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A Joint Dynamic Bi-Factor Model of the Yield Curve and the Economy as a Predictor of Business Cycles

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Abstract

This paper proposes an econometric model of the joint dynamic relationship between the yield curve and the economy to predict business cycles. We examine the predictive value of the yield curve to forecast both future economic growth as well as the beginning and end of economic recessions at the monthly frequency. The proposed multivariate dynamic factor model takes into account not only the popular term spread but also information extracted from the entire yield curve. The nonlinear model is used to investigate the interrelationship between the phases of the bond market and of the business cycle. The results indicate a strong interrelation between these two sectors. Although the popular term spread has a reasonable forecasting performance, the proposed factor model of the yield curve exhibits substantial incremental predictive value. This result holds in-sample and out-of-sample, using revised or real time unrevised data.

Keywords: Forecasting, Business Cycles, Yield Curve, Dynamic Factor Models, Markov Switching.

JEL Classification: C32, E32, E44

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1. Introduction

The yield curve, which relates bond yields to their time to maturity, has become one of the most popular leading indicators of the economy, as there is substantial evidence of systematic association between changes in its shape and future recessions. The slope of the yield curve (i.e. the term spread) is the difference between long term and short term interest rates. Generally, the yield curve is upward sloping since longer maturity is associated with higher yield. This is especially the case in the early stages of economic expansions, when the market expects a rise in the short term interest rates. Under the arbitrage pricing and liquidity preference theories, investors require a term and a risk premium, respectively, for acquiring long maturity bonds rather than the risk free short term rate. On the other hand, the slope of the curve tends to become flat or inverted towards the end of expansions. One of the possible reasons is that tight monetary policy generally precedes a recession. As short rates rise above long rates, the yield curve becomes inverted. In addition, according to the expectation theory, long-term rates reflect market expectation for future short-term rates. Hence, a flat or inverted curve indicates that the market expects a fall in future real interest rates given the prospect of future weak economic activity.

There is a large literature that investigates prediction of future economic activity using the term structure of interest rates.¹ In general, linear regression models are used to forecast the growth rate of economic activity and discrete choice models such as probit or logit specifications to predict the probability of a recession. While the term structure is predominantly used in these models, recent work by Ang, Piazzesi, and Wei (2006) shows that the information across the whole yield curve can result in more efficient and accurate forecasts of real economic growth.

This paper proposes an econometric model of the joint dynamic relationship between the yield curve and the economy to predict business cycles. In contrast with previous literature, we examine the predictive value of the yield curve to forecast both future economic growth as well as the beginning and end of economic recessions at the monthly frequency. In addition, the proposed dynamic latent bifactor model takes into account not only the term spread but also information extracted from the entire yield curve and from real economic activity.

Diebold and Li (2006) re-interpret the classical term-structure model of Nelson and Siegel (1987) as a modern three-factor model of the level, slope, and curvature to capture yield curve

¹ See, for example, Harvey (1988, 1989), Stock and Watson (1989), Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Chauvet and Potter (2002, 2005), Hamilton and Kim (2002), Wright (2006), and Ang, Piazzesi and Wei (2006), among many others, or Stock and Watson (2003) for an extensive survey of this literature.

dynamics. This paper is the pioneer attempt to dynamize Nelson-Siegel model, which is cast in a state space framework and used to produce successful term-structure forecasts. Diebold, Rudebusch, and Aruoba (2006) extend this approach by introducing a unified state-space model that simultaneously fits the yield curve at each point in time and estimates the underlying dynamics of the factors. This framework breaks new ground by allowing examination of the bivariate dynamic relationship of the yield curve and the macroeconomy within Nelson-Siegel's framework. Ang and Piazzesi (2003) also examine the joint dynamics of yields and macroeconomic variable using a vector autoregressive system, with identifying restrictions based on no-arbitrage condition.² The main goal of this paper is to investigate how macroeconomic variables affect bond prices and yield dynamics.

Following this literature, we represent the yield curve as composed of three variables generally called the level, slope, and curvature. Related asset pricing literature shows that these variables can explain most of the time variation of the yield curve.³ In our paper we use empirical time series proxies to measure these components of the yield curve, from which we extract a latent yield factor that summarizes their underlying common information. Notice that our goal is not to model yield dynamics, but to predict the economy.

A second latent factor is extracted from monthly industrial production to represent the economic sector.⁴ The model is cast on state space form and the lead-lag relationship between the yield factor and the economic factor is modeled in the transition equations. The two factors are then simultaneously estimated from the observable variables and from their relationship with each other.

Since some changes in the yield curve are cyclical and potentially related to future economic expansions and recessions, we allow the yield and economic latent factors to follow different

² The model is a discrete-time version of Duffie and Kan (1996) affine framework, but assuming macroeconomic variables and three latent factors for the term structure.

³ See, e.g., Litterman and Scheinkman (1991), Knez, Litterman, and Scheinkman (1994), Duffie and Kan (1996), Balduzzi et al. (1997), Chen (1996), Dai and Singleton (2000) or Ang and Piazzesi (2003), in addition to Diebold and Li (2006) and Diebold, Rudebusch and Aruoba (2006).

⁴ Notice that, in contrast with Diebold and Li (2006) and Diebold, Rudebusch, and Aruoba (2006), we do not model the yield curve as a dynamic latent three-factor model parameterized using Nelson-Siegel representation of the cross-section of yields at any point in time. Instead, we propose a nonlinear *single* factor to represent the yield curve, extracted from empirical time series proxies of the level, curvature and slope without imposing any a priori parameterization. The goal of our paper is not to model the yield curve itself but to obtain a best forecasting performing model of the yield curve to predict recessions.

two-state Markov switching processes.⁵ The Markov process for the yield curve factor represents the phases of bond market cycles, whereas the Markov process for the economic factor corresponds to business cycle states. These cyclical phases of the bond market and the economy are linked through the dependence structure of the factors in the transition equations. The Markov switching dynamic bi-factor model is closely related to the framework used in Chauvet (1998/1999) and Senyuz (2008), which apply this approach to study the relationship between the stock market and the economy.

The proposed framework has several advantages over previous literature on forecasting recessions using the yield curve. First, it uses comprehensive information from the entire yield curve in a parsimonious way without incurring in potential multicollinearity problems as in linear regressions. Second, the methodology takes into consideration the interrelationship between bonds market and the real economy through the dynamic factors and through the Markov processes. In particular, the Markov probabilities allow analysis of the interactions between the yield curve and the phases of the business cycle. Since the bond market phases anticipate the phases of the business cycles with a variable lead, rather than pre-imposing a structure to their linkages, the proposed flexible framework enables study of their specific lead-lag relationship over each one of the expansions and recessions that occurred in the U.S. in the last 40 years. As the results show, this information turns out to be very important in predicting the onset of business cycle phases.

Finally, the nonlinearities in the form of switching states can capture changes in the stochastic structure of the economy such as the possibility of recurrent breaks. Several recent papers have shown that the predictive content of the yield curve is not stable over time. In general, linear regression models that use output growth as the dependent variable indicate that the forecasting ability of the term spread has reduced since mid 1980s.⁶ Although the results from binary models of recession are less unambiguous,⁷ Chauvet and Potter (2002, 2005) find overwhelming evidence of breaks in the relationship between the yield curve and economic activity using Bayesian techniques to estimate probit models, and show that not taking them into

⁵ Bernadell, Coche and Nyholm (2005) extend Diebold and Li's (2006) dynamic Nelson-Siegel framework to include Markov switching in the factors with transition probabilities as a function of macroeconomic variables (GDP and CPI). The model is used to produce term-structure forecasts. More recently, Nyholm (2007) extends this framework to forecast recessions.

⁶ See, for example, Haubrich and Dombrosky (1996), Dotsey (1998), Friedman and Kuttner's (1998), Giacomini, and Rossi (2006) or Stock and Watson's (2000) survey.

⁷ See Neftci (1996), Dueker (1997), Estrella and Mishkin (1998), and Estrella, Rodrigues, and Schich (2000).

account lead to poor real time forecasts. Our proposed models are extended to include the possibility of abrupt changes in the underlying series, based on the results of endogenous breakpoint tests.

We investigate the in-sample and out-of-sample forecasting performance of the yield factor from our proposed framework to future economic activity both in form of linear projections, as well as in terms of event timing – the beginning and end of business cycle phases. The analysis is performed using revised data and real time unrevised data. In addition to the proposed joint model of the yield curve and the economy, we also estimate for comparison a multivariate model in which only the information on the yield components are used to extract a single yield factor, and univariate models of each of the yield curve components.

Our results show a strong correlation between the real economy and the bonds market. The yield factor extracted from the interrelationship between both sectors has a superior ability to anticipate economic recessions compared to alternative frameworks. In particular, the yield-economy factor predicts the beginning and end of all recessions in the sample studied with no false peaks or troughs and no missed turns – a perfect forecast score. An important feature of the model is its usefulness to predict not only the beginning but also the end of recessions. For example, the yield factor model has already predicted out-of-sample the end of the 2007-2009 recession. We also evaluate the forecasting performance of the proposed models and univariate alternatives in terms of calibration, resolution, and skill score. The yield-economy factor model is well calibrated and is the only one with positive skill score (i.e. forecasts better than the benchmark constant forecast). In addition, the model displays the highest discrimination power, the lowest conditional and unconditional biases, and a better balance between accuracy and resolution, leading to a substantially smaller Mean Squared Error compared to other models.

Finally, the forecasting performance of alternative models for future values of the industrial production growth is also examined. The joint bi-factor model of the yield curve and the economy outperforms the alternative specifications. The model reduces the dimensionality of the information on the yield curve down to one state variable that yields better predictions compared to a specification that uses the term spread or all three components of the yield curve in a linear regression. This result holds in-sample, out-of-sample, using revised data or in a real time exercise.

In summary, we find that the components of the yield curve have useful information to forecast recessions and expansions and future projections of industrial production growth. Although the popular term spread model has a reasonable forecasting performance, the proposed factor model that considers the interrelationship between the bonds market and the economy exhibits substantial incremental predictive value.

The paper is organized as follows. Section 2 introduces the data and the construction of the components of the yield curve. Section 3 discusses univariate Markov switching models and the multivariate dynamic factor models for the components of the yield curve. The proposed joint bifactor model of the bond market and the economy that allows for the interrelations between these sectors is presented in Section 4. The estimation results are discussed in Section 5. Sections 6 and 7 present, respectively, the turning point forecasting evaluation and the projection predictive performance of the proposed model compared to alternative specifications. Section 8 concludes.

