and liquidity premia. The series are provided by the Federal Reserve Bank of Cleveland. The TIPS are available beginning from 1997. D'Amico, Kim, and Wei (2007) find that TIPS provide useful proxies for inflation expectations.

\textsuperscript{16} The sample values of RMSE ratios must be interpreted with caution, because the bootstrapped confidence bounds reported in Table 1.6 are quite wide. In particular, the ratios are not significantly
Given the importance of the inflation expectations that we obtained from AO, on the one hand, and the distinct patterns in term biases that we obtained from AS, on the other, we perform a robustness check by estimating ASR. By construction, this model produces inflation expectations that are identical to AO, but it has the flexibility to capture the term biases as well. We find that this model has MAE that are similar to the results for AO and AS that were presented in Table 1.6. As highlighted earlier, MAE in AO and AS differ substantively only in the case of MCS. The MCS' MAE in ASR is very similar to that in the more flexible AS. The term biases are close to zero (conditionally and unconditionally) for all surveys except for MCS. These two results are consistent with our earlier observations that MCS is the only survey that could benefit from the extra flexibility that is offered by the subjective measures.

Given the importance of the $P^i = P$ restriction for identifying accurate forecasts, we perform another robustness check by estimating OFO. This model generates MAE that are larger than those of OF and a likelihood-ratio test rejects OFO in favour of the more flexible OF. Nonetheless, the model produces inflation expectations that are very similar to the ones from AO. These findings mean that if a researcher is confronted with a survey-only dataset, OF is a better statistical description of the data and OFO is a better description of the data from the economic viewpoint. Thus, if one is interested in accurate inflation forecasts at all dates and for all horizons, OFO will provide a set of accurate forecasts.

We conclude that using surveys is extremely important, because they help us to identify the objective dynamics of the state variables. However, the surveys have

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17 The details of ASR-based results are available upon request.

18 The details of OFO-based results are available upon request.

19 In this regard, our conclusion supports the approach of Kozicki and Tinsley (2006).
to be used in conjunction with yields, because the latter shed light on the issues addressed in our paper, that is, the interaction between monetary policy and inflation expectations and the behaviour of the inflation risk premium. Subjective probability measures could be important for interpreting the information contained in the survey forecasts, but from a statistical and forecasting perspective, a simpler model appears to be more attractive. We provide out-of-sample analysis in later sections.

The Term Structure of Inflation Expectations

Figure 1.6 shows the time-series of the inflation expectations at multiple horizons. These expectations are computed from AO. In contrast to the survey forecasts in Figure 1.6, these objective, or marginal, expectations can be computed each period at any horizon.

The term structure effects are pronounced. The inflation curve becomes inverted in 1973, right before the recession, and continues to be inverted until early 1982. This period coincides with the unstable period of monetary policy during the Burns and Miller chairmanship of the US Federal Bank and the monetary policy experiment under Volcker’s chairmanship. The curve became inverted again briefly in the early part of Greenspan’s tenure from 1987 to 1991. Afterwards, it had a normal, nearly flat, shape.

1.5.2 The Determinants of the Inflation Expectations

Factor Loadings

Given that the different versions of the model produce different inflation expectations, we would like to understand better how various factors influence these expectations. We begin our characterization of the forecasts’ determinants by plotting the factor loadings $b^p(0, \tau)$ in (1.3.17) for the AO and NF models, where subjective and objective measures coincide. Figure 1.6 plots the loadings by factor.

AO model uses inflation as a level factor, because the loadings are almost identical.
throughout the forecasting horizon spectrum. In contrast, inflation works as a slope in the NF model. The current inflation value features prominently at the short horizons, and there is almost no effect at long horizons. GDP is used as a slope by AO and as a curvature by NF.

It is more difficult to interpret the loadings on the latent factors, because there are multiple combinations, or rotations, of the factors that produce identical yields and expectations (Dai and Singleton (2000)). To aid the interpretation of the latent factors, we follow Mueller (2008) and rotate them so that the two latent factors are orthogonal to each other and \( x_1 \) is interpreted as the factor that affects surveys. The last property is achieved by maximizing the one-year forecast’s loading on \( x_1 \) (see appendix C for details).

The bottom panels of Figure 1.6 show the effect of such a rotation for the two models. We see that the largest loading on \( x_1 \) occurs at the one-year horizon. Moreover, in AO, the loadings on \( x_1 \) are similar across all the forecast horizons, which suggests that it is appropriate to interpret it as a “survey” factor. The orthogonal factor \( x_2 \) has a curvature effect in both models, but the effect is very small; it is an order of magnitude less than for other factors. This property of \( x_2 \) justifies our interpretation of \( x_1 \) further, because this is the only one of the two latent factors that has a material impact on expectations.

The Nature of Latent Factors

To gain further insight into the latent factors, we study their determinants in our models. The latent variables are filtered at the estimation stage by constructing a linear function of the observables (real activity, inflation, yields, and forecasts). We will make an attempt to establish which ones feature most prominently in the filters.

We use the following ad hoc procedure. Suppose a filter with a steady-state
forecast error covariance matrix can be represented as

\[ \dot{x}_{it} = A_{i0} + A_{iy}y_t + A_{ip}\bar{p}_t + A_{im}m_t + A_{ix}\dot{x}_{i-1}, \]  

(1.5.3)

where \( y, \bar{p} \) and \( m \) represent vectors of observable yields, forecasts, and macro variables, respectively. We visually inspect the vectors of loadings \( A_y, A_p \) and \( A_m \) and select the ones with the largest absolute values. Then we rerun the Kalman filter, using as a basis the parameter values estimated from the full setup, but using only the observables that correspond to the selected weights. To be conservative, we implement this procedure in several steps and stop when a new, simplified, filter has a correlation of less than 0.98 with the original full filter.

Table 1.6 lists the variables that we use in each filter. We can make the following observations. First, our procedure allowed us to eliminate most of the observables from the filter. We need three or four observable series, depending on a factor and a model. Second, the two models use the macro variables in a different way: the first latent factor loads on both and the second factor does not use them at all in AO, while the they load only on GDP or only on inflation in NF. Third, the factor \( x_1 \) in AO can be estimated using output, inflation, and one-year forecasts from the Livingston and SPF surveys.\(^{20}\) This property is consistent with our interpretation of \( x_1 \) as a “survey” factor.

The Incremental Impact of Surveys

The two previous sections provide evidence that survey forecasts are important for the determination of inflation expectations in our model. They channel through the latent variables. Still unaddressed is the quantitative impact on the inflation expectations of the surveys versus the macro variables. The difficulty in addressing this issue lies in the conditional and unconditional dependence of the macro and latent factors.

\(^{20}\) We explain the need for both surveys by the longer available span of LS and higher available frequency for SPF.
One needs to disentangle the information in surveys that is not related to the macro variables. In the discussion that follows, we focus on AO, because, as the previous section shows, the latent factor $x_1$ is not related to yields in this model.

We distinguish the surveys and macro variables by applying the projection procedure in equation (1.3.21). If surveys have any incremental information over the macro variables, the residual component $f$ will be correlated with some components of the inflation forecasts that are unrelated to the macro variables. We prewhiten the forecasts by regressing them on ten lags of real activity and inflation. This will enable us to relate the factors $f$ to the innovations in forecasts. We correlate $f_1$ and $f_2$ with the innovations in all 20 available forecasts. In the case of $f_1$, only 20% of all correlations are below 0.4 and the highest value is 0.72. In the case of $f_2$, 85% of all correlations are below 0.4 and the highest value is 0.45. Thus, the residual factor $f_1$ has inherited the “survey” interpretation from the original factor $x_1$.

The top panels of Figure 1.6 show the breakdown of expected inflation into the contribution of $M$ (inflation, real activity, and their history), $f_1$ and $f_2$. It is obvious that inflation and its lags play a major role in explaining expected inflation. In contrast, factor $f_2$ makes almost no contribution. Real activity and the “survey” factor $f_1$ make a modest, but non-negligible contribution. These observations are supported by the contents of Table 1.6A, which presents the variance of expectations explained by $M$ and $f$. Regardless of the forecast horizon, $M$ explains approximately 90% of the variation in expectations and $f_1$ explains the remaining 10%, according to AO. The forecasts affect expectations not only through factor $f_1$, but also through parameter values. As we argued in detail in section 1.5.1, an identical model with different parameter values yields less accurate expectations.

These findings lead us to the following three conclusions. First, the private sector expectations in the forward-looking interest rate rule representation (1.3.24) reflect information outside of the history of macro variables and yields. This information is

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21 NF implies slightly more variation in these numbers, but they are qualitatively similar.
captured by the residual $f_1$. Second, this information is contained in the survey forecasts. Third, the residual $f_1$ may reflect observable variables that are not incorporated in our model or genuinely unobservable components that affect survey forecasts, such as the professional judgements of the participants in the surveys.\textsuperscript{22} Regardless of its origins, the information lies outside the standard variables that are contemplated in the theoretical literature on monetary policy. As highlighted earlier, this information is required if the objective dynamics of the state variables are to be identified. Taken on their own, yields are not very informative about this aspect of the data-generating process, because pricing takes place under the risk-neutral probability measure.

The Interest Rate Response

The main finding of the previous section is that private sector expectations about inflation incorporate information that is orthogonal to the history of macro variables and, in the case of AO, to the history of yields. This bit of information is captured by the factor $f_1$. The remaining issue is whether the monetary policy responds to $f_1$.

We can evaluate how surveys affect nominal yields by breaking the latter down into the contribution of macro variables $M$ and residual factors $f$ using the projection (1.3.21). The residual factor $f_1$ is associated with information unique to the surveys and, therefore, represents the link between yields and forecasts. The bottom panels of Figure 1.6 display the projection-based breakdown. Table 1.6, panel B quantifies the contribution of $M$ vis-a-vis $f$. As is the case with inflation expectations, inflation and its lags play a big explanatory role. Overall, $M$ explain 40% to 50% of the yields' variation. Therefore, factors $f$ contribute much more to the variation of yields than they do to the variation of expectations. In contrast to expectations, much of the contribution comes from factor $f_2$.

This analysis does not provide the full picture of the policy response to $f_1$. So far, we have seen only the total impact of $f_1$ as a part of the latent factor $x_1$ that follows

\textsuperscript{22} Kozicki and Tinsley (2006) review the literature on the judgmental aspects of forecasting.
from equations (1.3.6) and (1.3.21). Equation (1.3.24) shows that \( f_1 \) affects the spot interest rate \( r \) via two channels: directly as a shock in the interest rate rule and indirectly via the inflation expectation. Because we want to gauge whether monetary policy responds to the determinants of expectations, we are interested primarily in the latter channel.

Equations (1.3.19) and (1.3.20) allow us to compute the specific impact of \( f_1 \) via the expectations channel. The total contribution of \( f_1 \), \( \delta_{\pi,1} \), can be broken down as

\[
\delta_{\pi,1} = \frac{\delta_{x,1}}{\Phi_{22}} + \gamma_{\pi,1},
\]

or, in relative terms,

\[
1 = \frac{\delta_{x,1}}{\delta_{\pi,1} \Phi_{22}} + \frac{\gamma_{\pi,1}}{\delta_{\pi,1}},
\]

where \( \Phi_{ij} \) denotes an individual element of the matrix \( \Phi \). The loading on the contribution of \( f_1 \) via the expectations channel is the first member of the sum. Our parameter estimates imply a value of 0.73.\(^{23}\) Thus, the contribution of \( f_1 \) to the volatility of \( r \) via the expectation component represents 73% of the overall contribution of \( f_1 \), which is 19% in AO.

1.5.3 Monetary Policy Effectiveness

We have established that it is important to use information from surveys and yields to construct an accurate measure of inflation expectations. Moreover, short-term inflation expectations are driven by output, inflation, and only one of the two latent factors. This factor affects inflation expectations at all horizons and is, therefore, termed a "survey" factor. Various breakdowns of this factor show that it is driven by the macro variables, their history, and a residual factor that reflects information that

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\(^{23}\) This value is statistically significant, because the 95% bootstrapped confidence interval is [0.11, 1.94].
is orthogonal to that contained in macro variables and the yield curve. The residual factor affects the short-term interest rate mostly via the inflation expectation channel.

Thus, we have established that the interest rate rule responds to the determinants of the expectations of the private sector, in addition to the standard macro variables. This conclusion is consistent with the prescription of the literature on the stability of monetary policy. The next natural issue to address is whether such an interest rate rule leads to monetary policy stability, or expectations anchoring, as predicted by the literature. We explore anchoring from three angles: the magnitude of inflation premia, long-run inflation expectations, and inflation persistence.

**Inflation Premia**

If inflation expectations are anchored, the inflation premium should be low. We extract inflation premia from nominal yields via the Fisher equation (1.3.25). We report summary statistics associated with the determinants of nominal yields in Table 1.6.

There are quite substantive differences between the nominal yield components across the two models. All of them, with the exception of the long-run expected inflation, are more volatile in NF. As we showed before, the NF-based inflation expectations are slightly higher, about 20 to 30 basis points on average. These modest differences translate into large divergences in real rates and inflation premia. The short-term real rate averages at 2% for both models. However, the long-term rate declines to 1.2% in AO and increases to 3.3% in NF. These differences feed back into the magnitudes of inflation premia. In AO, the average premium increases from 0.2% to 2.2%, while in the NF the average premium is negative and declines from -0.1% to -0.3%.

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24 This number is consistent with Buraschi and Jiltsov (2005) and is slightly higher than that reported by Ang, Bekaert, and Wei (2008).

Thus, using two versions of one and the same model, we were able to replicate the varying signs of inflation premium that have been reported in the existing research. Hordahl and Tristani (2007) provide a thorough discussion of this issue. In particular, the existing calibrations of various general equilibrium models imply a positive inflation premium. On the empirical side, the sign of the inflation premium depends on how inflation expectations are measured in a particular implementation. The AO model produces more accurate expectations and positive inflation premia. Thus, it is natural to conclude that the estimates of the real rates are more reasonable in AO as well.

Figure 1.6 displays the time series of the breakdown of nominal yields via the Fisher equation. We see that the 10-year inflation premium varies between -5% and 10% in NF. This appears to be excessive, particularly because expected inflation is stable around 5% in this model. Further, during the so-called disinflation period of the 1980s and 1990s, one would expect the absolute value of the inflation premium to decline, regardless of its sign. This conjecture is consistent with AO, but not with NF.

The last observation is precisely what we were looking for when gauging the anchoring of expectations. The more reasonable AO model implies that the 10-year inflation premium was gradually falling after the monetary experiment and was hovering between zero and 2.5 per cent after 1990. This is precisely what we would expect to see if inflation were stabilized.

Stability

To address the issue of the stability of inflation, we can study the evolution of the long-run inflation expectations (monetary policy is stable if inflation expectations are low and do not change) and the persistence of inflation (the long-run expectations about inflation are influenced by current transient shocks if inflation is persistent). We conduct an out-of-sample analysis to measure these quantities.
The out-of-sample framework offers two advantages. First, the Gaussian model that we use to describe the evolution of state variables implies a constant long-run mean and a constant persistence of these variables. This is an undesirable feature if one wants to evaluate how long-run inflation expectations or the responses of these expectations to shocks have changed over time.\textsuperscript{26} Second, the out-of-sample approach brings us closer to the adaptive expectations framework that has been used to evaluate optimal monetary policy (e.g., Evans and Honkapohja (2003), or Preston (2006)). Indeed, if our model is reestimated for each period, it can be interpreted as a reduced-form representation of the optimal monetary policy with adaptive expectations. This view can be rationalized within the anticipated utility framework of Kreps (1998). This approach essentially allows decision makers to update parameter values as new data arrive and to simultaneously make decisions as if current parameter values remain unchanged.\textsuperscript{27}

We implement the out-of-sample analysis by reestimating our model every quarter as new information arrives. This allows us to construct “online” expectations of inflation. We take a pre-disinflation period (1970 to 1982) as a burn-in sample to obtain the initial parameter estimates. There are at least two reasons to do so. First, it would be difficult, if not impossible, to estimate our relatively large model using too few data points. Taking roughly a third of the observations to obtain the initial values seems reasonable. Second, most of our surveys do not have observations during this period, so it would be difficult to evaluate the role of the forecasts.

Changing Parameters

We provide the time-series of some of the estimated parameters in Figure 1.6. We focus on the parameters that are related to inflation and real activity, because the

\textsuperscript{26} Kozicki and Tinsley (2006) offer an alternative approach for incorporating the time-varying long-run mean of inflation.

\textsuperscript{27} Cogley and Sargent (2006) discuss the connection between anticipated utility, rational expectations, and Bayesian decision-making.
parameters that pertain to the latent factors are more difficult to interpret. Indeed, the latent factors will change every period, not only because of the time variation in the state of the economy, but also because of changes in the values of parameters.\textsuperscript{28} On each plot, the last point corresponding to the fourth quarter of 2004 shows the estimated parameter values for the full sample.

Panel (a) reports the loadings on inflation (dashed lines) and real activity (solid lines), that is, parameters $\delta_m$ in the spot interest rate equation (1.3.6). Inflation loadings are similar across the two models. They gradually decline from 0.4 to 0.2. The real activity loadings are similar for the two models until 1990, when the loading in AO jumps from -0.2 to 0.2. The 10-year forecasts were introduced to the surveys after this date, which, we believe, affects the estimated values of the real activity loading.

The situation is the opposite for the long-run mean reported in panel (b). Now, the value of parameters controlling the real activity do not change much from one model to another. The long-run inflation declines from 6.6% to 2.3% in AO, while it does not change as dramatically in NF and declines only to 4.6%. This plot suggests that inflation has stabilized over time because, according to AO, its long-run expectations fell dramatically in the post-monetary-experiment period and were moving around 2-2.5% from the mid-1990s.

It is difficult to attribute persistence to a particular factor because the matrix $\Phi$ in (1.3.2) has off-diagonal elements. Instead, we report in panel (c) the most and the least persistent factors as measured by the eigenvalues of $\Phi$. Here again, the source of instability is associated with 1990. The least persistent component (dashed lines) was similar across the two models before the introduction of long-term forecasts, and became different after that. While in AO, it continued to be close to zero, in NF it has gradually increased in persistence. The most persistent component (solid lines) was similar across the two models throughout the full sample. Thus, relative to the

\textsuperscript{28} Collin-Dufresne, Goldstein, and Jones (2006) provide a detailed analysis of this phenomenon.
information in yields only, the surveys suggest the presence of a transient factor in the inflation dynamics, which helps to pull long-run expectations back on track after a shock.