2. The Data

The series on U.S. Treasury yields with maturities of 3 months, 2 years, and 10 years are used to construct the three components of the yield curve. We use data compiled and made publicly accessible by Gurkaynak, Sack, and Wright (2007). Monthly yields are obtained by taking the average of daily yields. The data are available from 1971:08 to 2007:12. The empirical proxies used to represent the level, the slope, and the curvature of the yield curve are then constructed as follows. The level factor (L_t) is computed as the arithmetic average of the 3-month, 2-year, and 10-year bond yields. The curvature (C_t) is measured as two times the 2-year bond yield minus the sum of the 3-month and 10-year bond yields. Finally, the slope of the yield curve (T_t) corresponds to the difference between the 10-year bond rate and the 3-month T-bill rate.

These empirical proxies for the level, curvature, and slope are highly correlated with estimated latent factors from models of the entire yield curve as shown in Diebold and Li (2006), Ang and Piazzesi (2003), and Diebold, Rudebusch, and Aruoba (2006).

Figure 1 plots the level, curvature, and slope of the yield curve and recessions as dated by the National Bureau of Economic Research (NBER). The level is highly persistent and it is often interpreted as the long run component of the yield curve. The curvature and the slope are considered the medium run and the short run components, respectively. Diebold and Li (2006)

and Diebold, Rudebusch and Aruoba (2006) show that the level is closely associated with inflation expectations, while the slope is associated with future economic activity (e.g. capacity utilization). The curvature is not generally associated with any specific macroeconomic variable. However, notice that the curvature displays a correlation with the NBER-dated recessions, although weaker than the term spread (slope).

The slope of the curve is considered the best predictor of recessions among the yield curve components. As it can be observed, it inverted before five out of six recessions in the sample as dated by the NBER. However, as found by several other authors, the slope did not turn negative before the 1990 recession. It is interesting to investigate the power of the slope in predicting previous recessions as well. Although data for the other series are not available before 1971, the slope series goes back to 1953:01 (Figure 2). During the period between 1953 and 1971 there were three recessions as dated by the NBER.⁸ The term spread had a much less clear-cut relationship with business cycle during this time. In particular, the slope only inverted before the 1969-1970 recession and did not become negative before the 1957-1958, and 1960-1961 recessions. In addition, the slope inverted in 1966-1967 and no recession followed. It is important to keep this performance in mind, as it illustrates the instability of the term spread in predicting recessions over time. We further investigate this for our period in the next section.

Rather than relying on only one variable, we use the empirical proxies of level, curvature, and slope of the yield curve to extract the yield factor. The economic factor is built from the monthly industrial production index, obtained from the Federal Reserve Bank of St. Louis. For consistency, we use the same sample as the one available for the yield curve data. The series is transformed by taking the log annual difference (ΔIP_t). We denote log real IP growth from $t-12$ to t expressed at the monthly frequency as:

$$\Delta IP_t = \frac{1}{12} (\ln IP_t - \ln IP_{t-12})$$

3. Univariate and Multivariate Nonlinear Single-Factor Models of the Yield Curve

As a first step, we specify univariate Markov switching models for each of the components of the yield curve, and a multivariate unobserved dynamic factor model of the yield curve that

⁸ The availability of the data does not allow evaluation of the inversion of the curve before the 1953-1954 recession.

summarizes the information content of the level, curvature, and the slope of the yield curve into a single factor. These models of the yield curve without linkage to the real economy are going to be used for comparison with our joint model of the yield curve that includes an economic factor as well.

3.1 Univariate Nonlinear Models of the Yield Curve

Before October 1979, the Fed used to target the price of bank reserves in the financial system. A measure of the tightness of monetary policy was the changes in the federal funds rate. In October 1979, the Federal Reserve Board adopted new operating procedures shifting their emphasis from targeting the federal funds rate to the supply of bank reserves in order to achieve the desired rates of growth in the monetary aggregates. As a consequence of this policy, there was a widening of the range for the federal funds rate, which increased to 400 basis points the following months. The funds rate rose drastically from 11.4% in September to 13.8% by the end of 1979, and peaked at 19.1% in June 1982. By the end of 1982, the funds had then decreased to 8.9%. The wide fluctuations in the average federal funds rate between 1979 and 1982 were associated with a double dip recession and also a sharp fall in inflation. The dramatic policy actions by the Federal Reserve not only corresponded to a change in the way monetary policy was conducted, but engendered potential structural breaks in interest rates and in its relationship with the real economy.

We test for potential breaks in each component of the yield curve series and in the growth rate of industrial production using the asymptotically optimal tests developed by Andrews (1993), Andrews and Ploberger (1994), and the sequential procedure of Bai (1997b) and Bai and Perron (1998) for multiple breaks. Since we examine the dynamics of each of its components, the tests allow us to investigate the source of the potential breaks in the yield curve.

We consider two separate hypotheses. First, we test for the possibility of a break in the variance of the series assuming that the mean has remained constant. However, the results of this test would be unreliable if there were a break in the parameters of the underlying model. In this case, evidence of a break in the volatility from this test could be due to neglected structural change in the conditional mean of the series. In order to account for this, we also test for a break in the conditional mean of the series, allowing for changing variance.⁹

⁹ The details of the tests are described in more detail in an appendix available upon request.

The tests indicate strong evidence of several breaks in the components of the yield curve. First, all three series display a break in volatility between 1980:05 and 1981:08. In the case of the term spread, there is also strong evidence of a break in its mean in this period. Several papers have found instability in the predictive power of the yield curve, particularly with respect to the 1990-1991 recession. We find significant structural breaks in the mean of both the curvature and the level series around 1990:06 and 1990:12. In addition, the variance of the level also displays a break in 1990:11. On the other hand, the tests applied to industrial production growth find a break in its volatility in 1983:12. These results are summarized in Table 1.

Based on this evidence, we specify a variant of Hamilton's univariate Markov switching model that takes into account changes in the mean and variance before and after the breakpoints in addition to the switching in the parameters related to cyclical changes in the components of the yield curve or industrial production.

Let \tilde{y}_t represent each of the components of the yield curve, which is modeled as the sum of two integrated components: a Markov trend term, \tilde{n}_t , and a Gaussian component, \tilde{z}_t , as in Hamilton (1989):

$$\tilde{y}_t = \tilde{n}_t + \tilde{z}_t \quad (1)$$

The Markov trend is given by,

$$\tilde{n}_t = \tilde{n}_{t-1} + \alpha_{S_t} \quad (2)$$

where S_t is an unobservable first-order 2-state Markov chain and α_{S_t} is the state-dependent drift term. The drift term α_{S_t} takes the value of α_0 when the economy is in a low-growth phase or in a recession ($S_t = 0$) and α_1 when the economy is in a high-growth state or in an expansion ($S_t = 1$). These switches are governed by the transition probability matrix \mathbf{P}_2 with elements $p_{ij} = pr[S_t = j | S_{t-1} = i]$ where i denotes the i^{th} column and j denotes the j^{th} row. Each column of \mathbf{P}_2 sums to one, so that $\mathbf{1}_2' \mathbf{P}_2 = \mathbf{1}_2'$, where $\mathbf{1}_2$ is a column vector of ones. The Gaussian component follows a zero mean ARIMA($r, 1, 0$) process:

$$z_t = \tilde{z}_{t-1} + \phi_1(\tilde{z}_{t-1} - \tilde{z}_{t-2}) + \dots + \phi_r(\tilde{z}_{t-r} - \tilde{z}_{t-r-1}) + \varepsilon_t \quad (3)$$

where $\varepsilon_t \sim \text{iid } N(0, \sigma^2)$ and ε_t is independent of $n_{t+h}, \forall h$. Taking the first difference of (1) we obtain:

$$y_t = \alpha_{S_t} + \phi_1(\tilde{z}_{t-1} - \tilde{z}_{t-2}) + \dots + \phi_r(\tilde{z}_{t-r} - \tilde{z}_{t-r-1}) + \varepsilon_t \quad (4)$$

for $y_t = \tilde{y}_t - \tilde{y}_{t-1}$. We assume that the Markov chains are first-order processes, which imply that all relevant information for predicting future states is included in the current state, i.e., $pr[S_{t+1}|I_t, S_t, S_{t-1}, \dots] = pr[S_{t+1}|S_t]$. This model is applied separately to the level (L_t), curvature (C_t), and slope (T_t) of the yield curve:

$$L_t = \alpha_{S_t^L} + \phi^L(L) L_{t-1} + \varepsilon_t^L \quad \varepsilon_t^L \sim (0, \sigma_{\varepsilon^L}^2) \quad (5)$$

$$C_t = \alpha_{S_t^C} + \phi^C(L) C_{t-1} + \varepsilon_t^C \quad \varepsilon_t^C \sim (0, \sigma_{\varepsilon^C}^2) \quad (6)$$

$$T_t = \alpha_{S_t^T} + \phi^T(L) T_{t-1} + \varepsilon_t^T \quad \varepsilon_t^T \sim (0, \sigma_{\varepsilon^T}^2) \quad (7)$$

where the state variables, S_t^k for $k = L, C, T$ are assumed each to follow two-state Markov processes with transition probabilities given by $p_{ij}^k = \Pr[S_t^k = j | S_{t-1}^k = i]$ for $i, j = 0, 1$, and $\alpha_{S_t^k} = \alpha_0^k S_t^k + \alpha_1^k (1 - S_t^k)$, which is the intercept that captures switches between low and high values of the series.

The models produce as output probabilities of low or high states, which will be used to evaluate their ability of the models to anticipate business cycle turning points in section 6. Notice, however, that Hamilton's model decomposes \tilde{y}_t into the sum of two unit roots processes that are not identifiable from each other. Thus, in the presence of structural breaks, both terms confound low and high phases with the breaks themselves.

There are different ways to handle the problem of structural breaks in Markov switching models. The venue that we pursue is to augment the model by allowing \tilde{y}_t to follow two independent two-state Markov processes: one that captures recurrent switches between low and high values of the series and the other that captures permanent structural breaks. The Markov process for detecting structural break has a switching drift and variance:

$$\alpha_{D_t} = \alpha_0(1 - D_t) + \alpha_1 D_t$$

$$\sigma_{D_t}^2 = \sigma_0^2(1 - D_t) + \sigma_1^2 D_t$$

where $D_t = 0$ if $t < t^*$ and $D_t = 1$ otherwise, and t^* is the break date. The transition probabilities for the Markov process are constrained to capture the endogenous permanent break as in Chib (1998):

$$\begin{aligned} \Pr[D_t = 0 | D_{t-1} = 0] &= q & 0 < q < 1 \\ \Pr[D_t = 1 | D_{t-1} = 1] &= 1. \end{aligned}$$

3.2 The Multivariate Nonlinear Single-Factor Model of the Yield Curve

We combine the information from each one of the components of the yield curve in a single factor, using a dynamic factor model with regime switching. Let \mathbf{y}_t be the 3×1 vector of observable variables, which consists of the empirical proxies of the level (L_t), slope (T_t) and the curvature (C_t) of the yield curve. The measurement equations are given by

$$\mathbf{y}_t = \Lambda YF_t + \mathbf{U}_t \quad (8)$$

where, YF_t is the scalar common factor, \mathbf{U}_t is a 3×1 vector of idiosyncratic components, which measure variable-specific movements not captured by the common factor, and Λ is the 3×1 vector of factor loadings that show to what extent each of the series is affected by the common factor. Individually, the equations that establish the link between the observable variables and the unobservable yield factor can be written as:

$$\begin{aligned} L_t &= \lambda_1^{YF} YF_t + u_{1t}^{YF} \\ C_t &= \lambda_2^{YF} YF_t + u_{2t}^{YF} \\ T_t &= \lambda_3^{YF} YF_t + u_{3t}^{YF} \end{aligned} \quad (9)$$

where λ_i^{YF} and $u_{i,t}$ are the factor loadings and the individual idiosyncratic terms for the i th series, respectively ($i = 1$ for level, $i = 2$ for curvature and $i = 3$ for slope). The yield factor is assumed to be uncorrelated with the idiosyncratic terms at all leads and lags.