The standard deviation of real activity (solid lines) in panel (d) is similar across the models and stable over time. The standard deviation of inflation (dashed lines) is higher in AO. It increases in both models until the early 1990s and then declines to approximately four per cent by the end of the sample. This evidence is again consistent with more stable inflation in recent history.

Changing Impulse Responses

We can also gauge the impact of the changing persistence of inflation on the anchoring of expectations via impulse responses. Our model allows the construction of impulse responses of expected inflation to shocks in inflation. As we add more data, estimated persistence of inflation! will change and so will the response of the long-run expected inflation. Monitoring these changes over time allows us to acquire a different perspective on the perceived stability of inflation.

We use the recursive identification scheme to compute the impulse responses. The order of the state variables is the same as in the original model specification. Figure 1.6 reports responses of the 10-year expected inflation to a one-basis-point inflation shock for four representative dates in our sample: 1987:1, 1989:2, 2000:1, and 2004:4.

The common characteristic of all responses is that expected inflation declines after the initial spike. The critical difference between the early and late periods is whether the effect of the shock is eliminated completely. In the early years, the initial response of 0.20 - 0.35 basis points quickly drops to the level of 0.05 - 0.10 basis points, but then it lingers at this level for at least three years. In the later part of the sample, the initial response dissipates almost completely in two quarters. We interpret these impulse responses as evidence that inflation became less persistent and better anchored.
Conditional Inflation Expectation

We complement the inflation that are presented in Figure 1.6(b) by revisiting the inflation expectations that are presented in Figure 1.6. However, because we want to see how long-run expectations are affected by new data, it is more appropriate to study out-of-sample expectations. Figure 1.6 presents such out-of-sample expectations for AO and NF and benchmarks them against the realized inflation and TIPS-implied expectations. Because of our focus on the stability of long-run expectations, we replace one-year forecasts in Figure 1.6 by five-year forecasts.

In contrast to in-sample estimation, we see that the NF 10-year forecasts decline over time from 6-7% to 3.5-4% at the end of the sample. However, the NF expectations are quite variable. Thus, yields-based estimation would lead one to conclude that inflation expectations are not anchored.

The AO-based expectations are much more stable, even at the five-year horizon. These expectations decline to a more intuitive level of 2%. The example of the five-year forecasts also shows that, beginning from 1999, the level of realized inflation matches up with expectations quite well. The 10-year realized inflation is not yet available for the most recent period. The out-of-sample expectations continue to agree well with TIPS-based expectations.

Changing Term Structure of Expectations

Figure 1.6 provides additional evidence regarding monetary policy by displaying the average term structure of expectations. The out-of-sample period is split into four five-year subsamples. We compute the time series of the expectations using out-of-sample parameter values, as in Figure 1.6, and then average them across the subsamples. This exercise provides a summary of how the expectations curve evolves over time.

The shape of the NF curve is normal first, then flattens out, and then becomes normal again in the last subsample. The normal shape of the curve suggests that
the monetary policy is less effective in handling inflation as it bounces around its long-run mean. AO paints a different picture of the monetary policy. The average curve becomes flatter over time, with declines in both the short and long ends of the curve. This phenomenon could be interpreted as evidence that monetary policy is effective.

1.5.4 The Implication of Stable Expectations

Inflation Forecasting

Table 1.6A shows the out-of-sample results for the forecasting of inflation. Ang, Bekaert, and Wei (2007) find that raw surveys dominate term-structure models for forecasts about inflation that are made one year in advance. Our results should complement their findings along two dimensions. First, we provide evidence for a term structure of inflation forecasts. Second, we evaluate the performance of term-structure models that are estimated using information from the surveys.

The reported RMSE ratios send a clear message. First, AO significantly dominates NF in different subsamples and across the entire range of forecasting horizons. The improvement ranges from 25% to 65%, depending on the sample and horizon. Second, AO performs on par with raw surveys. It does much better than MCS, but this is to be expected, given our earlier discussions. For almost all other surveys, the ratio of AO to surveys is greater than one, but the difference is statistically insignificant and it is so mild that it is difficult to imagine that it would matter economically. The 10-year forecasts from LS and SPF stand out, because both ratios are equal to 1.3. However, we have only 9 and 13 observations of these forecasts, respectively, so these ratios are hardly reliable.

The fact that there is essentially no difference between raw surveys and a complicated AO model may be disappointing to some readers. It is important to remember that a big limitation of raw surveys is that an end-user cannot select the frequency of forecasts and the forecast horizon. We have presented and defended a model that can
produce survey-quality forecasts, but at any time and at any horizon. An example of this is provided in Table 1.6B. Given that Ang, Bekaert, and Wei (2007), after searching through a list of 30 various models, could not find any such model even for one forecasting horizon, our achievement appears to be important.

**Yield Forecasting**

Table 1.6 displays out-of-sample results for the forecasting of yields. We use the random walk model (RW) as a reference and report all the results in the form of RMSE ratios of a model (AO or NF) to RW. To the best of our knowledge, this is the first analysis on such a scale. Typically, authors leave about five years for out-of-sample exercises. The parameters for out-of-sample analysis are either estimated from an earlier long sub-sample, or reestimated each period over the short subsample. The range of forecasting horizons is typically narrow, from the next period to one year ahead. Finally, statistical inference is not provided, that is, numerical values of RMSE are simply compared to each other.

Using point values of RMSE ratios as a basis, we see that in our first sample, which ranges from 1983 to 2004, RW dominates both models and AO, overall, fares better than NF. The exceptions are most forecasts that are made one-quarter ahead. However, the statistical uncertainty is so great that it is difficult to distinguish AO from NF. Moreover, AO cannot be distinguished from RW at longer forecasting horizons or for yields that have maturities of three years or more.

We noted earlier that AO can exploit the full benefit of the surveys only after 1990, when long-term forecasts began to appear in surveys. For this reason, our second sample ranges from 1990 to 2004. AO still underperforms NF for most short-term forecasts. However, it frequently beats RW. We still cannot distinguish AO from RW once statistical uncertainty is taken into account.

29 Our conjecture for the AO underperformance at short forecasting horizons is that NF fits yields better than AO (Table 1.6). The near-term forecasts should be similar to the current yields, so worse fit translates into more poor forecasting performance.
We conclude that incorporating forecasts about inflation helps when forecasting yields. However there remains room for improvement, because the results for forecasts of yields are not as clear as for those for forecasts of inflation. The analysis in this paper suggests that survey forecasts are very useful, so incorporating the forecasts of real activity or yields should help when forecasting yields and can reduce the statistical uncertainty.

1.6 Conclusion

We have built a dynamic macro-finance model that incorporates jointly the behaviour of inflation, real activity, nominal yields, and survey-based forecasts of inflation. The model prohibits arbitrage opportunities and allows for the heterogeneity of survey forecasters via a subjective probability measure. We find that the observed yields and survey forecasts are internally consistent with each other, at least in the context of our model. Moreover, both yields and forecasts are important for producing realistic expectations about future inflation and yields.

Using our model, we find evidence of systematic biases in survey forecasts. They overpredict inflation the most, and disagree the least, at the end of recessions. However, this does not imply that surveys are useless for forecasting. A model that restricts survey expectations so that they coincide with the expectations of the private sector and still uses information from surveys produces the most realistic inflation forecasts as judged by in- and out-of-sample RMSE, and by implied real yields and inflation premia.

The out-of-sample analysis of the model suggests that monetary policy became more effective over time. The long-run expectations are anchored at about 2%. The term structure of inflation expectations has flattened out over time. This suggests that the arrival of new data does not affect long-run expectations much, perhaps because the monetary policy is expected to address all short-term fluctuations successfully.
Table 1.1: Mean Absolute Errors

We report mean absolute fitting errors for four versions of our model. The full model that uses the survey and yield data is labeled as AS (All data, Subjective expectations). A model that uses all the data, but restricts subjective measures to coincide with objective measure is labeled as AO (All data, Objective expectations). A model that uses only yields for estimation is referred to as NF (No Forecasts). In this implementation the subjective measures cannot be estimated because they are not identified. Finally, we estimate a model that uses only forecasts and label it as OF (Only Forecasts). The notation for surveys is as follows: MCS - Michigan consumer survey; LS - Livingston survey; SPF - survey of professional forecasters; BCEI - Blue Chip economic indicators.

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We compare the in-sample inflation forecasting performance of the AO and NF models. We arbitrarily select forecasting horizons that are not necessarily available in the actual surveys. This is done to emphasize that the advantage of using a model is that a forecasting horizon or forecasting date can be arbitrary. We report RMSE ratio of AO to NF. In addition to the full sample, The RMSE ratios are reported for two sub-samples. The first sub-sample (from 1970 to 1982) represents the period when survey forecasts were rarely available. The second sub-sample (from 1983 to 2004) represents the full collection of the surveys. The bootstrapped 95% confidence bounds are provided in brackets.

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<td>1.22</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>[0.98, 1.12]</td>
<td>[1.10, 1.35]</td>
<td>[0.61, 0.78]</td>
</tr>
<tr>
<td>8</td>
<td>0.98</td>
<td>1.10</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>[0.86, 1.12]</td>
<td>[0.89, 1.36]</td>
<td>[0.51, 0.81]</td>
</tr>
<tr>
<td>12</td>
<td>0.94</td>
<td>1.05</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>[0.78, 1.15]</td>
<td>[0.78, 1.44]</td>
<td>[0.44, 0.87]</td>
</tr>
<tr>
<td>20</td>
<td>0.93</td>
<td>1.05</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>[0.65, 1.30]</td>
<td>[0.62, 1.70]</td>
<td>[0.24, 1.07]</td>
</tr>
<tr>
<td>28</td>
<td>0.98</td>
<td>1.14</td>
<td>0.56</td>
</tr>
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<td></td>
<td>[0.57, 1.55]</td>
<td>[0.54, 2.14]</td>
<td>[0.07, 1.39]</td>
</tr>
<tr>
<td>40</td>
<td>1.07</td>
<td>1.26</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>[0.40, 2.11]</td>
<td>[0.35, 2.75]</td>
<td>[0.01, 1.96]</td>
</tr>
</tbody>
</table>
Table 1.3: Simplified Filters

We summarize which data can nearly replicate the full filter of latent variables $x$. The results are reported for two versions of our model. In the case of AO, the estimation was conducted using all the data, that is, macro variables, $m_t$, yields, $y_t(\tau)$, and survey forecasts $\bar{p}_t(s,t)$. Therefore, the full filter was computed using all these data. In the case of NF, only $m_t$ and $y_t(\tau)$ were used. The table reports, which data are instrumental in constructing the filter as evidenced by the correlation of the simplified filter with the full filter (last column, labeled “corr”). The numbers in the $y_t(\tau)$ column refer to yields' maturity $\tau$ in quarters. The notation in the $\bar{p}_t(s,t)$ column refers to a particular survey (LS for Livingston, SPF for Survey of Professional Forecasters) and starting quarter and forecasting horizon (in quarters).

<table>
<thead>
<tr>
<th>Model</th>
<th>Factor</th>
<th>$m_t$</th>
<th>$y_t(\tau)$</th>
<th>$\bar{p}_t(s,t)$</th>
<th>corr</th>
</tr>
</thead>
<tbody>
<tr>
<td>AO</td>
<td>$x_1$</td>
<td>$g, \pi$</td>
<td>-</td>
<td>LS(0,4), SPF(0,4)</td>
<td>0.99</td>
</tr>
<tr>
<td>AO</td>
<td>$x_2$</td>
<td>1, 40</td>
<td>-</td>
<td>LS(0,4), SPF(0,4)</td>
<td>0.98</td>
</tr>
<tr>
<td>NF</td>
<td>$x_1$</td>
<td>$g$</td>
<td>1, 40</td>
<td>-</td>
<td>0.99</td>
</tr>
<tr>
<td>NF</td>
<td>$x_2$</td>
<td>$\pi$</td>
<td>1, 40</td>
<td>-</td>
<td>0.98</td>
</tr>
</tbody>
</table>
Table 1.4: Theoretical $R^2$ for Expected Inflation and Yields

We establish which fraction of the expectations, or yield curve variation is explained by various factors. Specifically, we distinguish $M$, the entire history of inflation and real activity, and $f$, the projection residual factors. Because the residual factors are orthogonal with respect to each other, we can further distinguish their individual contributions. The bootstrapped 95% confidence bounds are provided in brackets.

### Panel A. Expectations

<table>
<thead>
<tr>
<th>Horizon (qtr)</th>
<th>$M$</th>
<th>$f_1$</th>
<th>$f_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AO</td>
<td>NF</td>
<td>AO</td>
</tr>
<tr>
<td>1</td>
<td>0.93</td>
<td>0.95</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>[0.63, 0.95]</td>
<td>[0.05, 0.36]</td>
<td>[0.02, 0.11]</td>
</tr>
<tr>
<td>8</td>
<td>0.89</td>
<td>0.85</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>[0.44, 0.93]</td>
<td>[0.06, 0.56]</td>
<td>[0.05, 0.29]</td>
</tr>
<tr>
<td>40</td>
<td>0.88</td>
<td>0.83</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>[0.38, 0.93]</td>
<td>[0.06, 0.58]</td>
<td>[0.01, 0.32]</td>
</tr>
</tbody>
</table>

### Panel B. Yields

<table>
<thead>
<tr>
<th>Horizon (qtr)</th>
<th>$M$</th>
<th>$f_1$</th>
<th>$f_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AO</td>
<td>NF</td>
<td>AO</td>
</tr>
<tr>
<td>1</td>
<td>0.50</td>
<td>0.54</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>[0.14, 0.86]</td>
<td>[0.06, 0.43]</td>
<td>[0.11, 0.57]</td>
</tr>
<tr>
<td>8</td>
<td>0.41</td>
<td>0.52</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>[0.06, 0.84]</td>
<td>[0.06, 0.43]</td>
<td>[0.03, 0.50]</td>
</tr>
<tr>
<td>40</td>
<td>0.39</td>
<td>0.50</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>[0.02, 0.84]</td>
<td>[0.07, 0.47]</td>
<td>[0.01, 0.34]</td>
</tr>
</tbody>
</table>
We report the annualized mean and standard deviation of the nominal yield components in the decomposition

\[ y_t(\tau) = y_t^R(\tau) + \bar{p}_{t,0}(\tau) + IP_t(\tau), \]

where \( y_t^R(\tau) \) is the real yield, \( \bar{p}_{t,0}(\tau) \) is the inflation expectation under the \( \mathbb{F} \) measure, and \( IP_t(\tau) \) is the inflation premium.

\[ \begin{array}{cccc}
\text{Model} & \tau & y_t^R(\tau) & \bar{p}_{t,0}(\tau) & IP_t(\tau) \\
\hline
\text{AO} & 4 & \text{Mean} & 2.00 & 4.39 & 0.19 \\
 & & \text{Std. dev.} & 1.44 & 0.86 & 1.14 \\
 & 40 & \text{Mean} & 1.19 & 4.27 & 2.16 \\
 & & \text{Std. dev.} & 0.20 & 0.60 & 1.28 \\
\text{NF} & 4 & \text{Mean} & 2.05 & 4.64 & -0.07 \\
 & & \text{Std. dev.} & 3.60 & 2.06 & 2.12 \\
 & 40 & \text{Mean} & 3.29 & 4.63 & -0.31 \\
 & & \text{Std. dev.} & 1.20 & 0.44 & 2.06 \\
\end{array} \]
We compare the out-of-sample inflation forecasting performance of the AO and NF models and the observed survey forecasts. Panel A compares the models to the actual surveys by reporting RMSE ratio of a model to a survey. The notation for surveys is as follows: MCS - Michigan consumer survey; LS - Livingston survey; SPF - survey of professional forecasters; BCEI - Blue Chip economic indicators. In panel B we select alternative forecasting horizons. We report RMSE ratio of AO to NF as the surveys are not available for most of the selected horizons. Actual survey forecasts have missing observations. Therefore, the RMSE ratios will be different for the panel B forecasts even if a horizon matches the one from a survey in panel A. The RMSE ratios are reported for two samples. The first sample represents the full out-of-sample period from 1983 to 2004. The second sample begins in 1990 after the long-run forecasts were incorporated into the surveys. The bootstrapped 95% confidence bounds are provided in brackets.

### Panel A. Survey-selected horizons.

<table>
<thead>
<tr>
<th>Survey</th>
<th>Horizon, qtr</th>
<th>1983-2004</th>
<th>1990-2004</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>s</td>
<td>AO/Survey</td>
<td>NF/Survey</td>
</tr>
<tr>
<td>MCS</td>
<td>0</td>
<td>4</td>
<td>0.78 [0.60, 0.96]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>4</td>
<td>1.06 [0.80, 1.32]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>8</td>
<td>1.07 [0.51, 1.74]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>40</td>
<td>1.32 [0.68, 2.38]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4</td>
<td>1.05 [0.78, 1.34]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>4</td>
<td>1.13 [0.83, 1.46]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>0.95 [0.87, 1.25]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>4</td>
<td>1.10 [0.86, 1.38]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>40</td>
<td>1.34 [0.59, 2.59]</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
<td>1.05 [0.87, 1.25]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1</td>
<td>1.05 [0.87, 1.24]</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1</td>
<td>1.06 [0.89, 1.26]</td>
</tr>
<tr>
<td>SPF</td>
<td>0</td>
<td>1</td>
<td>1.07 [0.89, 1.28]</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
<td>1.04 [0.86, 1.23]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1</td>
<td>0.96 [0.80, 1.14]</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1</td>
<td>1.06 [0.88, 1.25]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1</td>
<td>1.08 [0.89, 1.29]</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1</td>
<td>1.06 [0.79, 1.33]</td>
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<td>1.10 [0.68, 1.55]</td>
</tr>
<tr>
<td>BCEI</td>
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<td>1.07 [0.89, 1.28]</td>
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<td>1</td>
<td>1</td>
<td>1.04 [0.86, 1.23]</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1</td>
<td>0.96 [0.80, 1.14]</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1</td>
<td>1.06 [0.88, 1.25]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1</td>
<td>1.08 [0.89, 1.29]</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1</td>
<td>1.06 [0.79, 1.33]</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>1</td>
<td>1.10 [0.68, 1.55]</td>
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</table>

### Panel B. Arbitrary horizons.

<table>
<thead>
<tr>
<th>Survey</th>
<th>Horizon, qtr</th>
<th>1983-2004</th>
<th>1990-2004</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>s</td>
<td>AO/NF</td>
<td>AO/NF</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.73 [0.71, 0.77]</td>
<td>0.73 [0.69, 0.77]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.61 [0.57, 0.67]</td>
<td>0.57 [0.51, 0.63]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.51 [0.43, 0.60]</td>
<td>0.45 [0.35, 0.55]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.46 [0.33, 0.63]</td>
<td>0.38 [0.21, 0.58]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.47 [0.29, 0.72]</td>
<td>0.37 [0.14, 0.65]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.47 [0.15, 0.97]</td>
<td>0.38 [0.01, 0.93]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.51 [0.02, 1.34]</td>
<td>0.44 [0.01, 1.50]</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.62 [0.01, 1.95]</td>
<td>0.55 [0.01, 2.27]</td>
</tr>
</tbody>
</table>
We compare the out-of-sample yield forecasting performance of the AO, NF and RW (random walk) models. We report RMSE ratio of a no-arbitrage model (AO or NF) to RW. The RMSE ratios are reported for two samples. The first sample represents the full out-of-sample period from 1983 to 2004. The second sample begins in 1990 after the long-run forecasts were incorporated into the surveys. The bootstrapped 95% confidence bounds are provided in brackets.

<table>
<thead>
<tr>
<th>Yield Maturities</th>
<th>Forecast Horizons</th>
<th>1983-2004</th>
<th>1990-2004</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AO/RW</td>
<td>NF/RW</td>
</tr>
<tr>
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<td>1.45 [1.38, 1.52]</td>
<td>1.18 [1.13, 1.22]</td>
</tr>
<tr>
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<td>4</td>
<td>1.29 [1.25, 1.48]</td>
<td>1.75 [1.29, 3.38]</td>
</tr>
<tr>
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<td>8</td>
<td>1.17 [0.95, 1.45]</td>
<td>1.53 [0.99, 3.29]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.35 [1.04, 1.88]</td>
<td>1.30 [0.66, 2.78]</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1.34 [1.27, 1.41]</td>
<td>1.27 [1.22, 1.31]</td>
</tr>
<tr>
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<td>4</td>
<td>1.27 [1.13, 1.45]</td>
<td>1.73 [1.30, 3.01]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.15 [0.93, 1.44]</td>
<td>1.52 [1.00, 2.90]</td>
</tr>
<tr>
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<td>1.30 [0.98, 1.90]</td>
<td>1.30 [0.66, 2.65]</td>
</tr>
<tr>
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<td>1</td>
<td>1.26 [1.19, 1.33]</td>
<td>1.21 [1.15, 1.24]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.24 [1.09, 1.44]</td>
<td>1.66 [1.22, 2.76]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.12 [0.90, 1.42]</td>
<td>1.49 [0.95, 2.51]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.24 [0.91, 1.87]</td>
<td>1.26 [0.59, 2.61]</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>1.10 [1.03, 1.16]</td>
<td>1.12 [1.06, 1.16]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.17 [1.01, 1.39]</td>
<td>1.60 [1.07, 2.52]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.09 [0.85, 1.45]</td>
<td>1.51 [0.88, 2.53]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.23 [0.88, 1.91]</td>
<td>1.26 [0.48, 2.59]</td>
</tr>
<tr>
<td>12</td>
<td>1</td>
<td>1.02 [0.95, 3.08]</td>
<td>1.04 [0.99, 3.08]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.12 [0.96, 1.37]</td>
<td>1.56 [0.92, 2.47]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.08 [0.83, 1.45]</td>
<td>1.54 [0.79, 2.63]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.26 [0.90, 2.02]</td>
<td>1.30 [0.43, 2.71]</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>1.05 [0.98, 1.11]</td>
<td>1.04 [0.99, 1.08]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.10 [0.93, 1.37]</td>
<td>1.55 [0.71, 2.64]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.07 [0.82, 1.48]</td>
<td>1.59 [0.66, 2.88]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.31 [0.93, 2.10]</td>
<td>1.35 [0.36, 2.83]</td>
</tr>
<tr>
<td>28</td>
<td>1</td>
<td>1.11 [1.05, 1.18]</td>
<td>1.05 [1.00, 1.09]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.09 [0.92, 1.35]</td>
<td>1.51 [0.55, 2.76]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.06 [0.81, 1.50]</td>
<td>1.58 [0.53, 3.04]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.36 [0.99, 2.19]</td>
<td>1.42 [0.37, 2.99]</td>
</tr>
<tr>
<td>40</td>
<td>1</td>
<td>1.19 [1.12, 1.26]</td>
<td>1.10 [1.04, 1.14]</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.10 [0.93, 1.36]</td>
<td>1.51 [0.47, 2.94]</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1.09 [0.84, 1.55]</td>
<td>1.63 [0.52, 3.12]</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>1.40 [1.02, 2.21]</td>
<td>1.42 [0.34, 3.08]</td>
</tr>
</tbody>
</table>
Figure 1.1: The Term Structure of Survey Forecasts

We plot the survey inflation forecasts that we use as inputs in our model. Our sample period is 1970 to 2004 at a quarterly frequency. Some forecasts do not start until a later date. Some are reported at a frequency lower than quarterly. The forecast horizon is indicated in the legend in quarters. The second number in brackets indicates the forecast horizon. The first number indicates when the forecast horizon starts. LS(2,4) for example denotes a one-year Livingston forecast starting two quarters from today.
Figure 1.2: Term Bias

The figure shows unconditional and conditional deviations of survey forecasts from the optimal P-forecasts. The conditional bias is compared with business cycles (shaded areas) and demeaned inflation (thick black line). The solid dark line in the right column of panels shows a measure of the survey disagreement. The shaded regions show the NBER recessions.
Figure 1.3: Inflation Expectations

The figure shows realized inflation and optimal inflation forecasts computed from three different versions of our model. The shaded regions show the NBER recessions.
Figure 1.4: The Term Structure of Inflation Expectations

The figure displays the marginal inflation expectations computed from the AO model. The shaded regions show the NBER recessions.
Figure 1.5: Factor Loadings for Inflation Expectations

We plot factor loadings that are used to compute inflation expectations and multiple horizons (0 to 40 quarters).
Figure 1.6: Expectations and Yields Decomposition

The figure shows the time series of the one-quarter and ten-year inflation expectations (top panels) and yields (bottom panels) decomposed into the contributions of output, $g$, and its history, inflation $\pi$, and its history, the "survey" residual factor $f_1$ and the residual factor $f_2$. The shaded regions show the NBER recessions. The decompositions are reported for AO only.
Figure 1.7: The Fisher Equation

The figure plots the time-series of the nominal yield components in the decomposition

\[ y_t(\tau) = y^R_t(\tau) + \bar{p}_{t,0}(\tau) + IP_t(\tau), \]

where \( y^R_t(\tau) \) is the real yield, \( \bar{p}_{t,0}(\tau) \) is the inflation expectation under the \( \mathbb{P} \) measure, and \( IP_t(\tau) \) is the inflation premium. The shaded regions show the NBER recessions.
Figure 1.8: Out-of-Sample Parameters

The figure plots the time-series of the parameters of the AO and NF models that were reestimated every quarter beginning from 1983. We mostly display parameters pertaining to inflation (dashed lines in panels (a), (b) and (d)) and real activity (solid lines in panels (a), (b) and (d)) because the latent ones are difficult to interpret. Panel (c) provides the highest (solid line) and the lowest (dashed line) eigenvalues of the matrix $\Phi$ (see (1.3.2)) to gauge the persistence of the factors.
Figure 1.9: Out-of-Sample Impulse Responses

The figure plots responses of 10-year expected inflation to one basis point shocks in inflation. The responses are computed from AO using parameters estimated using data available at four different dates.
Figure 1.10: Out-of-Sample Inflation Expectations

The figure shows realized inflation and out-of-sample inflation forecasts computed from AO and NF models. The shaded regions show the NBER recessions.
Figure 1.11: Out-of-Sample Average Term Structure of Inflation Expectations

The figure displays average term structure of inflation expectations, as implied by AO and NF based on the out-of-sample parameter values.
Chapter 2

Credit Spreads and Real Activity

2.1 Introduction

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

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

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

As a first step in my analysis, I use an OLS regression approach and examine the predictive power of credit spreads for the whole term structure and rating categories ranging from AAA to B by regressing future GDP growth on the spreads and control variables. I find that credit spreads across the whole spectrum of rating classes and across the whole term structure have predictive content above and beyond that contained in the term structure of Treasury yields and the history of GDP growth and inflation.

However, not every factor that affects credit spreads needs to be related to future GDP growth. Credit spreads could be related to GDP either through expectations of future rates, term premia, or one factor that is related to both.\(^2\) The OLS approach is not suited for establishing the differences between the various potential drivers

\(^2\) Credit spread term premia are defined as the difference between the credit spreads calculated under the risk neutral measure and the credit spreads calculated assuming zero prices of risk.
of the spreads. Understanding the difference between determinants of credit spreads and the drivers of the predictability helps learning about the transmission mechanism from borrowing conditions to real output.

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

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

I find that one common "credit" factor is responsible for the incremental predictive power of credit spreads above the information contained in the history of inflation

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

\(^4\) Using only Treasury yields, Ang, Piazzesi, and Wei (2006) demonstrate that a macro-finance term structure model leads to more efficient and accurate forecasts compared to those obtained by the standard approach using unrestricted OLS regressions. The term structure forecasts also outperform a number of alternative predictors. Methodologically, my paper is, to the best of my knowledge, the first to examine the predictive content of the term structure of credit spreads in a no-arbitrage framework.
and GDP growth. Moreover, credit spreads across the whole term structure and for all rating classes react strongly to movements in this factor, whereas Treasury yields are largely unaffected. Finally, the credit factor is strongly correlated with the index of tighter loan standards from the Federal Reserve’s quarterly “Senior Loan Officer Opinion Survey” and as such can be interpreted as a proxy for credit conditions.

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

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

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

The paper is organized as follows. Section 2.2 reviews the relevant literature in regards to the theoretical underpinnings why Treasury yields or credit spreads should be useful predictors of real activity. Section 2.3 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 2.4 and the estimation methodology is discussed in section 2.5. Section 2.6 presents the estimation results and identifies the sources of the predictive power and section 2.7 concludes. The appendix contains a detailed description of the data used in the paper, additional regression results and robustness checks, and technical details.

2.2 The External Finance Premium and Real Activity

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

2.2.1 The Financial Accelerator Mechanism

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

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

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

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

2.2.2 Proxies for the External Finance Premium and Forecasting Real Activity

The external finance premium is not directly observable. Moreover, the short review in section 2.2.1 indicates that the external finance premium can be affected by a variety of shocks. Empirically, risk-free interest rates and credit spreads may react differently to those shocks. For example, an increase in the external finance premium due to expectations of higher default rates should mainly be reflected in widening credit spreads, not rising risk-free rates. On the other hand, a higher external finance premium due to a positive monetary policy shock is reflected in a higher short-term interest, and not in credit spreads.\(^5\)

Because fluctuations in the external finance premium can be reflected in either risk-free interest 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.\(^5\) Historically, the term spread has been a widely used and reliable predictor of economic activity, but its forecasting power has been declining since the mid-1980s.\(^7\) However, this does not mean that the relationship between interest rates and real activity has disappeared but simply, that it is no longer detectable in the data. In fact, if the Federal Reserve reacts

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

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

\(^7\) See, for example, Dotsey (1998).
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 (2000) and Mody and Taylor (2004) argue that the right measure is a long-term high yield spread and they show that it outperforms other leading indicators—including the term spread—since the data has become available in the mid-1980s.\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. 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. Consequently, even though the model allows identifying latent factors that are unrelated to observed macro variables it is not possible to pinpoint exactly what the actual causal relationships are between the state variables in the model. However, as mentioned in section 2.2.1, 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.

2.3 Forecasting Regressions

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

\(^{10}\) Some robustness checks using an extended sample period are performed in appendix G.
2.3.1 Data and Methodology

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

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

Using this notation, $g_{t,1} = g_{t+1}$. Furthermore, denote the credit spread for a rating class $i$ and maturity $\tau$ as $CS_i^j(\tau) = y_i^j(\tau) - y_i^T(\tau)$, where $y_i^j(\tau)$ and $y_i^T(\tau)$ are the corporate and Treasury yields, respectively. The Treasury yields used are unsmoothed Fama-Bliss zero coupon bond prices for maturities ranging from three months up to ten years.\textsuperscript{11} Zero coupon corporate bond yields for the same maturities and rating classes AAA, BBB and B are taken from Bloomberg. Credit spreads are calculated as the difference between the corporate and the Treasury yields. GDP data are available through the FRED database (Federal Reserve Bank of St. Louis). A detailed description of the data is provided in appendix E.

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

$$g_{t,k} = \alpha_k^j(\tau) + \beta_k^j(\tau)CS_i^j(\tau) + controls + u_{t+k}. \quad (2.3.2)$$

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

Since GDP growth is serially correlated, its own past values are themselves useful predictors. This means, the $controls$ in the regression equation (2.3.2) should include

\textsuperscript{11} I thank Rob Bliss for providing me with the Treasury yield data.
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.\textsuperscript{12} To answer the question whether the term structures of credit spreads contain relevant information that is not already included in the history of GDP growth and inflation itself, current and lagged values of inflation, $\pi$, should also be added as control variables.\textsuperscript{13}

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

In addition to running the regression (2.3.2), I also run the following regression:

\begin{equation}
g_{t,k} = \alpha_k + \delta_k(L)g_t + \eta_k(L)\pi_t + u_{t+k},
\end{equation}

where $\delta(L)$ and $\eta(L)$ denote lag polynomials such that $\delta(L) = \delta^{(1)}g_t + \delta^{(2)}g_{t-1} + \ldots + \delta^{(p)}g_{t-p+1}$ and $p$ is the number of lagged values of GDP growth included ($g_t$ is a lagged value relative to the forecasted variable). Unless otherwise noted, regression (2.3.2) with controls and regression (2.3.3) are performed with $p = 2$, which means current and lagged GDP growth and inflation are included.

### 2.3.2 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

\textsuperscript{12} See, for example, Fischer (1993), or Bruno and Easterly (1998).

\textsuperscript{13} Inflation is calculated as the growth rate in CPI, available through the FRED database (Federal Reserve Bank of St. Louis).
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 $R^2$s; (3) combining spreads of different maturities and rating classes in a single regression helps improving adjusted $R^2$s suggesting that the forecasting power may be driven by more than a single factor.

Univariate Regressions

Table 2.7, panel A contains the results for the $\beta^j_k(\tau)$ coefficients in the simple univariate credit spread regression without controls for the sample period 1992:2–2005:4. Apart from short-term AAA spreads, almost all $\beta^j_k(\tau)$ coefficients are significantly different from zero. Panel B in Table 2.7 displays the same $\beta^j_k(\tau)$ coefficients for the credit spread regressions including control variables. All coefficients that are significant in the univariate regressions are also significant in the full multivariate regressions with all the controls. Current and lagged GDP values are insignificant in general, whereas coefficients for current and lagged inflation are significantly negative for forecast horizons one year and above, confirming the documented negative relationship between inflation and real activity. The coefficient for the term spread is insignificant in general. The addition of the history of macro variables has a positive effect on both, $R^2$s and adjusted $R^2$s, thus suggesting that macro variables are indeed relevant for explaining future GDP growth.

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. 1-year AAA spreads for example are not significant, and $R^2$s for 10-year

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

15 Adding more lags of the macro variables does not qualitatively change the results for the credit spread coefficients, i.e. the significant coefficients remain significant; however, adjusted $R^2$s do not improve further.
BBB spreads are much higher than those for 1-year spreads. The only exceptions to this regularity are horizons below one year for forecasting regressions using B spreads. At the same time, the results for B spreads are very robust to the choice of maturity—the discrepancy in terms of $R^2$s is very small.

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

Panel C in Table 2.7 summarizes the $R^2$s from the full regressions using all control variables. In addition, the table contains the $R^2$s from regressing future GDP growth on (1) the history of macro variables only (panel A) and (2) the history of macro variables and the short rate and various term spreads (panel B), respectively. This allows to assess the impact of adding variables to the regression with macro variables only. The results in panel B reveal that including either the short rate or various term spreads in regression (2.3.1) leaves $R^2$s basically unaffected (with the exception of short horizon forecasts using the 1-year spread). This lack of an effect is consistent with the demise of the term structure of Treasury yields as a predictor of real activity after the period of monetary tightening under Chairman Paul Volcker ended in the mid-1980s. The full regression results using Treasury yields documenting the declining predictive power of the short rate and the term spread are reported in appendix F.1.

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

**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 2.7, panels C (without controls) and D (including controls). Again, the controls do not drive the results.

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

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

Section 2.4 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.

2.4 A Macro-Finance Term Structure Model

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

Duffee (1999) and Driessen (2005) estimate a no-arbitrage term structure model with credit spreads but they do not include macro variables. Wu and Zhang (2005) is the first paper to examine the joint behavior of macro variables and credit spreads in a three-factor model with observable factors only. Amato and Luisi (2006) estimate a version that combines observable and latent factors but they do not allow for the

\textsuperscript{16} Results for this exercise are not reported.
latent variables to influence the macro factors. The model presented in this section is more general and specifically allows to investigate how shocks to latent factors can feed back into the real economy.

2.4.1 State Variables

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

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

$$z_t = \mu + \Phi z_{t-1} + \Sigma \epsilon_t,$$  \hspace{1cm} (2.4.4)

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

2.4.2 Treasury yields

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

$$r_t = \delta_0 + \delta'_z z_t = \delta_0 + \delta'_m m_t + \delta'_x x_t.$$  \hspace{1cm} (2.4.5)
In order to value the assets, the model needs to be completed by specifying the stochastic discount factor $\xi_t$:

$$\xi_t = -r_{t-1} - \frac{1}{2} \Lambda_{t-1}^\prime \Lambda_{t-1} - \Lambda_{t-1}^\prime \epsilon_t,$$

(2.4.6)

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

$$\Lambda_t = \Lambda_0 + \Lambda_z z_t.$$  

(2.4.7)

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

$$y_t^T(\tau) = a^Q(\tau) + b^Q(\tau)^\prime z_t$$

$$= a^Q(\tau) + b_m^Q(\tau)^\prime m_t + b_x^Q(\tau)^\prime x_t$$

(2.4.8)

$$\Delta$$

Short rate expectations

$$+ a^{TP}(\tau) + b^{TP}(\tau)^\prime z_t$$

(2.4.9)

Term premium

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 $b^Q(1) = \delta_z$.\textsuperscript{17} In particular, this means that $y_t^T(1) = r_t$; using quarterly data, the nominal risk-free rate is the 3-month Treasury yield.