We assume that the dynamics of the common yield curve factor can be represented by an autoregressive process whose intercept is subject to discrete changes depending on the state of the bond market cycle:

$$\phi^{YF}(L)YF_t = \alpha_{S_t^{YF}} + \varepsilon_t^{YF}, \quad \varepsilon_t^{YF} \sim (0, \sigma_{\varepsilon_{YF}}^2) \quad (10)$$

where $\phi^{YF}(L)$ is a polynomial in the lag operator with roots outside the unit circle, ε_t^{YF} is the transition shock and $\alpha_{S_t^{YF}} = \alpha_0 S_t^{YF} + \alpha_1(1 - S_t^{YF})$ is the switching intercept that drives the mean of the yield curve factor. The state variable, S_t^{YF} takes the value 0 or 1, according to a first order two-state Markov process, with transition probabilities given by $p_{ij}^{YF} = \Pr[S_t^{YF} = j | S_{t-1}^{YF} = i]$ where $i, j = 0, 1$. State 0 represents periods in which the yield factor takes low values whereas State 1 represents periods in which it takes high values.

In order to account for the potential remaining variation in the three yield curve factors not shared by all of them simultaneously, we model the idiosyncratic components as the following autoregressive processes:

$$\begin{aligned} u_{1t}^{YF} &= d_1 u_{1t-1}^{YF} + e_{1t}^{YF} \\ u_{2t}^{YF} &= d_2 u_{2t-1}^{YF} + e_{2t}^{YF} \\ u_{3t}^{YF} &= d_3 u_{3t-1}^{YF} + e_{3t}^{YF} \end{aligned} \quad e_{it}^{YF} \sim i.i.d N(0, \sigma_{e_{iYF}}^2), \quad i = 1, 2, 3 \quad (11)$$

4. The Multivariate Joint Bi-Factor Model of the Yield curve and the Economy¹⁰

We propose a unified model of bonds market cycles and economic cycles that takes into account their dynamic interrelationships. The state space model is now augmented to include two

¹⁰ Notice that Diebold, Rudebusch, and Aruoba (2006) model the yields with 17 different maturities, y_t , as a function of *three* unobserved factors, f_t – the level, curvature, and slope. Their coefficient matrix, Λ , linking f_t to y_t is parameterized based on Nelson-Siegel model. In Diebold, Rudebusch, and Aruoba’s version with macroeconomic variables, f_t also includes capacity utilization, the federal funds rate, and inflation. In our model, y_t (not f_t) includes three observable empirical proxies for the level, curvature, and slope of Treasury yields, which are used to extract *one* factor, f_t , representing the entire yield curve. In the version with macroeconomic variables, y_t (not f_t) includes additionally industrial production and we estimate 2 factors, the second one representing the economy. These factors follow different two-state Markov processes. There is no parametric restriction on the coefficient matrix linking the f_t to y_t related to Nelson-Siegel model. The only aspect from Nelson-Siegel model that we use is the idea of the yield as composed by the slope, curvature, and spread – but we do so by using empirical time series proxies of them.

unobserved factors, representing the yield curve and the economy. The latent yield curve factor, YF_t , is extracted from the empirical proxies for the level, the slope, and the curvature of the yield curve, as before. The industrial production series is used to construct the latent economic factor at the monthly frequency, EF_t .

The model is cast in state-space, which allows us to simultaneously estimate the two unobservable factors as well as their intertemporal relationship. The interactions are investigated by specifying the factors as following a vector autoregressive system. The measurement equations still take the following form:

$$\mathbf{y}_t = \Lambda \mathbf{F}_t + \mathbf{U}_t \quad (12)$$

but now $\mathbf{y}'_t = \{L_t, S_t, C_t, \Delta IP_t\}$, $\mathbf{F}'_t = \{YF_t, EF_t\}$, and Λ is the 4x2 matrix of factor loadings. The factors are assumed to be uncorrelated with the idiosyncratic terms, \mathbf{U}_t , at all leads and lags. We allow the idiosyncratic errors of the economic and yield variables to be serially correlated:

$$\mathbf{D}(L)\mathbf{U}_t = \Xi_t \quad (13)$$

where \mathbf{D} is the 4x4 matrix of autoregressive coefficients, Ξ_t is the 4x1 vector of measurement

errors with $\Xi_t \sim \mathbf{N}\left(0, \begin{pmatrix} \Sigma^{YF} & 0 \\ 0 & \Sigma^{EF} \end{pmatrix}\right)$, Σ^{YF} is the diagonal variance-covariance matrix

corresponding to the yield variables, and Σ^{EF} is the variance of the economic variable.¹¹

Each factor follows an unobservable autoregressive process whose intercept is a function of two distinct Markov variables, S_t^{YF} for the yield factor and S_t^{EF} for the economic factor. By

¹¹ Estimates of the yield curve model (8)-(10) in the previous section indicate that the level component of the yield curve is very persistent. The Augmented Dickey-Fuller's (1979) test, Phillips and Perron's (1988) test, and the log-periodogram regression (after accounting for the highly volatile dynamics of the series in the early 1980s and the mean break in the 1990) all fail to reject the unit root hypothesis. One way to deal with nonstationarity of the series within the proposed framework is to work with its first difference. However, the level of yield curve itself might have information that is relevant for forecasting the economy, as found in some recent papers such as Wright (2006) and Ang, Piazzesi, and Wei (2006). Thus, we model the level of the yield curve as composed of two parts: a stationary component, which is captured by the common yield factor, and a stochastic trend not shared with the spread or with the curvature (i.e., the coefficient corresponding to the level of the yield curve in the matrix \mathbf{D} is unity).

allowing for potentially independent Markov processes for the two factors, we do not restrict the latent variables representing bond markets and the real economy to switch between phases at the same time, which would be an unreasonable assumption given that the yield curve anticipates the business cycle. The transition equations are:

$$\mathbf{F}_t = \boldsymbol{\alpha}_{S_t} + \boldsymbol{\Phi} \mathbf{F}_{t-1} + \mathbf{N}_t, \quad \mathbf{N}_t \sim (0, \boldsymbol{\Omega}_t) \quad (14)$$

The coefficients of the 2x2 transition matrix, $\boldsymbol{\Phi} = \begin{bmatrix} \phi^{YF} & \theta^{YF} \\ \theta^{EF} & \phi^{EF} \end{bmatrix}$, capture the lead-lag relationship

between the yield factor and the economic factor, while we assume that $\boldsymbol{\Omega}_t$ is the diagonal variance covariance matrix of the common shocks to each factor.¹² The intercept terms,

$$\boldsymbol{\alpha}_{S_t} = \begin{bmatrix} \alpha_0^{YF} + \alpha_1^{YF} S_t^{YF} \\ \alpha_0^{EF} + \alpha_1^{EF} S_t^{EF} \end{bmatrix},$$

switch between states, governed by the transition probabilities of the

first order two-state Markov processes, $p_{ij}^{YF} = Pr[S_t^{YF}=j | S_{t-1}^{YF}=i]$, $p_{ij}^{EF} = Pr[S_t^{EF}=j | S_{t-1}^{EF}=i]$, with

$$\sum_{j=0}^1 p_{ij}^{YF} = \sum_{j=0}^1 p_{ij}^{EF} = 1, \quad i, j = 0, 1.$$

The Markov chain S_t^{YF} represents high ($S_t^{YF}=1$) or low

($S_t^{YF}=0$) bond market phases, while S_t^{EF} represents business cycle expansions ($S_t^{EF}=1$) or

contractions ($S_t^{EF}=0$). Given the assumptions of the model, the representation allows the

underlying process for the bonds market cycle and the business cycle to switch non-

synchronously over time. This structure can capture the variable average lead-lag relationship

between the phases of the two markets.

We estimate all parameters and factors simultaneously in one step. Compared to two step procedures, this joint modeling has the advantage that it does not carry out parameter estimation uncertainty associated with extracting the factors to the VAR model that specifies the dynamic relation between the factors. We first cast the models in state space form and then combine a

¹² Allowing for non-diagonal covariance matrix yields coefficients very close to zero.

nonlinear discrete version of the Kalman filter with Hamilton's (1989) algorithm. The increasing number of Markov cases is truncated at each iteration using an approximation suggested by Kim (1994). The nonlinear Kalman filter is initialized using the unconditional mean and unconditional covariance matrix of the state vector. A nonlinear optimization procedure is used to maximize the likelihood function, which is obtained as a by-product of the probabilities of the Markov states. In particular, we use Gauss-Newton and Berndt–Hall–Hall–Hausman algorithm, which is based on numerical derivatives and optimal step size. The convergence criterion for the change in the norm of the parameter vector in each iteration is set to $1e-5$. For maximization of the likelihood, the parameters are constrained so that the autoregressive processes are stationary, the innovation covariance matrices are positive definite, and the transition probabilities are between 0 and 1. The predictions of the unobserved factors and of the probabilities of the Markov states are obtained as final pass of the nonlinear filter based on the maximum likelihood estimates.

5. Estimation Results

We estimate our proposed dynamic single factor and bi-factor models and three alternative specifications for comparison, in addition to the benchmark model that produces the forecast object for the turning point analysis. The models are:¹³

Benchmark Model – univariate Markov switching model for industrial production.

Model 1 – univariate Markov switching model for the level of the yield curve.

Model 2 – univariate Markov switching model for the curvature of the yield curve.

Model 3 – univariate Markov switching model for the slope of the yield curve.

Model 4 – multivariate Markov switching single-factor model for the level, curvature, and slope of the yield curve.

Model 5 – multivariate Markov switching bifactor model for the level, curvature, and slope of the yield curve, and for the economy.

¹³ The best specifications of the models in terms of the lags of the common factor and the idiosyncratic components were selected based on likelihood ratio tests and the significance of the coefficients.