The second line of equation (2.4.8) 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.

\textbf{2.4.3 Corporate Bond Spreads}

Duffie and Singleton (1999) show that defaultable bonds can be valued as if they were risk-free by replacing the short rate $r_t$ with a default adjusted rate $r_t + s_t$, where

\textsuperscript{17} For the recursive equations see Ang and Piazzesi (2003).
\( s_t \) can be interpreted as the product of the risk-neutral default probability and loss given default and is called the "instantaneous default spread."

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

\[
s_t^i = \gamma_0^i + \gamma_z^i z_t = \gamma_0^i + \gamma_m^i m_t + \gamma_x^i x_t,
\]

(2.4.10)

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

\[
y_i^T(t) = \hat{a}_i Q(t) + \bar{b}_i Q(t) z_t.
\]

(2.4.11)

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

\[
\begin{align*}
CS^i_t(\tau) &\triangleq y_i^T(t) - y_i^i(t) \\
&= (\hat{a}_i Q(t) - a^Q(t)) + (\bar{b}_i Q(t) - b^Q(t)) z_t \\
&\triangleq a_i^Q(t) + b_i^Q(t) z_t \\
&= a_i^Q(t) + b_i^Q(t) m_t + b_i^Q(t) x_t \\
&\triangleq a_i^{TP}(t) + b_i^{TP}(t) z_t + a_i^{TP}(t) + b_i^{TP}(t) z_t \\
\end{align*}
\]

(2.4.12)

(2.4.13)

2.5 Econometric Methodology

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

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

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

The state equation in the model is defined by equation (2.4.4). In addition, we have the observed asset prices, which represent the observation equations as follows:

\[ y_t^T(\tau) = a^Q(\tau) + b_m^Q(\tau)'m_t + b_x^Q(\tau)'x_t + \varepsilon_t \] (2.5.14)

and

\[ CS_i^t(\tau) = a^iQ(\tau) + b_m^iQ(\tau)'m_t + b_x^iQ(\tau)'x_t + \varepsilon_i^t, \] (2.5.15)

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 \( \tau \). The right-hand side of equations (2.5.14) and (2.5.15) are expanded versions of equations (2.4.8) and (2.4.12).
The estimation errors are denoted by $\varepsilon_t$ and $\varepsilon_t^i$, respectively. I assume that the Treasury yield estimation errors are i.i.d normal with standard deviation $\sigma_\varepsilon$. The credit spread estimation errors are also assumed to be i.i.d normal with standard deviation $\sigma^i_\varepsilon$.

### 2.5.2 Number of Factors and Identification

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

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

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

Identification of the model needs to take into account that there is a mixture of macro and latent variables. Define \( \mu = (\mu_m \mu_x)' \). I let \( \mu_m, \Phi, \delta_0 \) and \( \delta_m \) be free. \( \mu_x \) is restricted such that the long-run mean of the latent factors is equal to zero, i.e.:

\[
e_i' = (I - \Phi) \mu = 0,
\]

where \( e_i \) is a vector of zeros with a one in the position of the respective latent factor. Furthermore, \( \delta_{1x} = \delta_{2x} = \delta_{3x} = 1 \). Finally, the matrix \( \Sigma \), controlling the variance in the state equation (2.4.4), is given by:

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

**2.5.3 Additional Considerations**

**Risk Premia.** Despite being identified in the model, risk premia are very hard to estimate in practice. Also, a rich specification of risk premia bears the danger of overfitting the data. I follow Bikbov and Chernov (2006) and augment the standard log-likelihood function, \( \mathcal{L} \), with a penalization term which is proportional to the
variation of the term premium in (2.4.9) and (2.4.13):

\[
\mathcal{L}_p = \mathcal{L} - \frac{1}{2\sigma_p^2} \sum_{\tau} \left( a^TP(\tau) \right)^2 + b^TP(\tau)' \cdot \text{Diag}(\text{var}(z_t)) \cdot b^TP(\tau) \\
- \frac{1}{2\sigma_p^2} \sum_{i,\tau} \left( a_{i,TP}(\tau) \right)^2 + b_{i,TP}(\tau)' \cdot \text{Diag}(\text{var}(z_t)) \cdot b_{i,TP}(\tau),
\]  

(2.5.18)

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, \( \mathcal{L}_p \) imposes an extra burden on the model to use the risk premia as a last resort in fitting the yields. This helps to stabilize the likelihood and simplifies the search for the global optimum. In particular, this setup helps avoiding very large values of risk premia.

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

The fit of credit spreads can be improved further by imposing appropriate restrictions on the estimation errors. I use the following restrictions to make the estimation

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18 See appendix E for a detailed description of data availability.
errors roughly proportional to the level of the yields and credit spreads:

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

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

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

### 2.6 Estimation Results and Sources of Predictive Power

This section presents the results from estimating the macro-finance term structure model described in section 2.4. Section 2.6.1 describes the model fit and verifies that the model implied spreads are able to pick up the predictive power observed in the data. Section 2.6.2 examines whether expectations, term premia or both together drive the forecasting ability. Section 2.6.3 decomposes the credit spreads into compo-
ments attributable to the observable macro and the unobservable finance factors and examines their contributions to the overall predictive power.

2.6.1 The Predictive Power of Model Implied Spreads

Model Fit

The model fit is directly relevant to the question whether it is possible to capture the information that drives the predictive power of the credit spreads with the specification proposed in section (2.4). As I am interested in examining the sources of the forecasting power, the model implied yields and spreads must also forecast GDP growth. If the implied spreads do not exhibit any predictive power, we are unable to make any statement about the sources of the predictive relationship with real activity other than recognizing that we need to introduce more factors into the model.

Using a fairly parsimonious model we cannot expect to be able to fit the whole term structures of Treasury yields and credit spreads for different rating classes perfectly. The results in section 2.3 suggest that there is relevant information contained in a wide variety of different spreads except in short maturity AAA spreads. Furthermore, long maturity spreads seem to be more informative in general. Hence, the better we are able to fit long maturity spreads for all rating classes and lower grade spreads for all maturities, the better we can expect the model to perform in producing implied spreads that contain the same forecasting power.

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

Treasury Yields. The model fits Treasuries very well. $R^2$s 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 $R^2$s are displayed in Table 2.7 along with the results for the fit of the corporate spreads. Figure 2.7 plots the actual and implied slope (panel A) and curvature (panel B).

**Corporate Yields and Credit Spreads.** The model fits $B$ spreads almost as well as Treasury yields with $R^2$s close to or above 97% for almost all maturities. For $BBB$ spreads, $R^2$s range between around 60% for short maturities and up to 80% for longer maturities. AAA spreads display the greatest disparity with an $R^2$ as low as 13% for the short spread, while the 10-year spreads are fitted well with an $R^2$ of almost 80%. The actual and implied spreads for selected maturities are displayed in Figure 2.7. The standard deviations of the errors in the observation equation (2.5.15) are 0.15 for AAA and $BBB$ spreads and 0.22 for $B$ spreads. This implies that the model values the high grade spreads within just under 30 basis points and the $B$ spreads within about 44 basis points ($2\sigma_e$). The mean absolute errors range between 6 and 11 basis points for AAA spreads, between 12 and 16 for $BBB$ spreads and between 12 and 25 for $B$ spreads. Expressed in fractions of the actual spread levels, the average errors for AAA spreads range between 15% and 58%, for $BBB$ spreads between 15% and 23%, and for $B$ spreads between 4% and 9%.

**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 2.3 using the model implied spreads. Namely, I replicate panel A from Table 2.7 using the implied credit spreads (Table 2.7, panel A) and the estimation errors (Table 2.7, panel B). The results confirm that overall, the implied spreads are performing satisfactorily. The coefficient for the estimation error is only significant for 10-year AAA and $BBB$ spreads at forecast horizons two and three years. This means that only long maturity high
grade spreads might contain additional information that can be used for forecasting GDP growth at long horizons, which the model is not able to capture.

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

2.6.2 Expectations and Term Premia

The state variables affect the credit spreads and Treasury yields through the expectations about the future short rate and through the term premia. Having estimated a full model, it is easy to decompose the credit spreads and investigate the role of the term premia in forecasting GDP growth in detail. The part of the credit spreads that is driven by the expectations about the future short rate can be computed by setting the risk parameters to zero in the equations for the Treasury yields and credit spreads, equations (2.4.8) and (2.4.12). The difference between a credit spread under the $Q$- and under the $P$-measure is defined as the credit spread term premium.

Figure 2.7, rows one through three, shows the implied credit spreads under the risk neutral measure, the spreads under the $P$-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 \( P \)-measure flatten out and almost all the variation comes from the term premia, this effect being even more pronounced for higher grade credits. The same pattern can be observed for Treasury yields (see Figure 2.7, row four). By definition, the term premium starts at zero for the 3-month spreads, thus implying that all the forecasting power of the shortest maturity spreads is attributed to the \( P \)-measure by default. Consequently, one would conjecture that, as maturity increases and the implied spreads based on expectations about the short rate flatten out, the importance of the term premia would increase.

Table 2.7 displays the coefficient estimates from running multivariate predictive regressions using the term premia and the credit spreads under the \( P \)-measure. The results are not entirely in line with what would be expected. For AAA spreads, expectations are never significant, whereas term premia are for all horizons; the forecasting power of AAA appears to be solely driven by term premia. For BBB and B however, the \( P \)-measure component is mostly significant for short maturity spreads while term premia are relevant for longer maturity spreads. This result implies, that it is not possible to determine what drives the forecasting power in the case of lower grade credit spreads as both, expectations and term premia are important depending on the maturity of the spreads.\(^1\)

Therefore, it is necessary to further decompose the implied spreads and explicitly consider the contributions of the state variables.

\(^{19}\) Hamilton and Kim (2002) decompose the Treasury term spread in a similar fashion. They also conclude that both components matter. In addition, they find that the contribution of the expectations piece is significantly larger than that of the term premium.
2.6.3 The Determinants of Credit Spreads and the Drivers of Forecasting Power

Macro Variables and Latent Factors

Apart from decomposing credit spreads (and Treasury yields) into expectations and term premia, it is also possible to directly assess the contributions of the five state variables to the predictive power of the credit spreads. Specifically, I am interested in disentangling the information in credit spreads that is not related to the macro variables. Even given the factor loadings in equations (2.4.12) and (2.4.8), separating out the contribution of the macro variables is not straightforward because they are correlated with the latent factors.

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

$$f_t = x_t - \hat{x}(M_t), \quad (2.6.20)$$
$$\hat{x}(M_t) = c(\Theta) + \sum_{j=0}^{t} c_{t-j}(\Theta)m_{t-j}, \quad (2.6.21)$$

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

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

Panel A in Figure 2.7 graphs the credit factor $f_1$ with the 3-month and 10-year spreads. The correlations are 70% and 57%, respectively. For BBB spreads, the correlations are slightly lower with 61% and 54%, whereas correlations with AAA spreads on the long and the short end reach 50% and 18%, respectively (50% and 40% if the correlations are measured with implied spreads). As already indicated by the factor loadings, Treasury yields are virtually uncorrelated with the credit factor (below 5%).

The credit factor is strongly associated with the index of tighter loan standards from the Federal Reserve's quarterly Senior Loan Officer Opinion Survey, as the correlation between the two is 62%. A plot of the two series is provided in Figure 2.7, panel B. 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 level factor $f_2$ is highly correlated with Treasury yields of all maturities. Figure 2.7, panel A, graphs $f_2$ with the 3-month and 10-year Treasury yields. The correlations between $f_2$ and the Treasury yields are 77% and 53%, respectively. Moreover, the level factor is also strongly associated with the Federal funds target rate; the two series are plotted in Figure 2.7, panel B, the correlation is 67%.

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20 The survey can be obtained from the Federal Reserve website (Board of Governors of the Federal Reserve System). To be specific, the correlation is measured between factor $f_1$ and the prewhitened index of tighter loan standards. I prewhiten the time series by regressing it on eight lags of GDP growth and inflation.

21 The Federal funds target rate is available through the FRED database (Federal Reserve Bank of St. Louis).
Federal funds rate is often considered as an indicator of monetary policy, $f_2$ can also be interpreted as a “monetary policy” factor.

**Factor Loadings**

Figure 2.7 plots the normalized loadings of credit spreads and Treasury yields. This allows visualizing the initial impact of a shock to the state variables on the yields or spreads for different maturities. To make them comparable, the loadings are normalized by the standard deviation of the factors and the credit spreads or yields, respectively; the figure shows the contemporaneous impact of a one standard deviation shock to any of the factors on the financial variables measured in standard deviations.

The plotted loadings on the macro variables take into account that GDP and inflation are correlated with the latent factors $x_t$ by modifying the original factor loadings $b_m^Q$ given in equations (2.4.9) and (2.4.13) and adding $c_t(\Theta)b_2^Q$, where $c_t(\Theta)$ is taken from equation (2.6.21). As such, the loadings represent the true contemporaneous impact of variations in either GDP or inflation on Treasury yields and credit spreads. Positive shocks to GDP cause spreads to narrow, although the effect on AAA short maturity spreads is only minor. Inflation appears to have almost no effect on either spreads or Treasuries.\(^{22}\)

The normalized factor loadings for the two residual factors $f_1$ and $f_2$ in Figure 2.7 illustrate the effect of the chosen rotation. Credit spreads load heavily on the credit factor, whereas Treasury yields are only marginally exposed. The largest loadings on $f_1$ occur for short maturity $BBB$ and $B$ spreads; the relevance of $f_1$ slightly decreases with maturity but the credit factor is an important 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.

\(^{22}\) Note that the factor loadings only reflect the immediate effect of shocks to the state variables and do not take into account the influence of lagged inflation.
While the loadings of credit spreads are very small (with the exception of short maturity AAA spreads).

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

Even though factor loadings differ between credit spreads of different rating classes it is noteworthy that the shapes of the term structure of factor loadings in Figure 2.7 are very similar for all credit spreads, implying that credit spreads are driven by common factors. This is consistent with findings by Collin-Dufresne, Goldstein, and Martin (2001) who conclude that most of the variation of credit spread changes for individual bonds is explained by an aggregate common factor.\(^{23}\)

**The Forecasting Power of Credit Spread Components**

The projection procedure described in section 2.6.3 allows to single out the component of the credit spreads driven by movements in the macro variables:

\[
CS^i_{M,t}(\tau) = a^{i,Q}(\tau) + b^{i,Q}(\tau)t^\prime m_t + b^{i,Q}(\tau)t^\prime \hat{x}(M_t) \tag{2.6.22}
\]

Similarly, the components of the credit spreads attributable to the residuals \( f_j \) can be calculated as the product of the respective factor loading times the realization of

\(^{23}\) In contrast, Driessen (2005) estimates a model that assumes firm-specific factors to begin with and Amato and Luisi (2006) conclude that one dominant latent factor per rating category drives most of the variation in credit spreads.
the factor, \( CS_{j,t}^i(\tau) = b_{j}^{i,Q}(\tau)'f_j \) for \( j = \{1, 2, 3\} \). Thus, the implied spreads \( \hat{CS}_t(\tau) \) can be decomposed into its components according to a variation of equation (2.4.12):

\[
\hat{CS}_t(\tau) = a^{i,Q}(\tau) + b^{i,Q}(\tau)'m_t + b^{i,Q}(\tau)'\hat{\alpha}(M_t) + b^{i,Q}(\tau)'f_t \\
\triangleq CS_{M,t}^i(\tau) + CS_{f_1,t}^i(\tau) + CS_{f_2,t}^i(\tau) + CS_{f_3,t}^i(\tau).
\] (2.6.23)

Figure 2.7 graphs the implied spreads and its various components, macro variables including the projection (and including the constant), credit factor \( f_1 \), level factor \( f_2 \) and slope factor \( f_3 \). A reflection of Figure 2.7, the \( f_2 \)-component is only marginal for all credit spreads. The part that can directly be attributed to the observable macro variables either directly or via projection seems to account for a large part of the variation in the implied credit spreads.

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

Panel A in Table 2.7 reports the coefficient estimates from the first set of regressions. Macro variables are relevant contributors to the forecasting power for horizons up to two years for longer maturity credit spreads. However, the macro factors do not contribute to predicting GDP for short maturity spreads.

The results of the second set of regressions are reported in Table 2.7, panel B. The credit factor \( f_1 \) has significant forecasting power at all horizons and \( R^2 \)'s range between 7% and 54% for the one quarter and three year horizons, respectively. The level and slope factors on the other hand do not have any predictive content. In the case of the slope factor, the lack of predictive power is notable as credit spreads at the long end load quite heavily on \( f_3 \). This means that while shocks to \( f_3 \) may significantly move credit spreads they contain no information as to the future direction of the economy.
Compared with actual credit spreads, the $R^2$s for the credit factor regressions are usually higher than those for short maturity spreads and below the numbers for longer maturities. This supports the conclusion that the credit factor accounts for a large part but not all of the forecasting power.

Table 2.7 displays the results from regressing future GDP growth on all the components of the implied spreads in equation (2.6.23). The results from the univariate regressions mostly carry over to the multivariate case. The significant effect of the credit factor $f_1$ largely remains intact but it is driven out by the contribution of the macro factors for short horizon forecasts (one and two quarters). The factors $f_2$ and $f_3$ are still insignificant, except for short maturity AAA spreads at one and two quarter horizons.

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

### 2.6.4 The Sources of Forecasting Power and the External Finance Premium

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

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

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

### 2.7 Conclusion

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

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

Disentangling term premia and expectations does not answer the question what drives the predictive power inherent in credit spreads as both components are important depending on forecast horizon and maturity of the credit spreads. Decomposing the spreads into contributions from the state variables on the other hand, yields more insights about the drivers of forecasting power. The most important contributor to the predictability of credit spreads is a credit factor, which is independent of the observed macro variables and can be interpreted as a proxy for credit conditions and explains between 50% and 100% of the overall predictive power. Current and past realizations of GDP growth and inflation contribute significantly to the forecasting power of spreads from all rating classes at short horizons. The macro factors and the credit factor account for virtually all predictive power found in credit spreads. Shocks to credit spreads that are not related to these factors are irrelevant for forecasting purposes. In particular, the level or monetary policy factor has no forecasting power. Consequently, the short rate, which loads heavily on the level factor, does not predict future real activity. This finding does not imply that monetary policy has no impact on output but can be explained by a stabilizing monetary policy regime over the sample period. The high predictive power of the credit factor lends support to the existence of a transmission channel from borrowing conditions to real activity consistent with the financial accelerator theory.
Table 2.1: Credit Spread Regressions

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

$$g_{t,k} = \alpha_k(\tau) + \beta_k(\tau)CS_i(T) + u_{t+k}. $$

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

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

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

### Panel A: Univariate credit spread regressions

<table>
<thead>
<tr>
<th>Horizon (Obs.)</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></td>
<td>$\beta_k(4)$</td>
<td>$R^2$</td>
<td>$\beta_k^{40}(40)$</td>
<td>$R^2$</td>
<td>$\beta_k(4)$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1 qtr (55)</td>
<td>-1.09</td>
<td>0.01</td>
<td>-2.39</td>
<td>0.15</td>
<td>-1.62</td>
<td>0.08</td>
</tr>
<tr>
<td>2 qtrts (55)</td>
<td>(2.02)</td>
<td>-0.01</td>
<td>(1.07)*</td>
<td>0.11</td>
<td>(0.65)*</td>
<td>0.07</td>
</tr>
<tr>
<td>(55)</td>
<td>(1.60)</td>
<td>0.02</td>
<td>(0.98)*</td>
<td>0.21</td>
<td>(0.57)*</td>
<td>0.16</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>-1.67</td>
<td>0.04</td>
<td>-2.41</td>
<td>0.34</td>
<td>-1.57</td>
<td>0.21</td>
</tr>
<tr>
<td>2 yrs (54)</td>
<td>-1.18</td>
<td>0.03</td>
<td>-2.35</td>
<td>0.52</td>
<td>-1.18</td>
<td>0.18</td>
</tr>
<tr>
<td>(54)</td>
<td>(0.78)</td>
<td>0.01</td>
<td>(0.71)*</td>
<td>0.51</td>
<td>(0.50)*</td>
<td>0.17</td>
</tr>
<tr>
<td>3 yrs (50)</td>
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<td>-2.07</td>
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<td>-1.13</td>
<td>0.24</td>
</tr>
<tr>
<td>(50)</td>
<td>(0.65)</td>
<td>0.02</td>
<td>(0.63)*</td>
<td>0.57</td>
<td>(0.47)*</td>
<td>0.22</td>
</tr>
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</table>

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

<table>
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<tr>
<th>Horizon (Obs.)</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></td>
<td>$\beta_k^{40}(4)$</td>
<td>$R^2$</td>
<td>$\beta_k^{40}(40)$</td>
<td>$R^2$</td>
<td>$\beta_k^{40}(4)$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1 qtr (55)</td>
<td>-2.75</td>
<td>0.21</td>
<td>-2.16</td>
<td>0.26</td>
<td>-1.68</td>
<td>0.24</td>
</tr>
<tr>
<td>(55)</td>
<td>(1.90)</td>
<td>0.09</td>
<td>(1.09)</td>
<td>0.15</td>
<td>(0.86)</td>
<td>0.12</td>
</tr>
<tr>
<td>2 qtrts (55)</td>
<td>-2.94</td>
<td>0.25</td>
<td>-2.36</td>
<td>0.35</td>
<td>-1.92</td>
<td>0.32</td>
</tr>
<tr>
<td>(55)</td>
<td>(1.64)</td>
<td>0.14</td>
<td>(1.01)*</td>
<td>0.25</td>
<td>(0.75)*</td>
<td>0.22</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>-2.06</td>
<td>0.24</td>
<td>-2.82</td>
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<td>-1.87</td>
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</tr>
<tr>
<td>(55)</td>
<td>(1.30)</td>
<td>0.13</td>
<td>(0.80)*</td>
<td>0.47</td>
<td>(0.68)*</td>
<td>0.29</td>
</tr>
<tr>
<td>2 yrs (54)</td>
<td>-1.74</td>
<td>0.23</td>
<td>-2.81</td>
<td>0.71</td>
<td>-1.54</td>
<td>0.38</td>
</tr>
<tr>
<td>(54)</td>
<td>(0.88)</td>
<td>0.11</td>
<td>(0.62)*</td>
<td>0.67</td>
<td>(0.54)*</td>
<td>0.28</td>
</tr>
<tr>
<td>3 yrs (50)</td>
<td>-2.11</td>
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<td>-2.48</td>
<td>0.75</td>
<td>-1.73</td>
<td>0.48</td>
</tr>
<tr>
<td>(50)</td>
<td>(0.68)</td>
<td>0.13</td>
<td>(0.55)*</td>
<td>0.69</td>
<td>(0.48)*</td>
<td>0.39</td>
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</table>
Table 2.1: Credit Spread Regressions (cont.)

Panel C: Bivariate credit spread regressions

<table>
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<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>S.E.</td>
<td>$R^2$</td>
<td>Coeff.</td>
<td>S.E.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 qrt</td>
<td>$\beta_1^{(1)}$</td>
<td>-0.71 (1.77)</td>
<td>0.15</td>
<td>-1.99 (0.77)*</td>
<td>0.13</td>
</tr>
<tr>
<td>(55)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 qrts</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.58 (1.02)*</td>
<td>0.12</td>
<td>-1.16 (0.64)</td>
<td>0.10</td>
</tr>
<tr>
<td>(55)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.56 (0.91)*</td>
<td>0.23</td>
<td>-1.26 (0.57)*</td>
<td>0.23</td>
</tr>
<tr>
<td>1 yr</td>
<td>$\beta_1^{(1)}$</td>
<td>-1.79 (1.30)</td>
<td>0.35</td>
<td>-2.07 (0.57)*</td>
<td>0.39</td>
</tr>
<tr>
<td>(55)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.48 (0.83)*</td>
<td>0.33</td>
<td>-1.26 (0.53)*</td>
<td>0.37</td>
</tr>
<tr>
<td>2 yrs</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.02 (0.99)*</td>
<td>0.52</td>
<td>-1.62 (0.53)*</td>
<td>0.48</td>
</tr>
<tr>
<td>(54)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.39 (0.69)*</td>
<td>0.50</td>
<td>-1.27 (0.46)*</td>
<td>0.46</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$\beta_1^{(1)}$</td>
<td>-1.99 (0.76)*</td>
<td>0.58</td>
<td>-1.48 (0.54)*</td>
<td>0.63</td>
</tr>
<tr>
<td>(50)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.08 (0.64)*</td>
<td>0.57</td>
<td>-1.24 (0.42)*</td>
<td>0.62</td>
</tr>
</tbody>
</table>

Panel D: Bivariate credit spread regressions with controls

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th></th>
<th>AAA</th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>S.E.</td>
<td>$R^2$</td>
<td>Coeff.</td>
<td>S.E.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 qrt</td>
<td>$\beta_1^{(1)}$</td>
<td>-0.96 (1.92)</td>
<td>0.27</td>
<td>-1.51 (0.93)*</td>
<td>0.23</td>
</tr>
<tr>
<td>(55)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 qrts</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.36 (0.99)*</td>
<td>0.34</td>
<td>-0.69 (0.67)</td>
<td>0.10</td>
</tr>
<tr>
<td>(55)</td>
<td>$\beta_1^{(1)}$</td>
<td>-0.93 (1.72)</td>
<td>0.38</td>
<td>-1.74 (0.85)*</td>
<td>0.34</td>
</tr>
<tr>
<td>1 yr</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.60 (0.93)</td>
<td>0.27</td>
<td>-1.15 (0.59)</td>
<td>0.23</td>
</tr>
<tr>
<td>(55)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.00 (1.18)</td>
<td>0.55</td>
<td>-1.89 (0.64)*</td>
<td>0.54</td>
</tr>
<tr>
<td>2 yrs</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.96 (0.77)</td>
<td>0.47</td>
<td>-1.64 (0.52)</td>
<td>0.36</td>
</tr>
<tr>
<td>(54)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.40 (0.88)</td>
<td>0.72</td>
<td>-1.58 (0.50)</td>
<td>0.66</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.88 (0.60)</td>
<td>0.67</td>
<td>-1.68 (0.41)</td>
<td>0.60</td>
</tr>
<tr>
<td>(50)</td>
<td>$\beta_1^{(1)}$</td>
<td>-2.55 (0.61)</td>
<td>0.73</td>
<td>-1.72 (0.45)</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Table 2.2: Summary of $R^2$s

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

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

In panel B, the short rate or various measures of the term spread are added to the regression. Panel C adds the 5-year term spread and various credit spreads. The sample period for all regressions is 1992:2–2005:4, GDP data is included up to 2007:3.
Table 2.3: Model Fit: $R^2$s for Implied Yields and Spreads

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

<table>
<thead>
<tr>
<th>Maturity</th>
<th>Maturity</th>
<th>Slope</th>
<th>Curvature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treasuries</td>
<td>0.979</td>
<td>0.992</td>
<td>0.979</td>
</tr>
<tr>
<td>AAA</td>
<td>0.132</td>
<td>0.206</td>
<td>0.790</td>
</tr>
<tr>
<td>BBB</td>
<td>0.592</td>
<td>0.669</td>
<td>0.817</td>
</tr>
<tr>
<td>B</td>
<td>0.981</td>
<td>0.990</td>
<td>0.921</td>
</tr>
</tbody>
</table>
Table 2.4: Implied Credit Spread Regressions

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

$$g_{t,k} = \alpha_i^k(\tau) + \beta_i^k(\tau)\widehat{CS}_i(\tau) + \epsilon_{t+k},$$

where $\widehat{CS}_i(\tau) = \widehat{y}_i(\tau) - \widehat{y}_f(\tau)$ and all the yields are model implied instead of actual yields. In panel B, $\widehat{CS}_i(\tau)$ is replaced by the estimation error given by $CS_i(T) - \widehat{CS}_i(\tau)$, the difference between the actual and the implied credit spread. Hodrick (1992) (1B) standard errors in parentheses.

* denotes significantly different from zero at 5% level. The sample period is 1992:2-2005:4, GDP data is included up to 2007:3.

<table>
<thead>
<tr>
<th>Panel A: Implied credit spreads</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>$\beta_i^k(4)$</td>
<td>$R^2$</td>
<td>$\beta_i^k(40)$</td>
<td>$R^2$</td>
<td>$\beta_i^k(4)$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1 qtr (55)</td>
<td>-5.89</td>
<td>0.05</td>
<td>-2.68</td>
<td>0.13</td>
<td>-2.68</td>
<td>0.16</td>
</tr>
<tr>
<td>2 qtrs (55)</td>
<td>(3.64)</td>
<td>0.03</td>
<td>(1.10)*</td>
<td>0.12</td>
<td>(0.75)*</td>
<td>0.14</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>(3.48)</td>
<td>0.10</td>
<td>(1.03)*</td>
<td>0.20</td>
<td>(0.69)*</td>
<td>0.25</td>
</tr>
<tr>
<td>2 yrs (54)</td>
<td>-7.27</td>
<td>0.21</td>
<td>-2.47</td>
<td>0.26</td>
<td>-2.24</td>
<td>0.29</td>
</tr>
<tr>
<td>3 yrs (55)</td>
<td>(3.14)*</td>
<td>0.19</td>
<td>(0.92)*</td>
<td>0.25</td>
<td>(0.71)*</td>
<td>0.28</td>
</tr>
<tr>
<td>4 yrs (55)</td>
<td>-5.27</td>
<td>0.17</td>
<td>-2.05</td>
<td>0.28</td>
<td>-1.51</td>
<td>0.20</td>
</tr>
<tr>
<td>5 yrs (54)</td>
<td>(2.65)</td>
<td>0.15</td>
<td>(0.74)*</td>
<td>0.27</td>
<td>(0.67)*</td>
<td>0.19</td>
</tr>
<tr>
<td>6 yrs (50)</td>
<td>-4.97</td>
<td>0.17</td>
<td>-1.91</td>
<td>0.35</td>
<td>-1.29</td>
<td>0.19</td>
</tr>
<tr>
<td>7 yrs (50)</td>
<td>(2.45)*</td>
<td>0.15</td>
<td>(0.69)*</td>
<td>0.33</td>
<td>(0.71)</td>
<td>0.17</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Panel B: Estimation errors</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>$\beta_i^k(4)$</td>
<td>$R^2$</td>
<td>$\beta_i^k(40)$</td>
<td>$R^2$</td>
<td>$\beta_i^k(4)$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1 qtr (55)</td>
<td>0.75</td>
<td>0.00</td>
<td>-1.48</td>
<td>0.01</td>
<td>0.55</td>
<td>0.00</td>
</tr>
<tr>
<td>2 qtrs (55)</td>
<td>(2.35)</td>
<td>-0.02</td>
<td>(2.25)</td>
<td>-0.01</td>
<td>(1.27)</td>
<td>-0.02</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>-0.06</td>
<td>0.00</td>
<td>-1.90</td>
<td>0.03</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>2 yrs (55)</td>
<td>(1.86)</td>
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<td>(2.22)</td>
<td>0.01</td>
<td>(1.13)</td>
<td>-0.02</td>
</tr>
<tr>
<td>3 yrs (54)</td>
<td>0.52</td>
<td>0.00</td>
<td>-2.95</td>
<td>0.11</td>
<td>-0.20</td>
<td>0.00</td>
</tr>
<tr>
<td>4 yrs (55)</td>
<td>(1.49)</td>
<td>-0.02</td>
<td>(1.70)</td>
<td>0.09</td>
<td>(1.01)</td>
<td>-0.02</td>
</tr>
<tr>
<td>5 yrs (54)</td>
<td>0.44</td>
<td>0.00</td>
<td>-4.17</td>
<td>0.34</td>
<td>-0.49</td>
<td>0.01</td>
</tr>
<tr>
<td>6 yrs (50)</td>
<td>(0.77)</td>
<td>-0.02</td>
<td>(1.29)*</td>
<td>0.32</td>
<td>(0.67)</td>
<td>-0.01</td>
</tr>
<tr>
<td>7 yrs (50)</td>
<td>-0.02</td>
<td>0.00</td>
<td>-3.74</td>
<td>0.37</td>
<td>-0.97</td>
<td>0.06</td>
</tr>
</tbody>
</table>
Table 2.5: Implied Credit Spread Regressions: Term Premia and Spreads Under $\mathbb{P}$-Measure

The table reports the coefficients $\beta_i^{TP}(\tau)$ and $\beta_i^{LP}(\tau)$, and the $R^2$ and $R^2$ (adjusted $R^2$) from the regression

$$g_{t,k} = \alpha_k(\tau) + \beta_i^{TP}(\tau)CS_{T,P,t}(\tau) + \beta_i^{LP}CS_{P,t}(\tau) + u_{t+k},$$

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

<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 qtr</td>
<td>$-17.12$</td>
<td>$(4.80)^*$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(3.77)$</td>
<td>$0.16$</td>
</tr>
<tr>
<td>2 qtr</td>
<td>$-15.78$</td>
<td>$(4.35)^*$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(3.76)$</td>
<td>$0.25$</td>
</tr>
<tr>
<td>1 yr</td>
<td>$-13.82$</td>
<td>$(4.06)^*$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(3.21)$</td>
<td>$0.31$</td>
</tr>
<tr>
<td>2 yrs</td>
<td>$-10.59$</td>
<td>$(3.63)^*$</td>
</tr>
<tr>
<td>(54)</td>
<td>$(2.45)$</td>
<td>$0.27$</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$-10.25$</td>
<td>$(3.60)^*$</td>
</tr>
<tr>
<td>(50)</td>
<td>$(2.15)$</td>
<td>$0.34$</td>
</tr>
</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 qtr</td>
<td>$-5.12$</td>
<td>$(2.24)^*$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(0.88)^*$</td>
<td>$0.15$</td>
</tr>
<tr>
<td>2 qtr</td>
<td>$-3.56$</td>
<td>$(2.15)$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(0.87)^*$</td>
<td>$0.24$</td>
</tr>
<tr>
<td>1 yr</td>
<td>$-2.55$</td>
<td>$(2.09)$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(0.63)^*$</td>
<td>$0.26$</td>
</tr>
<tr>
<td>2 yrs</td>
<td>$-2.32$</td>
<td>$(1.72)$</td>
</tr>
<tr>
<td>(54)</td>
<td>$(0.78)$</td>
<td>$0.18$</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$-2.71$</td>
<td>$(1.66)$</td>
</tr>
<tr>
<td>(50)</td>
<td>$(0.98)$</td>
<td>$0.20$</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 qtr</td>
<td>$-0.83$</td>
<td>$(0.72)$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(0.18)^*$</td>
<td>$0.13$</td>
</tr>
<tr>
<td>2 qtr</td>
<td>$-0.50$</td>
<td>$(0.70)$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(0.17)^*$</td>
<td>$0.24$</td>
</tr>
<tr>
<td>1 yr</td>
<td>$-0.04$</td>
<td>$(0.65)$</td>
</tr>
<tr>
<td>(55)</td>
<td>$(0.16)^*$</td>
<td>$0.28$</td>
</tr>
<tr>
<td>2 yrs</td>
<td>$-0.14$</td>
<td>$(0.53)$</td>
</tr>
<tr>
<td>(54)</td>
<td>$(0.15)^*$</td>
<td>$0.18$</td>
</tr>
<tr>
<td>3 yrs</td>
<td>$-0.20$</td>
<td>$(0.49)$</td>
</tr>
<tr>
<td>(50)</td>
<td>$(0.17)$</td>
<td>$0.15$</td>
</tr>
</tbody>
</table>
Table 2.6: The Forecasting Power of Determinants of Credit Spreads

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

$$g_{t,k} = \alpha_k(\tau) + \beta^M_k(\tau)CS^i_M(\tau) + u_{t+k}.$$  

Panel B reports the coefficient $\beta^f_k$, $R^2$ and $R^2$ (adjusted $R^2$) from the regression

$$g_{t,k} = \alpha_k + \beta^f_k f_{j,t} + u_{t+k},$$  

for $j = \{1, 2, 3\}$ and $f_j$ denotes the credit, level and slope factors, respectively.