5.1 Benchmark Univariate Model of the Economy

A two-state Markov switching model as described in section 3.1 is fitted to changes in the log of industrial production, ΔIP_t :

$$\Delta IP_t = \alpha_{S_t^{IP}} + \phi^{IP}(L) \Delta IP_{-1t} + \varepsilon_t^{IP} \quad \varepsilon_t^{IP} \sim (0, \sigma_{\varepsilon^{IP}}^2) \quad (15)$$

where the state variable S_t^{IP} is assumed to follow a two-state Markov process with transition probabilities given by $p_{ij}^{IP} = \Pr[S_t^{IP} = j | S_{t-1}^{IP} = i]$ for $i, j = 0, 1$, and $\alpha_{S_t^{IP}} = \alpha_0^{IP} S_t^{IP} + \alpha_1^{IP} (1 - S_t^{IP})$ is the intercept that captures switches between positive and negative growth mean rate of industrial production, representing recessions and expansions at the monthly frequency. The maximum likelihood estimates of the model are reported in Table 2. The phases of the growth rate of Industrial Production are symmetric with respect to their mean values, but asymmetric with respect to their duration. State 1 has a positive mean growth rate and a longer duration, which captures economic expansions, while state 0 has a negative mean growth rate and a shorter duration, representing recessions.

The estimated probability of regime 0 at time t conditional on the full sample information I_T , denoted $\Pr[S_t = 0 | I_T]$, is plotted in Figure 3. Since we are interested in obtaining specific turning point dates, we need to use a rule to convert the recession probabilities into a 0/1 variable that defines whether the economy is in an expansion or recession regime at time t . In particular, we assume that a business cycle peak occurs in month $t+1$ if the economy was in an expansion in month t , $\Pr[S_t = 0 | I_T] < 0.5$, and it entered a recession in $t+1$, $\Pr[S_{t+1} = 0 | I_T] \geq 0.5$. A business cycle trough occurs in month $t+1$ if the economy was in a recession in month t , $\Pr[S_t = 0 | I_T] \geq 0.5$, and it entered an expansion in month $t+1$, $\Pr[S_{t+1} = 0 | I_T] < 0.5$.

This simple rule produces a monthly business cycle dating that will be used as a benchmark for evaluation of the forecasting performance of the models. The phases of ΔIP_t closely match the NBER business cycle phases. The proposing dating has the advantage that it is readily available and can be estimated in real time, whereas the NBER dating is generally available ex-post and with long delays.

5.2 Univariate and Multivariate Single-Factor Yield Models

Table 3 shows the maximum likelihood estimates of the univariate Markov switching models and the multivariate nonlinear dynamic single factor model of the yield curve. The coefficients of the Markov states are statistically significant in all models.

The level, curvature, and slope of the yield curve switch between low and high values but these values are not stable over time. In particular, the level of the yield curve shows striking changes pre and post 1990. The high mean value was 10.1% whereas the one for the low mean state was 5.5% before 1990. After 1990, the mean in both states decreases substantially, with the high mean equal to 5.4% and the low mean equal to 3%. This can be visualized in Figure 4, which plots the level of the yield curve and the smoothed probabilities of the high level state. Notice that the high level state is the one that predicts future recessions – the probabilities indicate that the high level state generally occurs from the middle of an expansion until a couple of months before the beginning of recessions. The exception is during the period of the Great Inflation between 1978 and 1985, in which the probabilities remain high even during recessions. The estimated probabilities of the Markov states for the level are consistent with the dynamics of inflation expectations over the business cycle.

The curvature of the yield curve also shows dramatic changes before and after 1990. Before 1990, the high and low values were around 1.3% and 0.2%, respectively. After this point, the high mean decreases to 0.3%, whereas the low mean of the curvature becomes negative, decreasing to -1.3%. Figure 5 shows the probabilities of low mean state and the curvature series. In contrast with the level, it is the low mean state of the curvature that is associated with economic recessions. In particular, the probabilities of low mean increase (as the curvature decreases or becomes negative) right before or during recessions. Notice that after 1990-1991 and the 2001 recessions, the probabilities remain high even after the recessions were over and until the middle of the subsequent expansions. This and other features of the curvature make it a less reliable leading indicator of recessions, as discussed in section 6.

The dynamics of the slope of the yield curve – the term spread – has also changed significantly over time. The break date for this series is earlier than for the other two components, occurring in 1980-1981. We find that both the mean and variance of the slope display a break around this period. Prior to this date, the high mean state was around 2% and the low mean state was negative, at -1%. Differently from the other two components, both the high

and low state mean values have increased after the break: the high mean to 3%, and the low mean became positive at 0.9% in the posterior period. That is, since 1980-1981 a flat curve – rather than an inversion of the curve – signals recession. This can be seen in Figure 6, which plots the smoothed probabilities of the low slope state and the slope series. As for the curvature, low values of the term spread are associated with recessions. Notice that the probabilities of flat or inverted slope generally rise to around 100% towards the middle to the end of economic expansions and fall to values around 0% during recessions. The fact that the low mean state has turned positive since 1980-1981 illustrates the uncertainty on inferring subsequent recessions from changes in the term spread. For example, there were some instances – such as in 1995 or in 1998, in which the slope became flat but no recession followed. This will be discussed in more detail in section 6.

There is a large body of literature documenting changes in the volatility of the U.S. economy. In particular, McConnell and Perez-Quiros (2000) find evidence of a break towards more stability in the economy since 1984. We find that the level and slope of the yield curve also display an increased stability. The variance of the level fell to $\frac{1}{4}$ of its value after 1990, while the variance of the slope decreased to half its value after 1982. On the other hand, we do not find a significant change in the volatility of the curvature.

The last column of Table 3 shows the estimated coefficients from the multivariate dynamic single factor model of the yield curve. The model extracts an indicator from the common information underlying the level, curvature, and slope of the yield curve. An important feature of this model is that the nonlinear combination of several variables mitigates the instability of each individual series. The resulting yield factor does not display structural breaks. The high mean state is 0.6 and the low mean state is negative, -0.4. Notice that the low mean state is lengthier than the high mean state, as implied by the larger transition probability of the former. The factor loadings measure the sensitivity of the series to the extracted yield curve factor. The loadings are negative for the curvature and the slope and positive for the level. This implies that high values of the yield factor are associated with future recessions.

Figure 7 plots the smoothed probabilities of high state for the yield factor. The probabilities consistently rise above 50% a couple of years before economic recessions – in the middle of expansions – and remain high until the beginning of recessions. Notice that the probabilities were noisy in the period between 1994 and 2001 as did the probabilities of the level and

curvature described above. In fact, it would have been difficult to interpret movements of the yield curve factor at that time since it signaled the possibility of future recessions around 1995 and 1998 but no recession followed these high values of the yield curve factor. During this period, the level of the yield curve increased and the slope became flat.¹⁴ Thus, this model is still not able to extract unambiguous future recession signals when the movements in the components of the yield curve are subtle.

5.3 Multivariate Joint Bi-Factor Model of the Yield Curve and the Economy

We propose a bi-factor model that takes into account the dynamic interrelationship between the bonds market and the real economy. This model uses the components of the yield curve to extract the yield factor as before, but now it is estimated conditional on its relationship with the economic factor – which is extracted using information from the growth rate of industrial production.

Table 4 shows the maximum likelihood estimates.¹⁵ The yield factor extracted from this framework shares some similarities with the single yield factor that uses information on the yield curve only. Most parameters are close in value. In particular, the factor loadings have the same signs – positive for the level and negative for the curvature and slope, implying that the high state of the yield-economy factor is associated with future economic recessions. Figure 8 plots the extracted yield-economy factor and its components along with recessions as dated by industrial production. The yield-economy factor, which is a nonlinear combination of the yield components, is found to be stationary and with more pronounced cyclical fluctuations than its individual components. These features substantially increase the ability of the factor to signal future recessions, as will be discussed in more detail in the next section. Notice that the yield-economy factor rises substantially around two years before the beginning of recessions. This can also be observed in the dynamics of the smoothed probabilities of high value for the yield factor, as shown in Figure 8. Each one of the six recessions in the sample – including the most recent one that started in 2007:12 – is preceded by a rise in the probabilities of high yield factor above 50%. At the onset of recessions, however, the probabilities – and the yield factor – fall. This is a

¹⁴ During this period there was a mild economic slowdown in the U.S associated with international financial crises such as the Mexican Crisis in 1994, the Asian Crisis in 1997, and the Russian crisis in 1998.

¹⁵ For identification of the factors, we set the variance of the yield factor and the loading of the economic factor to one. This is a standard normalization to fix a scale for the factors and do not affect the estimated coefficients.

very interesting feature as the factor seems to convey additional information on future recessions. While an increase in the probability of high state signals recessions with a long lead, the beginning of recessions themselves – which is difficult to call in real time – can be identified by a subsequent fall in the probabilities of high state.

The main difference between the yield-economy factor extracted from the joint model of the yield curve components and economic information and the factor extracted only from the yield components is that the former has a lower transition probability in the high state compared to the latter. This implies a longer duration during the high phase for the yield-only factor as it can be observed by comparing Figures 7 and 9. The smoothed probabilities of the yield-only factor remain high and display two false signals during the mid-1990s, while the smoothed probabilities of high state for the yield-economy factor do not give any false signals during this period and only increase before the 2001 recession. Thus, by including the relationship between the bonds market and the real economy, we obtain a factor that more accurately anticipates economic recessions.

The last column of Table 4 reports the parameter estimates for the economic factor. The Markov switching coefficients are highly significant. The two states for the economic factor share very similar patterns to the phases of growth in industrial production (Table 2), with a negative mean growth rate in state 0 and a positive one in state 1. However, the two states do not have a symmetric duration, with expansions lasting longer than recessions.

The relationship between the yield factor and the economic factor is represented by the coefficients of the vector autoregression in the transition equations (14), $\Phi = \begin{bmatrix} \phi^{YF} & \theta^{YF} \\ \theta^{EF} & \phi^{EF} \end{bmatrix}$. The signs of the coefficients are as expected. The lagged yield factor is negatively correlated with the current economic factor ($\theta^{EF} = -0.12$). That is, high values of the lagged yield factor are associated with low future values of the economic factor. On the other hand, the lagged economic factor is positively associated with the yield factor ($\theta^{YF} = 0.04$). Notice that these coefficients reflect the average relationship over the states. The lead-lag dynamics of the bonds market and the real economy is better depicted by studying the linkages between their phases. This can be directly examined within our proposed nonlinear framework that allows for two distinct (but potentially dependent) Markov processes to represent the yield curve cycle and the business cycle.

6. Event Timing Forecast - Turning Point Analysis

The proposed Markov switching models are very powerful tools for event timing analysis, which is examined in this section. The forecast objects are turning points of business cycles – the beginning (peaks) and end (troughs) of economic recessions. Once the economy enters a recession (or in an expansion) its end is certain, but not the timing in which it will occur.