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

### Panel A: Projection component

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA 1 yr $\beta^M_k$ (4) $\beta^M_k$ (40)</th>
<th>AAA 10 yrs $\beta^M_k$ (4) $\beta^M_k$ (40)</th>
<th>BBB 1 yr $\beta^M_k$ (4) $\beta^M_k$ (40)</th>
<th>BBB 10 yrs $\beta^M_k$ (4) $\beta^M_k$ (40)</th>
<th>B 1 yr $\beta^M_k$ (4) $\beta^M_k$ (40)</th>
<th>B 10 yrs $\beta^M_k$ (4) $\beta^M_k$ (40)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 qrt (55)</td>
<td>-0.50 0.07</td>
<td>-0.50 0.07</td>
<td>-0.49 0.07</td>
<td>-0.56 0.09</td>
<td>-0.48 0.06</td>
<td>-0.56 0.09</td>
</tr>
<tr>
<td>2 qtrts (55)</td>
<td>(0.26) 0.05</td>
<td>(0.24)* 0.05</td>
<td>(0.26) 0.05</td>
<td>(0.22)* 0.07</td>
<td>(0.26) 0.05</td>
<td>(0.21)* 0.07</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>-0.48 0.11</td>
<td>-0.54 0.14</td>
<td>-0.44 0.09</td>
<td>-0.59 0.17</td>
<td>-0.45 0.10</td>
<td>-0.58 0.17</td>
</tr>
<tr>
<td>2 yrs (55)</td>
<td>(0.24)* 0.10</td>
<td>(0.23)* 0.13</td>
<td>(0.25) 0.08</td>
<td>(0.20)* 0.16</td>
<td>(0.25) 0.08</td>
<td>(0.20)* 0.15</td>
</tr>
<tr>
<td>3 yrs (54)</td>
<td>-0.42 0.13</td>
<td>-0.47 0.16</td>
<td>-0.28 0.06</td>
<td>-0.49 0.18</td>
<td>-0.29 0.06</td>
<td>-0.45 0.15</td>
</tr>
<tr>
<td>4 yrs (50)</td>
<td>(0.20)* 0.11</td>
<td>(0.19)* 0.15</td>
<td>(0.25) 0.04</td>
<td>(0.17)* 0.16</td>
<td>(0.25) 0.04</td>
<td>(0.17)* 0.14</td>
</tr>
</tbody>
</table>

### Panel B: Orthogonalized residuals

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>$f_1$ $\beta_k^1$ $R^2$ $R^2$</th>
<th>$f_2$ $\beta_k^2$ $R^2$ $R^2$</th>
<th>$f_3$ $\beta_k^3$ $R^2$ $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 qrt (55)</td>
<td>-0.50 0.07</td>
<td>0.23 0.02</td>
<td>0.36 0.04</td>
</tr>
<tr>
<td>2 qtrts (55)</td>
<td>-0.52 0.13</td>
<td>0.22 0.02</td>
<td>0.27 0.04</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>-0.54 0.21</td>
<td>0.07 0.00</td>
<td>0.23 0.04</td>
</tr>
<tr>
<td>2 yrs (54)</td>
<td>-0.48 0.26</td>
<td>0.15 0.03</td>
<td>0.20 0.05</td>
</tr>
<tr>
<td>3 yrs (55)</td>
<td>-0.64 0.54</td>
<td>0.25 0.10</td>
<td>0.26 0.11</td>
</tr>
</tbody>
</table>
Table 2.7: Implied Credit Spread Regressions: Full Decomposition

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

$$g_{t,k} = \alpha_k(\tau) + \beta_{t,k}^M(\tau)CS^t_M(\tau) + \beta_{t,k}^{i,F_1}(\tau)CS^t_{f,1}(\tau) + \beta_{t,k}^{i,F_2}(\tau)CS^t_{f,2}(\tau) + \beta_{t,k}^{i,F_3}(\tau)CS^t_{f,3}(\tau) + u_{t+k},$$

where $CS^t_M(\tau)$ and $\hat{CS}^t_f(\tau)$ 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, $\hat{CS}^t_f(\tau)$, is the sum of the four components. Hodrick (1992) (1B) standard errors in parentheses. * denotes significantly different from zero at 5% level. The sample period is 1992:2–2005:4, GDP data is included up to 2007:3.

<table>
<thead>
<tr>
<th>Panel A</th>
<th>AAA 1 yr</th>
<th>AAA 10 yrs</th>
</tr>
</thead>
</table>
| Horizon (Obs.) | Coeff. | S.E. | $R^2$ | $\bar{R}^2$ | Coeff. | S.E. | $R^2$ | $\bar{R}^2$
| 1 qrt (55) | \(\beta_{t,k}^M(\tau)\) | -24.18 (5.60)* | 0.27 | -4.07 (1.39)* | 0.21 |
| | \(\beta_{t,k}^{i,F_1}(\tau)\) | -4.15 (5.02) | 0.22 | -3.49 (3.66) | 0.14 |
| | \(\beta_{t,k}^{i,F_2}(\tau)\) | 19.85 (7.19)* | 0.25 | 162.90 (77.81)* | 0.31 |
| | \(\beta_{t,k}^{i,F_3}(\tau)\) | -57.20 (21.16)* | 0.29 | -2.44 (1.29) | 0.31 |
| 2 qrts (55) | \(\beta_{t,k}^M(\tau)\) | -19.75 (5.05)* | 0.35 | -3.88 (1.23)* | 0.31 |
| | \(\beta_{t,k}^{i,F_1}(\tau)\) | -6.43 (5.19) | 0.29 | -4.59 (3.81) | 0.25 |
| | \(\beta_{t,k}^{i,F_2}(\tau)\) | 12.96 (7.52) | 0.25 | 105.40 (80.13) | 0.25 |
| | \(\beta_{t,k}^{i,F_3}(\tau)\) | -42.41 (20.84)* | 0.29 | -1.80 (1.26) | 0.25 |
| 1 yr (55) | \(\beta_{t,k}^M(\tau)\) | -14.43 (4.46)* | 0.38 | -2.90 (1.04)* | 0.35 |
| | \(\beta_{t,k}^{i,F_1}(\tau)\) | -8.56 (4.19)* | 0.33 | -6.01 (3.07) | 0.30 |
| | \(\beta_{t,k}^{i,F_2}(\tau)\) | 6.19 (6.56) | 0.25 | 42.36 (68.88) | 0.25 |
| | \(\beta_{t,k}^{i,F_3}(\tau)\) | -31.56 (18.86) | 0.25 | -1.36 (1.15) | 0.25 |
| 2 yrs (54) | \(\beta_{t,k}^M(\tau)\) | -10.92 (2.87)* | 0.41 | -2.47 (0.69)* | 0.42 |
| | \(\beta_{t,k}^{i,F_1}(\tau)\) | -7.50 (2.83)* | 0.37 | -5.20 (2.08)* | 0.37 |
| | \(\beta_{t,k}^{i,F_2}(\tau)\) | 7.40 (3.97) | 0.37 | 64.95 (44.07) | 0.37 |
| | \(\beta_{t,k}^{i,F_3}(\tau)\) | -25.44 (16.09) | 0.37 | -1.12 (0.98) | 0.37 |
| 3 yrs (50) | \(\beta_{t,k}^M(\tau)\) | -5.38 (2.96) | 0.62 | -1.59 (0.76)* | 0.65 |
| | \(\beta_{t,k}^{i,F_1}(\tau)\) | -11.45 (3.31)* | 0.58 | -7.84 (2.44)* | 0.62 |
| | \(\beta_{t,k}^{i,F_2}(\tau)\) | 5.73 (3.61) | 0.58 | 58.80 (40.74) | 0.58 |
| | \(\beta_{t,k}^{i,F_3}(\tau)\) | -18.36 (17.72) | 0.58 | -0.93 (1.06) | 0.58 |
Table 2.7: Implied Credit Spread Regressions: Full Decomposition (cont.)

<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></td>
<td></td>
</tr>
<tr>
<td>1 qrt (55)</td>
<td>( \beta_{0M}^{1,1}(\tau) )</td>
<td>-2.59 (1.13)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{1,1}(\tau) )</td>
<td>-2.17 (1.07)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{1,1}(\tau) )</td>
<td>88.39 (81.32)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{1,1}(\tau) )</td>
<td>-21.21 (14.79)</td>
</tr>
<tr>
<td>2 qrts (55)</td>
<td>( \beta_{0M}^{2,1}(\tau) )</td>
<td>-2.47 (1.13)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{2,1}(\tau) )</td>
<td>-2.44 (1.03)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{2,1}(\tau) )</td>
<td>27.88 (81.23)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{2,1}(\tau) )</td>
<td>14.32 (13.89)</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>( \beta_{0M}^{1,1}(\tau) )</td>
<td>-1.78 (1.17)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{1,1}(\tau) )</td>
<td>-2.57 (0.90)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{1,1}(\tau) )</td>
<td>19.71 (71.80)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{1,1}(\tau) )</td>
<td>-10.86 (12.87)</td>
</tr>
<tr>
<td>2 yrs (54)</td>
<td>( \beta_{0M}^{2,1}(\tau) )</td>
<td>-0.49 (1.19)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{2,1}(\tau) )</td>
<td>-2.10 (0.72)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{2,1}(\tau) )</td>
<td>28.06 (40.81)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{2,1}(\tau) )</td>
<td>-8.77 (10.47)</td>
</tr>
<tr>
<td>3 yrs (50)</td>
<td>( \beta_{0M}^{1,1}(\tau) )</td>
<td>0.45 (1.06)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{1,1}(\tau) )</td>
<td>-2.50 (0.80)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{1,1}(\tau) )</td>
<td>50.50 (42.56)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{1,1}(\tau) )</td>
<td>-6.88 (11.59)</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Panel C</th>
<th>B 1 yr</th>
<th>B 10 yrs</th>
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<tbody>
<tr>
<td>Horizon (Obs.)</td>
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<td>Coeff.</td>
</tr>
<tr>
<td>1 qrt (55)</td>
<td>( \beta_{0M}^{1,1}(\tau) )</td>
<td>-0.49 (0.22)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{1,1}(\tau) )</td>
<td>-0.46 (0.23)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{1,1}(\tau) )</td>
<td>-3.37 (3.14)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{1,1}(\tau) )</td>
<td>-2.61 (1.85)</td>
</tr>
<tr>
<td>2 qrts (55)</td>
<td>( \beta_{0M}^{2,1}(\tau) )</td>
<td>-0.49 (0.22)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{2,1}(\tau) )</td>
<td>-0.52 (0.22)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{2,1}(\tau) )</td>
<td>-0.99 (3.13)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{2,1}(\tau) )</td>
<td>-1.75 (1.74)</td>
</tr>
<tr>
<td>1 yr (55)</td>
<td>( \beta_{0M}^{1,1}(\tau) )</td>
<td>-0.36 (0.23)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{1,1}(\tau) )</td>
<td>-0.55 (0.19)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{1,1}(\tau) )</td>
<td>0.82 (2.76)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{1,1}(\tau) )</td>
<td>-1.33 (1.61)</td>
</tr>
<tr>
<td>2 yrs (54)</td>
<td>( \beta_{0M}^{2,1}(\tau) )</td>
<td>-0.11 (0.23)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{2,1}(\tau) )</td>
<td>-0.45 (0.16)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{2,1}(\tau) )</td>
<td>-1.04 (1.92)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{2,1}(\tau) )</td>
<td>-1.09 (1.31)</td>
</tr>
<tr>
<td>3 yrs (50)</td>
<td>( \beta_{0M}^{1,1}(\tau) )</td>
<td>0.08 (0.21)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{1J1}^{1,1}(\tau) )</td>
<td>-0.54 (0.17)*</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J2}^{1,1}(\tau) )</td>
<td>-1.92 (1.64)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{2J3}^{1,1}(\tau) )</td>
<td>-1.09 (1.45)</td>
</tr>
</tbody>
</table>
Table 2.8: Term Spread and Short Rate Regressions

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

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

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

<table>
<thead>
<tr>
<th>Panel A: 1971:3–2005:4</th>
<th>short rate $r_t$</th>
<th>1 year</th>
<th>5 years</th>
<th>10 years</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Horizon (Obs.)</strong></td>
<td>$\gamma_k(1)$</td>
<td>$R^2$</td>
<td>$\gamma_k(4)$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1 qrts</td>
<td>-0.09</td>
<td>0.01</td>
<td>1.26</td>
<td>0.03</td>
</tr>
<tr>
<td>(138)</td>
<td>(0.10)</td>
<td>(0.00)</td>
<td>(0.83)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>2 qrts</td>
<td>-0.16</td>
<td>0.03</td>
<td>0.98</td>
<td>0.03</td>
</tr>
<tr>
<td>(138)</td>
<td>(0.11)</td>
<td>0.03</td>
<td>(0.63)</td>
<td>0.02</td>
</tr>
<tr>
<td>1 yr</td>
<td>-0.22</td>
<td>0.09</td>
<td>1.38</td>
<td>0.10</td>
</tr>
<tr>
<td>(138)</td>
<td>(0.11)</td>
<td>0.09</td>
<td>(0.45)</td>
<td>0.09</td>
</tr>
<tr>
<td>2 yrs</td>
<td>-0.16</td>
<td>0.09</td>
<td>1.36</td>
<td>0.18</td>
</tr>
<tr>
<td>(137)</td>
<td>(0.10)</td>
<td>0.09</td>
<td>(0.40)</td>
<td>0.17</td>
</tr>
<tr>
<td>3 yrs</td>
<td>-0.08</td>
<td>0.04</td>
<td>0.88</td>
<td>0.13</td>
</tr>
<tr>
<td>(133)</td>
<td>(0.10)</td>
<td>0.03</td>
<td>(0.33)</td>
<td>0.13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Horizon (Obs.)</strong></td>
<td>$\gamma_k(1)$</td>
<td>$R^2$</td>
<td>$\gamma_k(4)$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1 qrts</td>
<td>-0.20</td>
<td>0.02</td>
<td>1.13</td>
<td>0.03</td>
</tr>
<tr>
<td>(83)</td>
<td>(0.17)</td>
<td>0.01</td>
<td>(0.99)</td>
<td>0.01</td>
</tr>
<tr>
<td>2 qrts</td>
<td>-0.33</td>
<td>0.08</td>
<td>0.91</td>
<td>0.03</td>
</tr>
<tr>
<td>(83)</td>
<td>(0.18)</td>
<td>0.07</td>
<td>(0.75)</td>
<td>0.01</td>
</tr>
<tr>
<td>1 yr</td>
<td>-0.44</td>
<td>0.21</td>
<td>1.59</td>
<td>0.12</td>
</tr>
<tr>
<td>(83)</td>
<td>(0.17)</td>
<td>0.20</td>
<td>(0.56)</td>
<td>0.11</td>
</tr>
<tr>
<td>2 yrs</td>
<td>-0.30</td>
<td>0.18</td>
<td>1.66</td>
<td>0.25</td>
</tr>
<tr>
<td>(83)</td>
<td>(0.16)</td>
<td>0.17</td>
<td>(0.51)</td>
<td>0.24</td>
</tr>
<tr>
<td>3 yrs</td>
<td>-0.12</td>
<td>0.06</td>
<td>1.02</td>
<td>0.17</td>
</tr>
<tr>
<td>(83)</td>
<td>(0.14)</td>
<td>0.05</td>
<td>(0.42)</td>
<td>0.16</td>
</tr>
</tbody>
</table>

| Panel C: 1992:2–2005:4 |
|-------------------------|------------------|--------|---------|---------|
| **Horizon (Obs.)** | $\gamma_k(1)$ | $R^2$ | $\gamma_k(4)$ | $R^2$ | $\gamma_k(20)$ | $R^2$ | $\gamma_k(40)$ | $R^2$ |
| 1 qrts | 0.17 | 0.02 | 2.02 | 0.12 | 0.14 | 0.00 | -0.00 | 0.00 |
| (55) | (0.17) | 0.00 | (0.61) | 0.11 | (0.25) | -0.01 | (0.20) | -0.02 |
| 2 qrts | 0.11 | 0.02 | 1.40 | 0.10 | 0.07 | 0.00 | -0.01 | 0.00 |
| (55) | (0.16) | -0.00 | (0.64) | 0.09 | (0.25) | -0.02 | (0.19) | -0.02 |
| 1 yr | 0.05 | 0.00 | 0.59 | 0.03 | 0.00 | 0.00 | -0.01 | 0.00 |
| (55) | (0.15) | -0.01 | (0.62) | 0.01 | (0.24) | -0.02 | (0.18) | -0.02 |
| 2 yrs | 0.03 | 0.00 | 0.24 | 0.01 | 0.07 | 0.01 | 0.06 | 0.01 |
| (54) | (0.14) | -0.02 | (0.36) | -0.01 | (0.21) | -0.01 | (0.17) | -0.01 |
| 3 yrs | 0.04 | 0.01 | 0.47 | 0.04 | 0.13 | 0.02 | 0.09 | 0.02 |
| (50) | (0.11) | -0.01 | (0.34) | 0.02 | (0.19) | 0.00 | (0.16) | -0.00 |

| Panel D: 1985:1–2005:4 |
|-------------------------|------------------|--------|---------|---------|
| **Horizon (Obs.)** | $\gamma_k(1)$ | $R^2$ | $\gamma_k(4)$ | $R^2$ | $\gamma_k(20)$ | $R^2$ | $\gamma_k(40)$ | $R^2$ |
| 1 qrts | 0.04 | 0.00 | 2.24 | 0.15 | 0.30 | 0.02 | 0.10 | 0.00 |
| (84) | (0.10) | -0.01 | (0.47) | 0.14 | (0.20) | 0.01 | (0.16) | -0.01 |
| 2 qrts | -0.01 | 0.00 | 1.73 | 0.15 | 0.28 | 0.03 | 0.13 | 0.01 |
| (84) | (0.10) | -0.01 | (0.49) | 0.14 | (0.20) | 0.02 | (0.15) | -0.00 |
| 1 yr | -0.07 | 0.01 | 1.21 | 0.10 | 0.29 | 0.04 | 0.19 | 0.03 |
| (84) | (0.10) | 0.00 | (0.48) | 0.09 | (0.19) | 0.03 | (0.15) | 0.02 |
| 2 yrs | -0.11 | 0.05 | 0.86 | 0.07 | 0.35 | 0.10 | 0.25 | 0.10 |
| (83) | (0.10) | 0.04 | (0.33) | 0.06 | (0.20) | 0.09 | (0.16) | 0.08 |
| 3 yrs | -0.10 | 0.06 | 0.52 | 0.05 | 0.33 | 0.13 | 0.24 | 0.12 |
| (79) | (0.09) | 0.04 | (0.26) | 0.03 | (0.17) | 0.12 | (0.14) | 0.11 |
Table 2.9: Credit Spread Regressions: Lehman and Merrill Lynch Bond Indices