Tables 5 and 6 report turning point signals and errors of our proposed models and the univariate alternatives in signaling recessions, as dated by the benchmark model of industrial production. The turning points for all models are determined according to the simple rule based on the full sample probabilities of the Markov states as described in section 5.1.

In addition to in-sample turning point forecasts, we also test the ability of the models to forecast the current recession out-of-sample using unrevised real time data. In particular, we estimate the models up to 2003:12 and recursively re-estimate them out-of-sample until 2007:12. The results are shown in the last row of the two panels in Table 5.

The level of the yield curve (Model 1) misses 3 out of 6 peaks and 3 out of 5 troughs, while the curvature of the yield curve (Model 2) misses 2 peaks and 4 troughs. Note that the probabilities of a recession from the level series remained above 50% from 1994 to 2001, giving very mixed signals of a recession since the early stages of the longest expansion in the U.S. history. This is related to the fact that the level series decreased substantially in the last two decades, which contributes to confound the low and high state phases compared to previous decades. The worst performance is from model 2. In addition to missing many turning points, the curvature also signals 2 false peaks and 2 false troughs. As it can be seen in Figure 5, these false signals took place in 1976-1978 and in 1984-1989.

As it is found in the literature, the term spread does very well in forecasting business cycle turning points (Model 3). It signals all troughs and five out of six peaks. However, it falsely signals a peak and trough in 1985-1986 and gives very mixed signals for the 2001 recession. As for the model for the level, the smoothed probabilities of recession from the term spread rose above 50% since 1995 and remained high until the beginning of the recession in 2001, six years later. The reason for this uncertainty can be visualized in Figure 6. The slope of the curve became flat from 1995 to 1999, but it only inverted in 2000. If this model were to be used to forecast recession at that time, there would certainly be large uncertainty on whether and when

the economy would be heading to a recession during these six years, since prior to this period the spread identified recessions with an average lead of two years.

The advantage of our proposed models is that it combines information from the level, curvature, and slope of the yield curve and filter out idiosyncratic movements in these components that are not common to all. The resulting factors are much improved leading indicators of the economy – especially the one obtained from Model 5, which in addition to the yield components uses information on the lead-lag relationship between the yield curve and the real economy.

As shown in Tables 5 and 6, Models 4 (single yield factor) and 5 (yield-economy factor) signal all peaks and troughs in the sample. Although Model 4 correctly signals the 2001 recession with a lead of 13 months, the smoothed probabilities of recession increase above 50% in 1995-1996 and again in 1997-1998 (Figure 7). Thus, as Models 1 and 3, the single factor model that uses information from the three yield components still does not correctly filter the information from the flat yield curve from 1994 on.

On the other hand, Model 5 has a striking performance, with a perfect forecast score (i.e, zero turning point errors, Table 6). It anticipates all 6 peaks and 5 troughs in-sample with an average lead of 23 months and 19 months, respectively. In addition, it does not give any false signals, even when the yield curve turns flat and no recession follows as in the mid-1990s. Finally, Model 5 (and model 4) not only signals the beginning of the 2007 recession out-of-sample, it has already identified its end – the probabilities of recession fell below 50% in the end of 2007 – which none of the alternative models did.¹⁶

Tables 7, 8, and 9 compare the forecasting performance of the alternative models in predicting business cycle turning points using different measures. Generally, the accuracy (or calibration) of probability to forecast the occurrence of a binary event is evaluated by the match between forecasts and realizations. Resolution (or discrimination) is another important measure of probability forecast performance, which refers to the ability of forecasts to discriminate states with relatively high conditional probabilities of the event from states with relatively low conditional probabilities. Finally, a popular test is the forecast skill, which refers to the accuracy of forecasts relative to a benchmark forecast. There are a number of different measures of

¹⁶ This paper was written in December 2008. At this time the peak of the 2007-2009 recession had already been announced to be December 2007, but not the trough.

accuracy, resolution, and skill, but most are based on a probability counterpart of the mean squared error. We evaluate the probability forecasts using the Quadratic Probability Score (QPS) (Brier and Allen 1951), which was popularized by the seminal work of Diebold and Rudebusch (1989), the Yates (1982) Decomposition, and the Murphy (1988) Skill Score.

The QPS is the most used probabilistic evaluation test. It measures the closeness of the probability forecasts from the realization of the event:

$$MSE_1 = QPS = \frac{2}{T} \sum_{t=1}^T \{f_t - N_t\}^2 \quad (16)$$

where f_t are the smoothing probabilities from the models (the model predictions), N_t is the 0/1 dummy variable that takes the value of one during recessions dated by ΔIP as measured by the simple rule described in section 5.1, and zero otherwise. The QPS ranges between 0 and 2, with the maximum accuracy corresponding to zero. The QPS penalizes larger forecast errors more than smaller ones.

Resolution or discrimination is not measured by the QPS, which also does not allow for evaluation of the probability of occurrence against non-occurrence. We use a test proposed by Yates (1982), which decomposes the covariance of the Mean Squared Error into calibration and resolution as:

$$\begin{aligned} MSE_2 &= Var(N_t) + \Delta Var(f_t) + MinVar(f_t) + (\mu_f - u_N)^2 - 2Cov(f_t, N_t) \\ MinVar(f_t) &= (\mu_{f|N=1} - \mu_{f|N=0})^2 Var(N_t) \\ \Delta Var(f_t) &= Var(f_t) - MinVar(f_t) \end{aligned} \quad (17)$$

where $Var(\cdot)$, $\mu(\cdot)$ and $Cov(\cdot)$ denote the sample variance, mean, and covariance, and $\mu_{f|N=1}$ and $\mu_{f|N=0}$ are the mean conditional on state one and zero, respectively. The first term, the variance of the observed event, reflects the forecast difficulty. The second term, $\Delta Var(f_t)$, can be interpreted as the excess variability of the forecast, while the conditional minimum forecast variance, $MinVar(f_t)$ is a measure of resolution. The fourth term is a measure of unconditional bias, and the fifth term is the association of the forecast to the observed event. Notice that there is a trade-off between calibration and resolution in minimizing the MSE_2 . A perfect discrimination

would imply miscalibrated forecasts given that it attains at the constant forecast ($MinVar(f_t) = 0$) that results in a zero correlation between the forecast and the observed event. On the other hand, a high degree of calibration implies only a fair degree of discrimination.

Finally, we also use Murphy's decomposition of the Skill Score (MSE_4). The basic skill score compares the accuracy of the forecast with the constant forecast of the mean of N_t :

$$MSE_4 = 1 - (MSE_1 / MSE_3) \quad (18)$$

where $MSE_3 = 2/T \sum_{t=1}^T \{N_t - \mu_N\}^2$ is the benchmark forecast. The skill score is 1 for perfect forecasts, 0 if the forecast is only as accurate as the benchmark forecast, and negative if the forecast is less accurate than the reference. Murphy (1988) decomposes the skill score as:

$$MSE_5 = [Corr(N_t, f_t)]^2 - [Corr(N_t, f_t) - (SD_f / SD_N)]^2 - [(\mu_f - \mu_N) / SD_N]^2 \quad (19)$$

where $Corr(.)$ and $SD(.)$ stand for correlation and standard deviation, respectively. The first term, the squared correlation between the forecast and the IP-dated recessions, is a measure of resolution, which is high if the forecasts associated with the occurrence are generally higher than the forecasts associated with nonoccurrence. The second term is the 'conditional bias,' and it evaluates how well the standard deviation of the forecasts reflects the lack of perfect correlation. The third term is the 'unconditional bias,' and it measures how close the average forecast matches the mean of the observed event. Note that the second and third terms are nonnegative, which implies that the first term would be a measure of the forecast skill if the bias could be eliminated.

Table 7 compares the accuracy of different models in predicting the IP-dated recessions, using the Quadratic Probability Score. The table shows the forecast horizons in which the models perform best in the short run, medium run, and long run, which are found to be at 3, 15, and 22 months, respectively. The level (Model 1) and the slope (Model 3) of the yield curve produce the most accurate forecasts at the 15-month horizon, while the curvature (Model 2), the yield factor (Model 4), and the yield-economic factor (Model 5) do best at the 22-month horizon. None of the models perform as well in the short run. The joint dynamic factor model of the yield and the economy (Model 5) displays the best accuracy at any horizon, with QPS values less than half of

the non-factor models. Our yield-only factor model (Model 4) displays the second best performance. At the 22-month horizon, Models 5 and 4 have QPS = 0.209 and QPS = 0.362, respectively, while the term spread (Model 3) has QPS=0.549. The worst accuracy is again for the curvature (Model 2), with its lowest QPS = 1.088 (22-month horizon), while the level (Model 1) has its lowest QPS=0.805 (15-month).

Notice that the benchmark forecast, MSE_3 , which is the constant forecast of the mean of the observed event, ranges between 0.28-0.29. Thus, with the exception of Model 5, all the other models have no advantage at any horizon compared to the benchmark forecast. This poor performance is not conveyed by the QPS values, which show a fair accuracy for the models. The source of the forecast inaccuracy can be examined using Murphy's decomposition of the skill score (Table 8). Model 5 is the only one that displays a positive skill score (from horizon 14 to 24). The main contributor of its superior performance is its larger correlation with the business cycle dating, although the biases are also very small. The other models have negative skill at any horizon. In particular, the forecasts from the level and curvature of the yield curve (Models 1 and 2) have large conditional bias and very low resolution. The term spread (Model 3) and the yield-only factor (Model 4) models have high resolution at the 15 and 22-month horizons, but this advantage is offset by their high conditional and unconditional biases. In particular, the model that uses the popular term spread shows a reasonable degree of resolution (Table 8 column 4). The tests indicate that the main weakness of the spread model is the high variability of its forecasts, in addition to a relative large unconditional bias, which together imply a high degree of miscalibration.

The forecasting performance in terms of resolution can be examined in more detail in Table 9, which shows Yates' decomposition. For any horizon, Model 5 displays the lowest mean squared error compared to the other models. The decomposition shows that this performance is achieved due to the small unconditional bias of this model, $(\mu_f - \mu_N)^2$ and the low excess variability of the forecast, $\Delta Var(f_t)$. In addition, the conditional minimum value of forecast variance, which reflects forecast discrimination with respect to times of occurrence and non-occurrence of the event, is also the smallest for Model 5. The lowest $MSE_2 = 0.102$ for Model 5 is achieved at horizon 22. This value is less than half of the MSE_2 for all the univariate models at

any horizon. Model 4 also displays a good forecasting performance, especially at longer horizons, achieving a good balance between resolution and calibration.