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

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

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

Panel A: 1992:3-2005:4

<table>
<thead>
<tr>
<th>Horizon (Obs.)</th>
<th>AAA IM</th>
<th>AAA L</th>
<th>BBB IM</th>
<th>BBB L</th>
<th>LB HY</th>
<th>ML HY</th>
</tr>
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<tbody>
<tr>
<td>1 qrt</td>
<td>-1.55</td>
<td>-0.94</td>
<td>-1.34</td>
<td>-0.42</td>
<td>0.19</td>
<td>-0.92</td>
</tr>
<tr>
<td>(54)</td>
<td>(0.74)*</td>
<td>(0.27)*</td>
<td>(0.43)*</td>
<td>(0.11)*</td>
<td>(0.11)*</td>
<td></td>
</tr>
<tr>
<td>2 qtrs</td>
<td>-1.84</td>
<td>-1.93</td>
<td>-1.36</td>
<td>-0.41</td>
<td>0.31</td>
<td>-0.48</td>
</tr>
<tr>
<td>(53)</td>
<td>(0.77)*</td>
<td>(0.29)*</td>
<td>(0.41)*</td>
<td>(0.10)*</td>
<td>(0.10)*</td>
<td></td>
</tr>
<tr>
<td>1 yr</td>
<td>-1.44</td>
<td>-0.83</td>
<td>-1.32</td>
<td>-0.37</td>
<td>0.37</td>
<td>-0.41</td>
</tr>
<tr>
<td>(51)</td>
<td>(0.82)*</td>
<td>(0.30)*</td>
<td>(0.39)*</td>
<td>(0.10)*</td>
<td>(0.10)*</td>
<td></td>
</tr>
<tr>
<td>2 yrs</td>
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<td>-0.60</td>
<td>-1.06</td>
<td>-0.30</td>
<td>0.36</td>
<td>-0.27</td>
</tr>
<tr>
<td>(47)</td>
<td>(0.73)*</td>
<td>(0.26)*</td>
<td>(0.34)*</td>
<td>(0.10)*</td>
<td>(0.11)*</td>
<td></td>
</tr>
<tr>
<td>3 yrs</td>
<td>-1.25</td>
<td>-0.53</td>
<td>-0.88</td>
<td>-0.25</td>
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<td>(43)</td>
<td>(0.75)*</td>
<td>(0.25)*</td>
<td>(0.34)*</td>
<td>(0.10)*</td>
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Panel B: all available data

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<tr>
<th>Horizon (Obs.)</th>
<th>AAA IM</th>
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<th>BBB IM</th>
<th>BBB L</th>
<th>LB HY</th>
<th>ML HY</th>
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<tr>
<td>1 qrt</td>
<td>-1.77</td>
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<td>-2.15</td>
<td>-0.34</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>(74)</td>
<td>(0.69)*</td>
<td>(0.31)*</td>
<td>(0.44)*</td>
<td>(0.10)*</td>
<td>(103)</td>
<td></td>
</tr>
<tr>
<td>2 qtrs</td>
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<td>-1.18</td>
<td>-2.00</td>
<td>-0.29</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>(73)</td>
<td>(0.77)*</td>
<td>(0.28)*</td>
<td>(0.44)*</td>
<td>(0.16)*</td>
<td>(102)</td>
<td></td>
</tr>
<tr>
<td>1 yr</td>
<td>-2.29</td>
<td>-0.48</td>
<td>-1.44</td>
<td>-0.22</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>(72)</td>
<td>(0.73)*</td>
<td>(0.27)*</td>
<td>(0.41)*</td>
<td>(0.14)*</td>
<td>(100)</td>
<td></td>
</tr>
<tr>
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<td>-0.43</td>
<td>-0.12</td>
<td>0.04</td>
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</tr>
<tr>
<td>(60)</td>
<td>(0.60)</td>
<td>(0.23)</td>
<td>(0.34)</td>
<td>(0.12)</td>
<td>(96)</td>
<td></td>
</tr>
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<td>0.25</td>
<td>-0.05</td>
<td>-0.14</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>(67)</td>
<td>(0.61)</td>
<td>(0.25)</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td>(92)</td>
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</tbody>
</table>


<table>
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<tr>
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<th>AAA L</th>
<th>BBB IM</th>
<th>BBB L</th>
<th>LB HY</th>
<th>ML HY</th>
</tr>
</thead>
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<tr>
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<td>-1.53</td>
<td>-1.35</td>
<td>-0.55</td>
<td>0.32</td>
<td>-0.58</td>
</tr>
<tr>
<td>(80)</td>
<td>(0.60)*</td>
<td>(0.56)*</td>
<td>(0.36)*</td>
<td>(0.09)*</td>
<td>(75)</td>
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</tr>
<tr>
<td>2 qtrs</td>
<td>-1.53</td>
<td>-1.53</td>
<td>-1.35</td>
<td>-0.55</td>
<td>0.32</td>
<td>-0.58</td>
</tr>
<tr>
<td>(80)</td>
<td>(0.56)*</td>
<td>(0.23)*</td>
<td>(0.35)*</td>
<td>(0.09)*</td>
<td>(74)</td>
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</tr>
<tr>
<td>1 yr</td>
<td>-1.53</td>
<td>-1.53</td>
<td>-1.35</td>
<td>-0.55</td>
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<td>(0.23)*</td>
<td>(0.35)*</td>
<td>(0.09)*</td>
<td>(74)</td>
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<tr>
<td>2 yrs</td>
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<td>-1.53</td>
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<td>-0.55</td>
<td>0.32</td>
<td>-0.58</td>
</tr>
<tr>
<td>(80)</td>
<td>(0.56)*</td>
<td>(0.23)*</td>
<td>(0.35)*</td>
<td>(0.09)*</td>
<td>(74)</td>
<td></td>
</tr>
<tr>
<td>3 yrs</td>
<td>-1.53</td>
<td>-1.53</td>
<td>-1.35</td>
<td>-0.55</td>
<td>0.32</td>
<td>-0.58</td>
</tr>
<tr>
<td>(80)</td>
<td>(0.56)*</td>
<td>(0.23)*</td>
<td>(0.35)*</td>
<td>(0.09)*</td>
<td>(74)</td>
<td></td>
</tr>
</tbody>
</table>
Figure 2.1: Treasury Yields: Actual and Implied Slope and Curvature

The figure shows the actual and model implied slope and curvature of the Treasury yields.
Figure 2.2: Credit Spreads: Actual and Implied Levels

The figure shows the fit of the credit spreads levels. I plot actual and model implied 1- and 10-year credit spreads for AAA, BBB and B credits.
Figure 2.3: Implied Spreads and Treasury Yields, and Term Premia

The figure shows the decomposition of the implied credit spreads (thin black line) and Treasury yields into a part based on expectations about the future short rate (thick blue line) and a term premium (thick green line).
Figure 2.4: Normalized Factor Loadings

The figure shows how Treasury yields and credit spreads change in response to a one standard deviation change in any of the state variables. The responses are also expressed in standard deviations to facilitate comparison and gauge the relevance of the various state variables.
Figure 2.5: Factor $f_1$, $B$ Spreads and Index of Tighter Loan Standards

Panel A plots the quarterly time series of the estimated factor $f_1$ against 3-month and 10-year $B$ spreads. Correlations between $f_1$ and the credit spreads are 70% and 57%, respectively. Panel B plots the factor $f_1$ against the prewhitened index of tighter loan standards from the Senior Loan Officer Opinion Survey. The prewhitened series are residuals from regressing the original series on eight lags of inflation and real activity. The correlation between the two series is 62%. All series are normalized to facilitate comparison.
Figure 2.6: Factor $f_2$, Treasury Yields and Federal Funds Target Rate

Panel A plots quarterly time series of the estimated factor $f_2$ against 3-month and 10-year Treasury yields. Correlations between $f_2$ and the Treasury yields are 77% and 52%, respectively. Panel B plots the factor $f_2$ against the prewithened Federal funds target rate. The prewithened series are residuals from regressing the original series on eight lags of inflation and real activity. The correlation between the two series is 68%. All series are normalized to facilitate comparison.
Figure 2.7: Decomposition of Implied Spreads

The figure shows the implied credit spreads and the decompositions thereof into the contributions from the various factors. The projection piece includes the constant, the direct contribution of the macro variables and the projection. The contribution of the orthogonalized factors is calculated by multiplying the factor loading by the realizations.
Figure 2.8: Treasury Yields and Credit Spreads

Panel A shows the 3-month, 1-year and 1-year Treasury yields, and 10-year corporate bond yields. Panels B through D show the 3-month, 1-year and 10-year credit spreads, respectively for AAA, BBB and B credits.
Figure 2.9: Impulse Response Functions for Bivariate VARs

I plot the impulse response functions for simple bivariate VARs with lag length equal to four quarters. Panels A through C show the impulse response functions of real GDP and the term spread to a 100bp shock in the term spread for different sample periods. Panel D plots the impulse response functions for GDP and the 10-year $B$ spread to a 100bp shock in the $B$ spread. The lag length is determined using Bayes criterion.
Figure 2.10: Impulse Response Functions for VARs

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

A A Model of Learning with Heterogeneous Beliefs

We start out by describing the evolution of inflation \( \pi_t \) in the most basic form:

\[
\pi_t - \pi_{t-1} = p_{t-1} + \sigma e_t
\]  
(A-1)

where \( p_t \) represents expected inflation rate. We fill this equation with more content by assuming that \( p_t \) is determined by the inflation \( \pi_t \) and some state variable \( s_t \) that is unobservable to the agents. We further assume that the vector \( u_t = (\pi_t, s_t)' \) follows a VAR(1) process

\[
\begin{align*}
    u_t &= \mu^u + \Phi^u u_{t-1} + \Sigma^u \epsilon^u_t \\
    &= \begin{bmatrix} \mu^\pi \\ \mu^s \end{bmatrix} + \begin{bmatrix} \phi^{\pi\pi} & \phi^{\pi s} \\ \phi^{s\pi} & \phi^{s s} \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \sigma^{\pi\pi} & 0 \\ \sigma^{s\pi} & \sigma^{s s} \end{bmatrix} \begin{bmatrix} \epsilon^\pi_t \\ \epsilon^s_t \end{bmatrix}.
\end{align*}
\]  
(A-2)

(A-3)

In particular, this specification implies that the spot expectation of inflation is:

\[
p_t = E_t(\pi_{t+1}) = \pi + \phi^\pi_t \pi_t + \phi^s_t s_t,
\]  
(A-4)

Since \( s_t \) is not observable the agents must filter it. We use a setup that is similar to the one in Scheinkman and Xiong (2003), who develop stock pricing in the context of investors with heterogeneous beliefs. For transparency, we assume that there are only two forecast surveys being conducted: \( A \) and \( B \). Participants of the surveys signals \( \theta^A_t \) and \( \theta^B_t \) about \( s_t \). Members of survey \( A \) think of the signal \( \theta^A_t \) as their own, but can observe both. Specifically, forecaster \( A \) believes that only her signal
is correlated with innovations in $s_t$, i.e., the vector $w_t = (\pi_t, \theta_t^A, \theta_t^B, s_t)'$ follows a restricted VAR(1) process:\footnote{A symmetric argument applies to the members of survey $B$.}

\begin{equation}
\begin{split}
w_t &= \mu^w + \Phi^w w_{t-1} + \Sigma^w \varepsilon_t^w \\
&= \begin{bmatrix}
\mu^\pi \\
0 \\
\mu^s
\end{bmatrix} + 
\begin{bmatrix}
\phi^\pi \\
\phi^s \\
0
\end{bmatrix}
\begin{bmatrix}
\pi_{t-1} \\
\theta_{t-1}^A \\
\theta_{t-1}^B \\
\sigma^\pi \\
\sigma^{\theta A} \\
\sigma^{\theta B} \\
\sigma^{s \theta A} \\
\sigma^{s \theta B} \\
\sigma^{s s}
\end{bmatrix}
\begin{bmatrix}
\varepsilon_t^\pi \\
\varepsilon_t^A \\
\varepsilon_t^B \\
\varepsilon_t^s
\end{bmatrix}
\end{split}
\end{equation}

where $\varepsilon_t \sim N(0, I)$. The restrictions ensure that the private signal is not correlated with inflation rate $\pi_t$, and that the expected change in the private signal is equal to the unobserved state variable. The element $\sigma^{s \theta A}$ controls the degree of informativeness of the signal regarding the state variable $s$.

We solve the forecaster’s filtering problem using the results from appendix B, expression (B-7), in particular. In our Gaussian setup the filtered value of the state variable $s$ is going to be a linear function of inflation $\pi$, the private signals and their lags:

\begin{equation}
\hat{s}_t = c_0^i + \sum_{j=0}^1 \left( c_{t-j}^i \pi_{t-j} + c_{\theta t-j}^i \theta_{t-j} + c_{\theta^{-i}}^i \theta_{t-j}^{-i} \right),
\end{equation}

where $i$ and $-i$ generically refer to one of the surveys, and all others, respectively. Therefore, the survey $i$ expected inflation value of inflation is equal to:

\begin{equation}
p_t^i = E_t^i(\pi_{t+1}) = \mu^\pi + \phi^\pi \pi_t + \phi^s \hat{s}_t^i.
\end{equation}

As a next step, we adopt this result to our empirical setting. An econometrician does not observe the private signals $\theta^i$, therefore she has to estimate them, which would require adding a second layer of filtering equations. We want to avoid this complication and introduce additional notations and some approximations.

First, we assume that first $p$ lags of the variables are sufficient to accurately approximate $\hat{s}_t^i$ in (A-6). We stack up the contemporaneous and lagged values of the variables in (A-6) into a vector: $c_t^i = (\pi_{t-1}, \ldots, \pi_{t-p}, \theta_{t-1}^i, \ldots, \theta_{t-1-p}^i, \theta_{t-1}^{-i}, \ldots, \theta_{t-p}^{-i})'$. Now we can rewrite $\hat{s}_t^i$ as:

\begin{equation}
\hat{s}_t^i \approx c_0^i + c_{\pi t}^i \pi_t + c_{\theta^i}^i \theta_t^i + c_{\theta^{-i}}^i \theta_t^{-i}.
\end{equation}
Second, we assume that a vector $x_t$ of first $k$ principal components of $q^t$ explains most of the variation in this variable. Therefore,

$$s^t_t \approx c_0^t + c^t_x x_t + \alpha^t x_t$$  \hspace{1cm} (A-9)

where $\alpha^t$ is a convolution of $c^t$ and the principal components loadings on $q^t$. In particular, these assumptions combined with the inflation forecast equation (A-4) implies that, regardless of the survey, inflation forecasts are going to be linear functions of $\pi_t$ and $x_t$, but the weights in these function will be survey specific:

$$p^t_t = E_t(\pi_{t+1}) = \nu_0^t + \nu_x^t \pi_t + \nu_x^t x_t,$$  \hspace{1cm} (A-10)

Note that, because the vector $(\pi_t, q^t)'$ follows a VAR(1), the vector $(\pi_t, x_t)'$ will do so as well. This observation yields our setup in section 1.3.25

**B Projection**

The model controlling the evolution of state variables $z$ in equations (1.3.2) and (2.4.4) can be rewritten in block representation as:

$$z_t = \begin{bmatrix} \mu_m \\ \mu_x \end{bmatrix} + \begin{bmatrix} \Phi^{mm} & \Phi^{mx} \\ \Phi^{xm} & \Phi^{xx} \end{bmatrix} \begin{bmatrix} m_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \Sigma^{xx} & \Sigma^{zx} \\ \Sigma^{zx} & \Sigma^{xx} \end{bmatrix} \begin{bmatrix} \epsilon_t^m \\ \epsilon_t^x \end{bmatrix}$$  \hspace{1cm} (B-1)

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

$$\hat{x}(M_t) = \mu + \Phi^{zx} \hat{x}(M_{t-1}) + \Phi^{xm} m_{t-1}$$

$$= \left( \Sigma^{xx} \Sigma^{zx} + \Sigma^{zm} \Sigma^{mm} + \Phi^{zx} P_{t-1} \Phi^{mz} \right)^{-1} \left( \Sigma^{zx} \Sigma^{mm} + \Sigma^{mm} \Sigma^{mm} + \Phi^{mx} P_{t-1} \Phi^{mx} \right) m_{t-1} - \mu_m + \Phi^{mx} \hat{x}(M_{t-1}) - \Phi^{xm} m_{t-1}$$  \hspace{1cm} (B-2)

25 In practice the accuracy of the approximation can be achieved by using a sufficient number of the latent factors $x_t$. The sufficiency can be established via model specification analysis.
\[ P_t = \Phi x z P_{t-1} \Phi x z' + (\Sigma x x \Sigma x z + \Sigma z m \Sigma m z) \]
\[ - (\Sigma x x \Sigma m z + \Sigma z m \Sigma m m + \Phi x z P_{t-1} \Phi m z) (\Sigma m z \Sigma m z + \Sigma m m \Sigma m m + \Phi m z P_{t-1} \Phi m z)^{-1} \]
\[ \times (\Sigma x x \Sigma m z + \Sigma z m \Sigma m m + \Phi x z P_{t-1} \Phi m z)' \]  

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

We introduce additional notation to describe the projection initialization. The long run mean \( z \) is:

\[ (I - \Phi)^{-1} \mu = \begin{bmatrix} \Theta^m \\ \Theta^z \end{bmatrix} \]

The steady-state matrix \( P \) satisfies:

\[ P = \Phi x z P \Phi x z' + (\Sigma x x \Sigma x z + \Sigma z m \Sigma m z) \]
\[ - (\Sigma x x \Sigma m z + \Sigma z m \Sigma m m + \Phi x z P \Phi m z) (\Sigma m z \Sigma m z + \Sigma m m \Sigma m m + \Phi m z P \Phi m z)^{-1} \]
\[ \times (\Sigma x x \Sigma m z + \Sigma z m \Sigma m m + \Phi x z P \Phi m z)' \]  

Then the projection is initialized as follows:

\[ \hat{x}(m_0) = \Theta^z + V z m (V m m)^{-1} (m_0 - \Theta^m), \quad P_0 = P \]  

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

The lags of the projected \( x \) in the expression (B-2) could be recursively substituted out so that the current projection is expressed as a distributed-lag function of macro variables:

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

where the matrices \( c \) are functions of parameters \( \Theta = (\mu, \Phi, \Sigma) \) that control the dynamics of the state variables \( z \) in (1.3.2) and (2.4.4), respectively.