Overall, the tests suggest that all models of the yield curve perform best at leads of at least 15 months. Although the QPS shows that the models generally have reasonable accuracy, with the exception of Model 5 the other models have very poor skill. On the other hand, Model 5 is well calibrated and has positive skill score (forecasts better than the benchmark constant forecast). In addition, the probabilities from Model 5 have effective information with respect to the event occurrence, showing the highest discrimination power – the highest resolution and the lowest conditional and unconditional biases, compared to the other models. Moreover, it has a better balance between accuracy and resolution, leading to the smallest MSE.

In summary, we find that the components of the yield curve have useful information to forecast recession and expansions. Although the popular term spread model has a reasonable forecasting performance, the proposed factor models that use information of the whole yield curve and of the economy exhibit superior predictive value to anticipate the beginning and end of recessions. Using information from the yield curve only as in Model 4 leads to the second best forecast performance, but the results of Model 5 shows that a substantial incremental predictive value is achieved when the interrelationship between the bonds market and the economy are considered.

7. Out-of-Sample Forecasting Analysis

The out-of-sample forecasting performance of alternative models for future values of the industrial production growth is examined in this section. In addition to revised data, we also use real-time data for Industrial Production obtained from the Federal Reserve Bank of Philadelphia. These are the unrevised series as available at any given date in the past instead of the revised data currently available. Industrial production has been substantially revised over the period considered.

We consider three models to examine the usefulness of the information of the components of the yield curve in predicting the growth rate of Industrial Production. Model 6 uses lags of the slope and lags of Industrial Production itself. Model 7 uses lags of the level, curvature, and slope of the yield curve in addition to lags of Industrial Production. Finally, we estimate a model that includes lags of the yield curve factor extracted from the Markov-switching dynamic bifactor

yield-economy model in addition to lags of Industrial Production (Model 8). The lags for each model are selected using Akaike, Schwarz and Hannan-Quinn criteria. The best specifications for the autoregressive model of the growth of Industrial Production are the following:

$$\textbf{Model 6: } \Delta IP_t = \beta_0 + \beta_1 \Delta IP_{t-1} + \beta_2 \Delta IP_{t-4} + \beta_3 T_{t-10} + u_{1t}$$

$$\textbf{Model 7: } \Delta IP_t = \delta_0 + \delta_1 \Delta IP_{t-1} + \delta_2 \Delta IP_{t-4} + \delta_3 T_{t-10} + \delta_4 L_{t-10} + \delta_5 C_{t-10} + u_{2t}$$

$$\textbf{Model 8: } \Delta IP_t = \gamma_0 + \gamma_1 \Delta IP_{t-1} + \gamma_2 \Delta IP_{t-4} + \gamma_3 YF_{t-10} + \gamma_4 YF_{t-14} + u_{3t}$$

Variables that exhibit high power in explaining the linear long-run variance of output may be less important in specific situations. In fact, the largest errors in predicting output occur around business cycle turning points. Thus, we choose to investigate the period before, during, and after the 2001 recession, which will allow analysis of the ability of the models in predicting in an out-of-sample real time exercise the substantial fall and recovery in the rate of growth of industrial production during this phase.¹⁷

The models are first estimated using data from 1971:08 to 1999:12 and then recursively re-estimated for each month for the period starting in 2000:1 and ending in 2003:12. We use the in-sample estimates to generate h -step ahead forecasts in real time, using only collected real time realizations of industrial production as first released at each month for this analysis. We consider forecast horizons from 1 to 10 months, $h = 1, \dots, 10$. The loss functions are evaluated using h -step ahead forecast errors obtained through a recursive forecasting scheme. We consider three loss functions: the root mean squared error (RMSE), Theil inequality coefficient (THEIL) and the LINLIN asymmetric loss function of Granger (1969):

$$RMSE = \sqrt{\frac{1}{R} \sum_{t=T+1}^{T+R} (\Delta \hat{IP}_t - \Delta IP_t)^2}$$

¹⁷ This is the last recession phase for which both the peak and the trough are known at the time this paper was written.

$$THEIL = \frac{\sqrt{\frac{1}{R} \sum_{t=T+1}^{T+R} (\Delta \hat{P}_t - \Delta P_t)^2}}{\sqrt{\frac{1}{R} \sum_{t=T+1}^{T+R} \Delta \hat{P}_t^2} + \sqrt{\frac{1}{R} \sum_{t=T+1}^{T+R} \Delta P_t^2}}$$

$$LINLIN = \frac{1}{R} \sum_{t=T+1}^{T+R} I(\Delta \hat{P}_t - \Delta P_t) a |\Delta \hat{P}_t - \Delta P_t| + [1 - I(\Delta \hat{P}_t - \Delta P_t)] b |\Delta \hat{P}_t - \Delta P_t|$$

where T and R denote the number of observations in the estimation and forecast samples, respectively, and $\Delta \hat{P}_t$ is the forecast and ΔP_t is the observation. $I(\cdot)$ is the standard indicator function that takes the value of 1 if the forecast error is positive and takes the value of 0 if the forecast error is negative, and $a = 1$, $b = 3$. Notice that although LINLIN is linear on each side of the origin, negative errors are penalized differently from positive errors because the lines have different slopes on each side of the origin. The ratio a/b measures the cost of underpredicting relative to the cost of overpredicting. We consider the loss associated with a negative error three times as much as the loss associated with a positive error of the same magnitude.

Table 10 summarizes the results of the out-of sample forecast performance of the models in real time. For all considered forecast horizons, the model that includes lags of the extracted yield-economy factor (Model 8) does better than the other models with respect to each loss function, and its advantage increases for longer horizons. Model 8 also performs relatively better when we consider the asymmetric loss function that penalizes negative errors more than the positive ones.

We repeat the same exercise using revised Industrial Production data in order to evaluate the models forecasting performance in terms of what actually happened to the economy rather than in real time. The results are reported in Table 11. Once again, for all horizons considered, Model 8 outperforms the alternative ones. This is especially the case for horizons longer than six, for which the already superior predictive ability of Model 8 increases substantially. For example, the asymmetric loss function LINLIN at $h = 10$ for Model 8 is 55% the value for Model 7 and 61% the value for Model 6.

8. Conclusion

We propose a new model of the yield curve that uses information from the entire curve and of its interrelationship with the economy. The multivariate bi-factor model follows two separate Markov processes, each representing phases of the bonds markets and of the business cycle. The framework allows direct analysis of the lead-lag relationship between the cyclical phases of these two sectors. We use the model to forecast the beginning and end of future recessions and future projections of industrial production growth at the monthly frequency.

The results show a strong correlation between the real economy and the bonds market. The yield factor extracted from the interrelationship between both sectors has a superior ability to anticipate economic recessions compared to alternative frameworks. In particular, it predicts the beginning and end of all recessions in the sample studied with no false peaks or troughs and no missed turns. In addition, the yield-economy factor model is well calibrated and exhibits a high discrimination power. Its balance between accuracy and resolution yields a small mean squared error compared to alternative models. The proposed model also outperforms alternative specifications in terms of linear time series forecasting.

In summary, we find that the components of the yield curve – especially the term spread – have useful information to forecast recessions and expansions and future projections of industrial production growth. However, the proposed nonlinear model reduces the dimensionality of the information on the yield curve down to one state variable that exhibits substantial incremental predictive value compared to each of the components individually or even all the components combined in a linear regression, especially when this unobserved variables is combined with information on the economic activity.

We conclude that several attributes lead to the better predictive performance of the model: the use of combined information from the entire yield curve in a latent factor, the extraction of the yield factor based on the interrelationship of the yield curve with the real economic activity, and the flexibility of the model, which allows for nonlinearities and asymmetries in the cyclical phases of the bond markets and of the business cycle, as represented by the Markov processes.

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Table 1 – Results of Structural Break Tests

Breakdate Interval – Yield Components	Level		Curvature		Slope		Industrial Production	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
1980:05-1981:08	-	1980:05 ^{***}	-	1980:08 ^{**}	1982:01 ^{**}	1980:06 ^{***} 1981:02 ^{**} 1981:08 ^{***}	-	1983:12 ^{**}
1990:06-1990:12	1990:11 ^{***}	-	1990:6 ^{**}	-	-	-	-	-

* significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Table 2: Maximum Likelihood Estimates for the Univariate Markov Switching (MS) Model for ΔIP

Parameter	Estimates
α_1	4.13 (0.16)
α_0	-4.24 (0.42)
p_{11}	0.99 (0.01)
p_{00}	0.93 (0.03)
σ^2_{IP}	8.28 (0.57)
LogL	-395.12

Standard errors in parentheses

Table 3: Maximum Likelihood Estimates of the Univariate and Multivariate MS Models of the Yield Curve

Parameters	Univariate Models			Multivariate Yield Factor
	Level	Curvature	Slope	Model
$\alpha_1^{<t^*}$	10.12 (0.17)	1.27 (0.67)	1.99 (0.08)	0.59 (0.162)
$\alpha_0^{<t^*}$	5.48 (0.10)	0.190 (0.05)	-0.96 (0.12)	-0.42 (0.15)
$\alpha_1^{\geq t^*}$	5.44 (0.06)	0.327 (0.03)	3.04 (0.06)	-
$\alpha_0^{\geq t^*}$	3.03 (0.12)	-1.27 (0.07)	0.89 (0.06)	-
$\sigma_\eta^{2,<t^*}$	2.60 (0.18)	0.25 (0.02)	0.63 (0.07)	-
$\sigma_\eta^{2,\geq t^*}$	0.54 (0.05)	0.32 (0.03)	0.37 (0.03)	-
p_{11}	0.98 (0.01)	0.94 (0.03)	0.97 (0.02)	0.93 (0.04)
p_{00}	0.99 (0.01)	0.97 (0.01)	0.96 (0.01)	0.96 (0.02)
ϕ	-	-	-	0.89 (0.03)
λ_{Level}	-	-	-	0.015 (0.00)
$\lambda_{Curvature}$	-	-	-	-0.10 (0.02)
λ_{Slope}	-	-	-	-0.27 (0.01)
d_{Level}	-	-	-	0.99 (0.00)
$d_{Curvature}$	-	-	-	0.95 (0.02)
d_{Slope}	-	-	-	-0.91 (0.04)
$\sigma_{e,Level}^2$	-	-	-	0.04 (0.00)
$\sigma_{e,Curvature}^2$	-	-	-	0.37 (0.01)
$\sigma_{e,Slope}^2$	-	-	-	0.01 (0.00)
LogL	-395.12	25.23	-91.89	1680.66

Asymptotic standard errors in parentheses correspond to the diagonal elements of the inverse hessian obtained through numerical calculation. The variance of the single factor is set to one for normalization.

Table 4: Maximum Likelihood Estimates of the Joint Bi-Factor Model of the Yield Curve and the Economy

Parameters	Yield Factor	Economic Factor
α_1	0.596 (0.184)	0.802 (0.068)
α_0	-0.374 (0.136)	-0.934 (0.100)
P_{11}	0.930 (0.041)	0.877 (0.045)
P_{00}	0.971 (0.021)	0.962 (0.017)
σ_η^2	1	0.856 (0.029)
ϕ	0.883 (0.011)	0.885 (0.017)
λ_{IP}	-	1
λ_{Level}	0.015 (0.002)	-
$\lambda_{Curvature}$	-0.274 (0.009)	-
λ_{Slope}	-0.102 (0.015)	-
$\sigma_{e,Level}^2$	0.043 (0.001)	-
$\sigma_{e,Curvature}^2$	0.371 (0.010)	-
$\sigma_{e,Slope}^2$	0.002 (0.582)	-
θ	0.038 (0.018)	-0.116 (0.009)
$d_{Curvature}$	0.946 (0.014)	-
Log L	367.212	

Asymptotic standard errors in parentheses

Table 5 - Turning Point Signals of the Reference Cycle (IP)

Turning Point IP	Model 1 Level	Model 2 Curvature	Model 3 Slope	Model 4 Yield-only	Model 5 Yield- Economy
6 peaks					
In-sample					
1974:09	-	-38	-19	-22	-22
1980:03	-21	-14	-19	-31	-22
1981:11	-	-	-14	-17	-17
1990:12	-31	-	-27	-27	-29
2001:02	-	-3	-	-13	-13
Out-of-Sample					
Real Time					
2007:12	-25	-4	-34	-34	-35
5 Troughs					
Turning Point IP	Model 1 Level	Model 2 Curvature	Model 3 Slope	Model 4 Yield-only	Model 5 Yield- Economy
In-Sample					
1975:11	-	-9	-12	-4	-16
1981:03	-	-	-11	-13	-13
1983:04	-	-	-19	-18	-24
1991:10	-13	-	-9	-23	-23
2002:05	-9	-	-11	-21	-19
Out-of-Sample					
Real Time					
Not announced*	-	-	-	Yes	Yes

The criterion adopted to determine turning points in cols. (2)-(5) is if the smoothed probability of state 0 is equal or greater than 0.5: $P(S_t=0|I_T) \geq 0.5$. The minus sign refers to the lead in which the models anticipate the recession dates. An increase in the probabilities above 50% more than 4 years before a recession is not considered a recession signal, but a false signal.

The last row of both tables refers to the models recursively estimated using real time data from 2004:01 to 2007:12.

(*) The trough of the 2007-2009 had not been announced at the time the paper was written, in December 2008.

Table 6 - Turning Point Signal Errors of the Reference Cycle (IP)

Turning Point Evaluation	Model 1 Level	Model 2 Curvature	Model 3 Slope	Model 4 Yield-only	Model 5 Yield-Economy
6 Peaks					
Correct TP	3	4	5	6	6
Missed TP	3	2	1	0	0
False TP	0	2	2	2	0
TP Error	3	4	3	2	0
5 Troughs*					
Correct TP	2	1	4	5	5
Missed TP	3	4	1	0	0
False TP	0	2	1	2	0
TP Error	3	6	2	2	0

(*) It does not include the trough for the current recession (2007-2009), which Models 4 and 5 have already signaled.

Correct TP refers to prediction of a turning point when one does occur. Missed TP refers to prediction of no turning point when one does occur. False TP refers to prediction of a turning point when one does not occur. TP error refers to the total of Missed and False TP. A perfect forecast is when TP error is zero.

**Table 7 - Evaluation of Turning Point Forecasts of the Reference Cycle (IP)
Using the Quadratic Probability Score (MSE_1)**

Forecast Horizon	MSE_3	MSE_1				
		Model 1 Level	Model 2 Curvature	Model 3 Slope	Model 4 Yield Only	Model 5 Yield-Economy
3-month	0.278	0.977	1.105	0.919	0.790	0.552
15-month	0.286	0.805	1.092	0.549	0.436	0.259
22-month	0.290	0.808	1.088	0.604	0.362	0.209

Table 8 – Skill Score - Murphy Decomposition (MSE₅)

Models	Forecast Horizon	Total Score	Squared Correlation	Conditional Bias	Uncond. Bias
Model 1	3	-2.502	0.003	1.561	0.944
	15	-1.888	0.070	1.081	0.876
	22	-1.777	0.058	1.073	0.761
Model 2	3	-2.967	0.001	1.689	1.280
	15	-2.951	0.000	1.582	1.369
	22	-2.771	0.000	1.449	1.322
Model 3	3	-2.281	0.000	1.712	0.569
	15	-0.972	0.219	0.683	0.507
	22	-1.067	0.141	0.787	0.422
Model 4	3	-1.835	0.026	1.436	0.425
	15	-0.555	0.195	0.355	0.396
	22	-0.233	0.299	0.210	0.322
Model 5	3	-0.982	0.001	0.904	0.079
	15	0.094	0.299	0.139	0.065
	22	0.295	0.396	0.062	0.039

Table 9 - Evaluation of Turning Point Forecasts of the Reference Cycle (IP) Using Yates' Decomposition (MSE₂)

Models	Forecast Horizon	MSE ₂	Var (N _t)	ΔVar (f _t)	Min Var (f _t)	(μ _f - μ _N) ²	2*cov(f _t , N _t)
Model 1	3	0.488	0.139	0.236	0.001	0.132	0.019
	15	0.401	0.139	0.230	0.007	0.122	0.098
	22	0.403	0.145	0.234	0.003	0.111	0.090
Model 2	3	0.553	0.139	0.221	0.000	0.179	-0.014
	15	0.551	0.139	0.217	0.003	0.191	-0.001
	22	0.548	0.145	0.215	0.002	0.192	0.006
Model 3	3	0.458	0.139	0.236	0.000	0.079	-0.003
	15	0.272	0.139	0.209	0.024	0.071	0.172
	22	0.300	0.145	0.229	0.003	0.061	0.139
Model 4	3	0.396	0.139	0.143	0.007	0.059	-0.047
	15	0.215	0.139	0.087	0.063	0.055	0.130
	22	0.179	0.145	0.121	0.025	0.047	0.160
Model 5	3	0.276	0.139	0.120	0.000	0.011	-0.006
	15	0.124	0.139	0.079	0.039	0.009	0.143
	22	0.102	0.145	0.093	0.019	0.006	0.161

N_t is the 0/1 dummy that takes the value 0 if the smoothed probability of state 0 for ΔIP is equal to or greater than 0.5: P(S_t=0|I_T) ≥ 50%. Yates' decomposition is: MSE₂ = Var (N_t) + Δ Var (f_t) + Min Var(f_t) + (μ_f - μ_N)² - 2Cov (f_t, N_t).

**Table 10: Out of Sample Real Time Performance of the Linear Models
Using Unrevised Data**

	$h = 1$			$h = 2$			$h = 3$		
	M6	M7	M8	M6	M7	M8	M6	M7	M8
RMSE	0.615	0.670	0.598	0.966	1.121	0.909	1.384	1.645	1.270
THEIL	0.092	0.101	0.090	0.144	0.166	0.135	0.206	0.241	0.188
LINLIN	1.112	1.294	1.062	2.048	2.498	1.939	3.097	3.780	2.833
	$h = 4$			$h = 5$			$h = 6$		
	M6	M7	M8	M6	M7	M8	M6	M7	M8
RMSE	1.872	2.236	1.693	2.314	2.781	2.085	2.726	3.314	2.476
THEIL	0.278	0.323	0.250	0.341	0.393	0.307	0.396	0.452	0.361
LINLIN	4.393	5.292	4.022	5.493	6.753	5.072	6.650	8.164	6.141
	$h = 7$			$h = 8$			$h = 9$		
	M6	M7	M8	M6	M7	M8	M6	M7	M8
RMSE	3.120	3.800	2.845	3.453	4.210	3.169	3.733	4.555	3.450
THEIL	0.447	0.502	0.412	0.487	0.540	0.456	0.519	0.568	0.493
LINLIN	7.662	9.455	7.046	8.666	10.648	7.925	9.440	11.666	8.599
	$h = 10$								
	M6	M7	M8						
RMSE	3.943	4.824	3.673						
THEIL	0.543	0.589	0.524						
LINLIN	10.056	12.461	9.192						

The data on ΔIP_t is released in the middle of the month with information for the previous month. We use real time data on ΔIP_t starting with the vintage 1971:9, which includes the value for 1971:8 and ending with 2004:1 that includes the value for 2003:12. Estimation Period: 1971:M8-1999:12. Forecast Period: 2000:1-2003:12. Numbers in bold indicate the smallest loss among all models for the particular forecast horizon.

Table 11: Out-of-Sample Performance of the Linear Models Using Revised Data

	$h = 1$			$h = 2$			$h = 3$		
	M6	M7	M8	M6	M7	M8	M6	M7	M8
RMSE									
THEIL	0.092	0.101	0.090	0.144	0.166	0.135	0.206	0.241	0.188
LINLIN	1.209	1.244	1.133	1.764	1.763	1.560	2.121	2.225	1.874
	$h = 4$			$h = 5$			$h = 6$		
	M6	M7	M8	M6	M7	M8	M6	M7	M8
RMSE									
THEIL	1.872	2.236	1.693	2.314	2.781	2.085	2.726	3.314	2.476
LINLIN	0.278	0.323	0.250	0.341	0.393	0.307	0.396	0.452	0.361
	2.467	2.671	1.929	2.833	2.996	1.941	3.410	3.638	2.363
	$h = 7$			$h = 8$			$h = 9$		
	M6	M7	M8	M6	M7	M8	M6	M7	M8
RMSE									
THEIL	3.120	3.800	2.845	3.453	4.210	3.169	3.733	4.555	3.450
LINLIN	0.447	0.502	0.412	0.487	0.540	0.456	0.519	0.568	0.493
	3.776	4.121	2.522	4.077	4.487	2.565	4.486	4.877	2.750
	$h = 10$								
	M6	M7	M8						
RMSE									
THEIL	3.943	4.824	3.673						
LINLIN	0.543	0.589	0.524						
	4.859	5.332	2.940						

Revised data on ΔIP_t is used from 1971:8 to 2003:12. Recursive forecasting scheme is used. Estimation Period: 1971:08-1999:01. Forecast Period: 2000:01-2003:12. Numbers in indicate the smallest loss among all models for the particular forecast horizon.