## C Latent Factor Indeterminacy

Dai and Singleton (2000) point out that identifying restrictions imposed at the estimation stage
are not necessarily unique. There are many sets of restrictions, or invariant transformations of the model, such that the yields or inflation expectations are left unchanged. Naturally, when a parameter configuration changes, the respective latent variables change as well by “rotating.” This can be exploited by using invariant transformations that are useful for interpreting the latent factors. 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.

C.1 Rotations: Term Structure of Inflation Expectations

We examine two types of rotations. The first rotation, \( O \), ensures that the two factors are orthogonal to each other. We define a rotation \( O = R x_t \), 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 pairs of orthogonal factors \( x \). Our second proposed rotation, \( M \), can be applied after any of the rotations from the class \( O \), resolves this type of indeterminacy. Define \( M = U x_t \), where the matrix \( U \) is the orthogonal matrix; i.e., \( U U' = I \), that preserves the correlation structure between the factors. In our two-dimensional case, the matrix \( U \) is determined by a single parameter, which is established by maximizing the loading of one-year inflation expectation on \( x_1 \).

C.2 Rotations: Credit Spreads and Real Activity

Again, the first rotation, \( O \), ensures that the three factors are orthogonal to each other. As before, I define a rotation \( O = R x_t \), 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 \( M = U x_t \), where the matrix \( U \) is the orthogonal matrix; i.e., \( U U' = I \), that preserves the correlation structure between the factors. In the three-dimensional case, the matrix \( U \) is determined by two parameters, which are established by maximizing the loading of the 3-month \( B \) spread on \( x_1 \). After the second rotation, the first latent factor, \( x_1 \), is identified. Define \( x_t^{(1)} = [ x_{2,t} \ x_{3,t} ]' \), the vector of latent variables excluding \( x_{1,t} \). Further define the third rotation, \( N = S x_t^{(1)} \), where \( S \) again is the orthogonal matrix. In the two-dimensional case the matrix \( S \) is determined by a single parameter, which is established by maximizing the factor loading of the Treasury short rate on \( x_2 \).
D Data Description:

Term Structure of Inflation Expectations

D.1 Yields

We use quarterly time series of bond data from 1970 to 2004. We use an unsmoothed Fama-Bliss approximation of the zero coupon bond prices of maturities at three and six months, and one, two, three, five, seven, and ten years.\(^{26}\) It is important to measure the full yield curve because its slope is correlated with the macro environment (Estrella and Hardouvelis (1991); Estrella and Mishkin (1998)). Given this constraint, we do not consider earlier years, because the longest maturity available was five years. In addition, using rich yield data helps to identify the risk premia.

D.2 Macro Variables

We use quarterly time series of linearly detrended real per capita GDP and log changes in seasonally adjusted CPI to proxy for \(g_t\) and \(\pi_t\), respectively. GDP and CPI numbers are available from FRED. CPI is the consumer price index for all urban consumers (all items, seasonally adjusted) and real GDP is a three decimal time series in billions of chained 2000 USD (seasonally adjusted annual rate).

All the inflation forecasts that we are using are released some time in the third month of a quarter. Therefore, in order to avoid a look-ahead bias in how we construct and use the state variable \(\pi_t\), we use the price level reported in the second month of the quarter, which corresponds to price level in the first month of a quarter.

To construct the GDP growth series we follow two steps. First, we divide the quarterly GDP number by the mid-month population in the third month of the quarter. Second, we linearly detrend real per capita GDP. The detrending is done on a period-by-period basis to avoid a look-ahead bias. Because GDP numbers for quarter \(t\) are released in quarter \(t + 1\) (first estimate in the first month of quarter \(t + 1\) and then revisions in the two following months), we shift the time series by one period to account for the fact that in quarter \(t\) we only know information about quarter \(t - 1\).

\(^{26}\) We are grateful to Robert Bliss for providing us with the data.
D.3 Survey Forecasts

We use the following survey data:

1. Michigan Consumer Survey (MCS). This is a monthly survey conducted by the University of Michigan from 1978. The quarterly forecasts that we use are available from 1960. The forecasts of the annualized percentage price change \( P_{t+T}/P_t - 1 \), are released early in the third month of a quarter. The respondents answer the question: "By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?" Therefore, the forecast is not tied to a particular CPI statistic. We have observations for \( p_{t,0}(4) \).

2. Livingston Survey (LS). This is a semi-annual survey of economists from industry, government, banking, and academia. The forecasts of the price level \( P_{t+T} \), specifically of non-seasonally adjusted CPI, are released in the last month of the second or fourth quarter and are based on the CPI information released in the first month of a quarter. Because of the timing of this survey, Carlson (1977) argues that the six-month ahead and 12-month ahead level forecasts should be converted to the inflation rate using the eight- and 14-month horizons, respectively, as a basis. As a result, we have observations for \( p_{t,0}(\tau), \tau = 2, 4 \) (available from 1947). We also have annual forward forecasts available from 1974: \( p_{t,0}(4) \) (released in the second quarter), and \( p_{t,4}(4) \) (released in the fourth quarter). Finally, ten-year forecasts, \( p_{t,0}(40) \), are available semi-annually from 1991, and two-year forecasts \( p_{t,0}(8) \), are available annually in the fourth quarter from 1992. The fact that the respondents forecast seasonally unadjusted CPI, while our state variable is seasonally adjusted, matters only for the six-month forecasts, \( p_{t,0}(2) \). We perform a simple seasonal adjustment of the forecast. We compute the average annual inflation, and the average inflation over the first and second half-a-year in our sample. Then we adjust the six-month forecasts by the respective differences in annual and semi-annual annualized average inflations. Ghysels and Osborn (2001) provide the details of, and justification for, this procedure. This adjustment involves some look-ahead bias because we are performing the adjustment on the whole sample. However, this bias should be very small, because the seasonal adjustment is tiny.

3. Survey of Professional Forecasters (SPF). This is a quarterly survey available from the third quarter of 1981. The forecasts of the annualized percentage price change \( P_{t+T}/P_t - 1 \), specifically of the changes in seasonally adjusted CPI, are released in the middle of the second month of the quarter and are based on the CPI information released in the previous month. We have...
observations for $\bar{p}_{l,s}^3(1)$, $s = 0, 1, 2, 3; \bar{p}_{l,0}^3(\tau), \tau = 4, 40$. The ten-year forecast is available from the fourth quarter of 1991.

4. Blue Chip Economic Indicators (BCEI). This is a monthly survey of economic forecasters at approximately 50 banks, corporations, and consulting firms. It is available from 1981. The forecasts of the annualized percentage price change $P_{t+\tau}/P_t - 1$, specifically of the changes in seasonally adjusted CPI, are released in the beginning of the third month of the quarter and are based on the CPI information released in the previous month. We have observations for $\bar{p}_{l,s}^3(1)$, $s = 0 - 6$. The forecasts with $s = 4, 5, 6$ are available in the first three, two, and one quarters of a year, respectively.

E Data Description:

Credit Spreads and Real Activity

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.

E.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. We are grateful to Randell Moore for providing us with the data.

More information can be found on the Bureau of Economic Analysis (BEA) website.
I do try to avoid a look ahead bias by shifting the GDP time series by one period to account for the fact that in quarter \( t \) we only have information available about quarter \( t - 1 \). Thus, implicitly I assume that the final revised figures are the same as those of the “final” release by the BEA in the third month of the following quarter.

\[
g_t = 400 \times \log \left( \frac{GDP_t}{GDP_{t-1}} \right), \tag{E-8}
\]

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,

\[
\pi_t = 400 \times \log \left( \frac{P_t}{P_{t-1}} \right), \tag{E-9}
\]

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

### E.2 Treasury Yields

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

There are several potential sources for Treasury yields, all of which have some benefits and costs. Cochrane and Piazzesi (2008) use the well known Fama-Bliss dataset available from CRSP, which is not smoothed across maturities but which only has zero coupon bond prices with maturities up to 5 years. In order to incorporate longer maturities they also work with the new Guerkaynak, Sack, and Wright (2006) dataset, which has smoothed zero coupon yields.\(^{30}\) Cochrane and Piazzesi (2008)

\(^{29}\) An overview of the available real time data sets can be found on the Federal Reserve Bank of Philadelphia website.

\(^{30}\) The data are available from the Federeal Reserve Board website (last accessed November 22, 2008, http://federalreserve.gov/econresdata/researchdata.htm).
point out that even small amounts of smoothing across maturities have the potential to lose a lot of information.

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

In short, neither the Guerkaynak, Sack, and Wright (2006) nor the Fama-Bliss dataset satisfy all needs. For the most part of the sample period I use a proprietary dataset of unsmoothed Fama-Bliss approximation of the zero coupon bond prices, which has yields for all desired maturities, i.e. up to ten years.\footnote{I thank Robert Bliss for providing me with the data} The starting point of my sample period is determined by the first quarter in which the ten year yield is available. However, this dataset has not been updated since 2002:4 so the data has to be augmented by using yields from other sources for the last part of the sample period. From 2003:1 to 2005:4 I use data from CRSP. The three month risk free rate is taken from the Fama Risk Free Rates file, the six month yield is taken from the Fama T-bill structure file and the yields up to five years are taken from the Fama-Bliss dataset. All are continously compounded.

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

\section*{E.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 \( \textit{BBB} \) start in 1991:2, \( B \) yields are available from 1992:2. The chosen maturities are the same as those of the Treasury yields. Figure (2.7) displays Treasury yields and credit spreads for 3-month, 1-year and 10-year maturities.

Unfortunately, data for the whole term structure of corporate yields is not available before 1992:2. However, there are a few corporate bond indices available starting in the early 1970s, such as the Lehman Brothers corporate bond indices for investment grade bonds. For each rating class \( i = \{\text{AAA, BBB}\} \) there is an index for “long” (normally above 10 years) and “intermediate” (between 1 and 10 years) maturities. Using redemption yields and the corresponding Treasury bond indices, it is possible to construct approximate credit spreads for different maturities. This in turn allows calculating a credit spread slope by taking the difference of the two. Lehman Brothers also provides a high yield bond index but only starting in 1987:1. The high yield bond index with the longest maturity that is available through Datastream is the “Merill Lynch US High Yield 100,” which starts in 1980:1. For both yield indices I calculate a high yield spread using the redemption yield of the Lehman Brothers Treasury index (all maturities). The additional spread data, while unsuitable to use in a term-structure model, are used to perform robustness checks for the results in section 2.3.2 and can be found in appendix G.

F The Forecasting Power of Treasury Yields

F.1 Treasury Yield Regressions

In this section, I document the declining importance of the short rate and the term spread in forecasting real activity since the mid-1980s. Analogous to regression equation (2.3.2), I run the following regressions to examine the predictive power of the short rate and the term spread, respectively:

\[
g_{t,k} = \alpha_k(1) + \gamma_k(1) y^T_t(1) + \text{controls} + u_{t+k}, \tag{F-10}
\]

\[
g_{t,k} = \alpha_k(\tau) + \gamma_k(\tau) (y^T_t(\tau) - y^T_t(1)) + \text{controls} + u_{t+k} \tag{F-11}
\]

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

The $\gamma_s(\tau)$ coefficients for the term spread regressions presented in Table 2.7, panels A and B, are significant for horizons between one and three years in the full and in the pre-1992:2 sample. $R^2$'s range between 20% and 36% in the full sample and go up to 50% in the early sample for the 5-year term spread. In the post-1992:2 sample period (Table 2.7, panel C), the term spread loses its predictive power. Coefficients are not significant anymore and $R^2$'s 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 (F-10) is only significant for a one year forecast horizon. This result is not consistent with Bernanke and Blinder (1992) who find that the short rate is particularly informative about future movements of real activity, and with Ang, Piazzesi, and Wei (2006) who conclude that the nominal short rate dominates the term spread in forecasting GDP growth.

Apart from using slightly different sample periods, both papers also employ different methodologies. Bernanke and Blinder (1992) for example use Granger-causality tests and estimate VARs, while Ang, Piazzesi, and Wei (2006) draw their conclusions from a macro-finance term structure model. Although the macro-finance model presented in this paper is not the same as the one used in Ang, Piazzesi, and Wei (2006) (the largest difference being that they do not consider credit spreads), the results presented in section 2.6.3 along with the regression results presented in this section suggest that the findings of Ang, Piazzesi, and Wei (2006) could also be driven by a strong predictive relationship between the Treasury yield curve and economic activity pre-1980. Appendix F.2 provides some additional results from simple VAR specifications, which (1) provide evidence that the effect found by Bernanke and Blinder (1992) is present in the data used in this paper during the early but not during the late sample period and (2) reconfirm the finding that the Treasury yield curve has lost its predictive power since the mid-1980s.

The subsamples for the Treasury yield regressions in Table 2.7, 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 1985:1–2005:4, which excludes the period of monetary policy tightening under Paul Volcker. The results are in line with those reported in panel C, namely that the term spread no longer exhibits predictive power. The declining importance of the term spread in predicting GDP growth is consistent with a monetary policy regime that has been more concerned with inflation since the mid-1980s.

F.2 Evidence from VARs

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

This section has two purposes. First, using simple bivariate VAR specifications it provides a robustness check for the regression results. The main results of sections 2.3 and F.1 are confirmed, namely that the term spread has lost its importance in the late sample period 1992:2–2005:4, whereas information that manifests itself in credit spreads significantly affects future GDP. Second, estimating appropriate VARs allows comparing the results for my data with those reported in Bernanke and Blinder (1992) and Bernanke and Gertler (1995). For the pre-1992:2 sample, I find results that are consistent with the theory of a credit channel—an unanticipated tightening of monetary policy, represented by a shock to the short rate, results in economic slowdown. In the late sample period however, this effect disappears, suggesting that the findings reported by Bernanke and Blinder (1992) and Bernanke and Gertler (1995) need to be interpreted with caution in the current environment.

To confirm the results from section 2.3, I estimate simple bivariate reduced form VARs using log real GDP and term or credit spreads for the full sample, as well as for the pre- and post-1992:2 sample. Figure 2.7 plots the impulse-response functions for a 100bp shock to the 5-year term spread (panels A to C for the full, late and early sample periods) or the 10-year spread (panel D), respectively. A negative shock to the term spread only has a negative effect on real GDP in the full and early sample; during the late sample period, GDP is practically unaffected by movements in the term. An unanticipated positive shock to the high yield spread however, leads to a significant decline in output.

To further gauge the effect of monetary policy shocks and to compare the results with those of Bernanke and Blinder (1992) and Bernanke and Gertler (1995), I consider a slightly more complicated VAR using the short rate as the monetary policy instrument, and including the logs of real GDP
and of CPI in the estimation.\textsuperscript{32} The lag length is chosen to be two, based on Bayes information criterion, and the short rate is ordered last in the VAR. The impulse response functions for a 100bp increase in the short rate are displayed in Figure 2.7, panels A through C. The results exhibit a "price puzzle," i.e. prices react positively to a shock in the short rate.\textsuperscript{33} Although this effect is counterintuitive, I do not attempt to fix this by adding other time series to the VAR since this is not the focus of my paper. The response path for GDP however, is in line with the results for the simple bivariate VARs. In the full and in the early sample, output declines following a shock to the short rate. This is consistent with the results reported by Bernanke and Blinder (1992) and Bernanke and Gertler (1995). In the late sample however, the effect of a shock to the short rate almost reverses, again suggesting that the relationship reported in the earlier literature has disappeared.

I add the 10-year $B$ spread to the VAR and order it last in the system. This implies that monetary policy can have a contemporaneous effect on the spread but it is assumed that the Fed does not react to current shocks to the spread. The impulse response functions to a 100bp rise in the credit spread are plotted in Figure 2.7, panel D. GDP and the short rate both react negatively to a positive shock in the high yield spread; CPI is largely unaffected. Again, the results are in line with the findings of section 2.3 and consistent with the existence of a financial accelerator: a shock that is orthogonal to the short rate, GDP and the price level and that manifests itself in the credit spread has a significant effect on the future path of the economy.

\section*{G Robustness Checks for Credit Spread Regressions}

It would be desirable to have a longer history for the full term structure of credit spreads. Unfortunately, the data availability is limited in this regard. However, it is possible, to extend the data set for high grade spreads back to the mid-1970s and for high yield spreads back to the mid-1980s using alternative data from Lehman Brothers and Merrill Lynch (see appendix E). To check whether the alternative data, which is arguably less rich, yields qualitatively similar results to the ones presented

\textsuperscript{32} Instead of the Federal funds rate however, I use the 3-month Treasury yield as this is per definition the short rate used in the macro-finance model presented in section 2.4.

\textsuperscript{33} See for example Eichenbaum (1992). Sims (1992) suggests that one potential explanation is that simple VARs omit information about future inflation that is actually available to the Fed. He proposes to include a commodity price index to account for this information.
in section 2.3.2, I replicate Table 2.7, panel A using the additional data set. The results in Table 2.7, panel A indicate that the spreads constructed from the bond indices more or less capture the same variation in future GDP growth as the data available from Bloomberg. In terms of $R^2$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 ($R^2$s are sharply decreasing for longer horizons). The results for the extended sample periods are then presented in Table 2.7, panels B and C. Panel B displays the regressions using all available data (different starting points depending on data availability) while panel C reports the results for the subsample 1985:1–2005:4 (or 1987:1–2005:4 for the Lehman Brothers high yield index). Comparing results using all and only post-1985:1 data in Table 2.7, it is apparent that the relationship between real activity and the high yield spread becomes stronger in the late-1980s. The market for high yield debt did not really develop until after the mid-1980s. Before, most high yield debt were bonds that were originally issued by former investment grade firms. This might distort results in the early periods. It is also evident that spreads for investment grade credits become better predictors for real activity over time.

In order to check whether the results for credit spreads are solely driven by the late sample, I also repeat the regressions using pre-1985:1 and a pre-1992:2 only, respectively. The results are weaker but in line with what is reported in Table 2.7. Long maturity investment grade spreads significantly predict GDP for a horizon up to one year. High yield spreads predict GDP growth well for horizons up to three years in the pre-1992:2 sample. Pre-1985:1 results are either distorted (Merrill Lynch high yield index) or not available (Lehman Brothers high yield index).

In summary, the results reported in section 2.3.2 are quite robust to alternative data and extended sample periods, which gives further confidence that the limited availability of the whole term structure of credit spreads is not distorting the overall findings.