Figure 1: Empirical Proxies for the Level, Slope, and Curvature of the Yield Curve and NBER-Dated Recessions

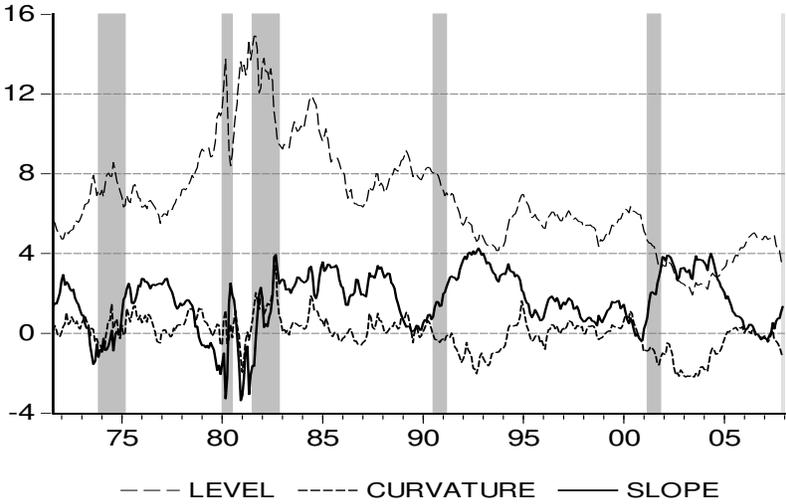


Figure 2: The Term Spread and NBER-Dated Recessions

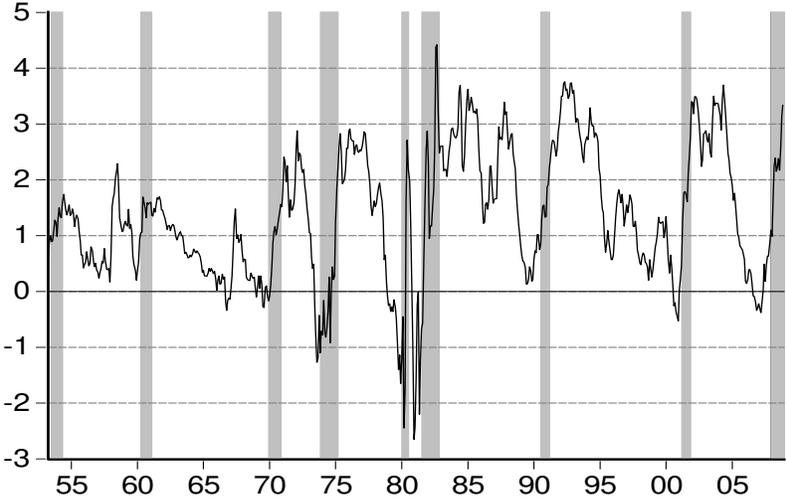


Figure 3: Smoothed Probabilities of Recession from Growth Rate of Industrial Production (IP-Dated Recessions)

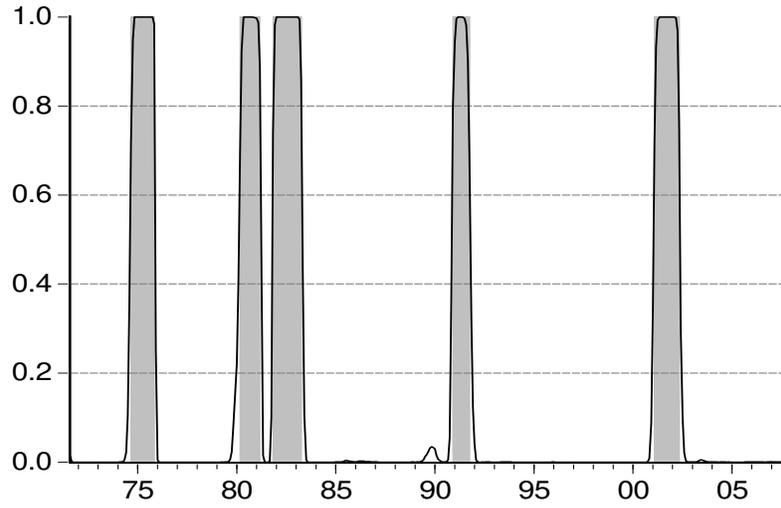


Figure 4: Level, Smoothed Probabilities of High Level State, and IP-Dated Recessions (Shaded Area)

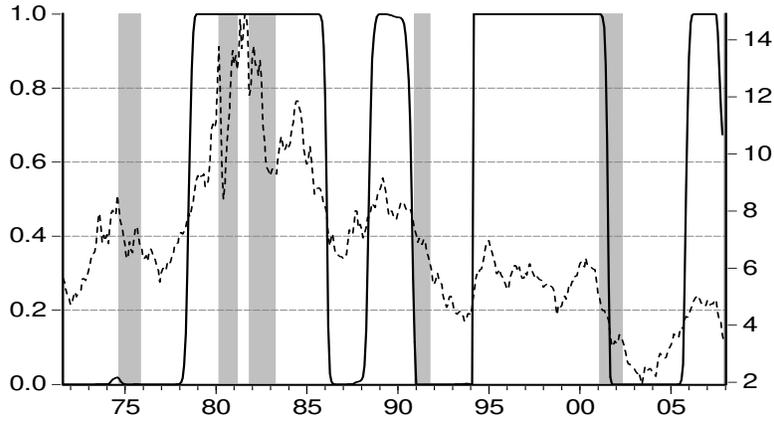


Figure 5: Curvature, Smoothed Probabilities of Low Curvature State, and IP-Dated Recessions (Shaded Area)

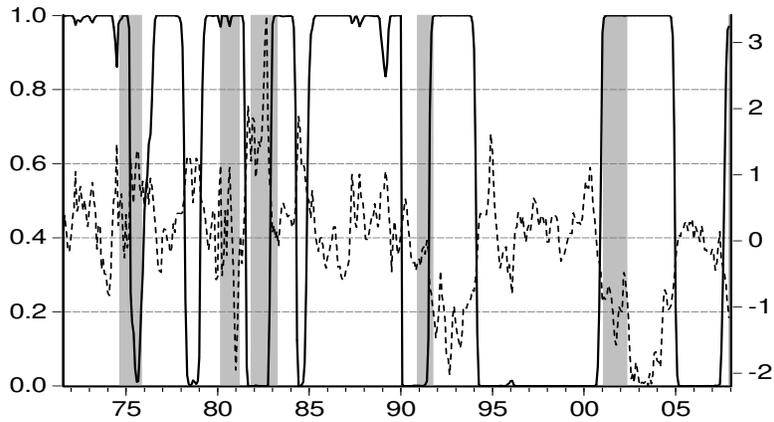


Figure 6: Slope and Smoothed Probabilities of Flat or Inverted Slope State and IP-Dated Recessions

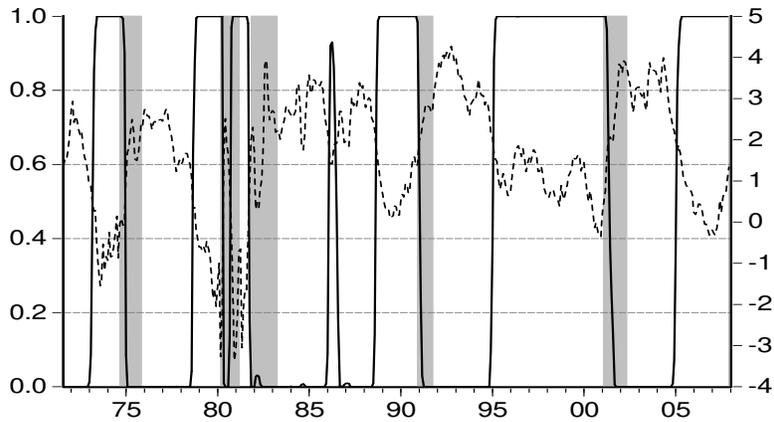


Figure 7: Smoothed Probabilities of High State for the Yield Curve Single Factor, IP-Dated Recessions (Shaded Area)

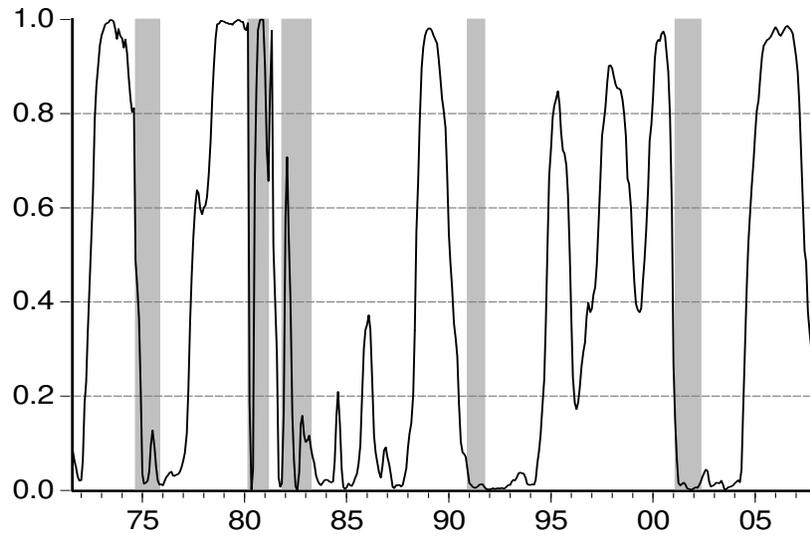


Figure 8: Yield Curve Factor from Joint Bifactor Model of the Yield Curve and the Economy and its Components. Shaded Areas are IP-Dated Recessions

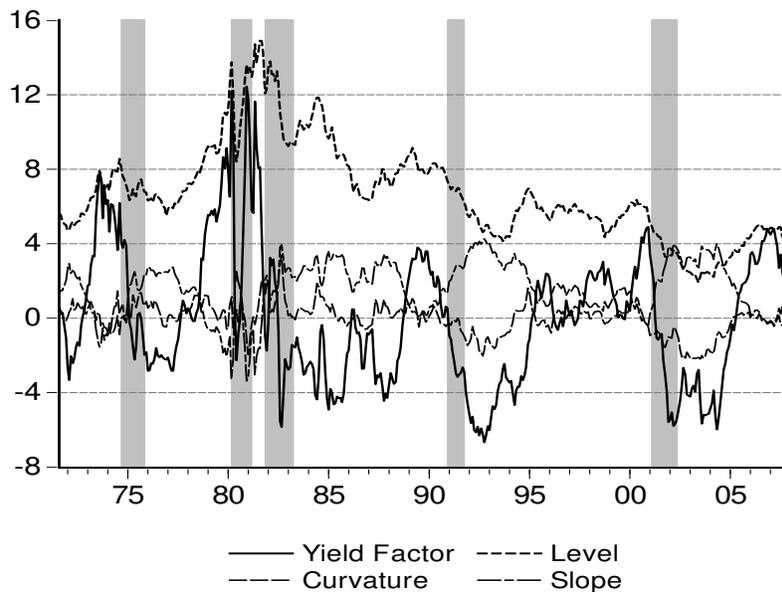


Figure 9: Smoothed Probabilities of the Yield Curve Factor from the Joint Model of the Yield Curve and the Economy. Shaded Areas are IP-Dated Recessions

