



Conference on

Forecasting and Monetary Policy

Berlin, 23-24 March 2009

Francis X. Diebold
University of Pennsylvania

Keynote Address „Arbitrage-free (yet simple) Yield Curve Forecasting“

The Affine Arbitrage-Free Class of Nelson-Siegel Term Structure Models[†]

Jens H. E. Christensen

Federal Reserve Bank of San Francisco

jens.christensen@sf.frb.org

Francis X. Diebold

University of Pennsylvania and NBER

fdiebold@sas.upenn.edu

Glenn D. Rudebusch

Federal Reserve Bank of San Francisco

glenn.rudebusch@sf.frb.org

Abstract

We derive the class of arbitrage-free affine dynamic term structure models that approximate the widely-used Nelson-Siegel yield-curve specification. Our theoretical analysis relates this new class of models to the canonical representation of the three-factor arbitrage-free affine model. Our empirical analysis shows that imposing the Nelson-Siegel structure on the canonical representation of affine models greatly improves its empirical tractability; furthermore, we find that improvements in predictive performance are achieved from the imposition of absence of arbitrage.

[†]For helpful comments we thank seminar/conference participants at the University of Chicago, Copenhagen Business School (especially Anders Bjerre Trolle and Peter Feldhütter), Stanford University (especially Ken Singleton), the NBER summer Institute, the Warwick Royal Economic Society annual meeting, the Coimbra Workshop on Financial Time Series, and the inaugural meeting of SoFiE (the Society for Financial Econometrics). For outstanding research assistance we thank Georg Strasser and Rong Hai. The views expressed are those of the authors and do not necessarily reflect the views of others at the Federal Reserve Bank of San Francisco.

This version: January 2009.

1 Introduction

Understanding the dynamic evolution of the yield curve is important for many tasks, including pricing financial assets and their derivatives, managing financial risk, allocating portfolios, structuring fiscal debt, conducting monetary policy, and valuing capital goods. To investigate yield-curve dynamics, researchers have produced a vast literature with a wide variety of models. However, many of those models have tended to be either theoretically rigorous but empirically disappointing or empirically successful but theoretically lacking. In this paper, we introduce a theoretically rigorous yield curve model that simultaneously displays empirical tractability, good fit, and good forecasting performance.

Because bonds trade in deep and well-organized markets, the theoretical restrictions that rule out opportunities for riskless arbitrage across maturities and over time hold a powerful appeal, and they provide the foundation for a large finance literature on arbitrage-free (AF) models that started with Vasiček (1977) and Cox, Ingersoll, and Ross (1985). These models specify the risk-neutral evolution of the underlying yield-curve factors as well as the dynamics of risk premiums. Following Duffie and Kan (1996), the affine versions of these models are particularly popular because yields are convenient linear functions of underlying latent factors (state variables that are unobserved by the econometrician) with parameters, or “factor loadings,” that can be calculated from a simple system of differential equations.

Unfortunately, the canonical affine AF models often exhibit poor empirical time series performance, especially when forecasting future yields (Duffee, 2002). In addition, the estimation of these models is known to be problematic, in large part because of the existence of numerous model likelihood maxima that have essentially identical fit to the data but very different implications for economic behavior (Kim and Orphanides, 2005). These empirical problems appear to reflect an underlying model over-parameterization, and as a solution, many researchers (e.g., Duffee, 2002, and Dai and Singleton, 2002) simply restrict to zero those parameters with small t -statistics in a first round of estimation. The resulting more parsimonious structure is typically somewhat easier to estimate and has fewer troublesome likelihood maxima. However, the additional restrictions on model structure are arbitrary from both theoretical and statistical perspectives, and their arbitrary application and the computational burden of estimation effectively preclude robust model validation and thorough simulation studies of the finite-sample properties of the estimators.

In part to overcome the above-stressed problems with empirical implementation of the canonical affine AF model, we consider in this paper a new class of affine AF models based on the workhorse yield-curve representation introduced by Nelson and Siegel (1987) and extended to dynamic environments by Diebold and Li (2006). (We refer to the Diebold-Li extension as dynamic Nelson-Siegel, or DNS.) Thus, in part, we take the theoretically rigorous but empirically problematic affine AF model and make it empirically tractable via DNS thinking.

Alternatively and conversely, in part we take the Nelson-Siegel model – empirically successful but theoretically lacking – and make it theoretically rigorous via affine AF thinking. This is important because the Nelson-Siegel model is extremely popular in practice, among both financial market practitioners and central banks (e.g., Svensson, 1995; Bank for International Settlements,

2005; Gürkaynak, Sack, and Wright, 2007; Nyholm, 2008). The popularity stems from several sources, both empirical and theoretical, as discussed in Diebold and Li (2006). Empirically, for example, (1) It is simple and stable to estimate, (2) It is quite flexible and fits both the cross section and time series of yields remarkably well, in many countries and periods, and for many grades of bonds, and (3) It forecasts well. Theoretically, for example, the Nelson-Siegel functional form imposes economically desirable properties, such as requiring the discount function to approach zero with maturity, and DNS can be shown to correspond to a modern linear three-factor model with level, slope and curvature factors.

However, despite its good empirical performance and a certain amount of theoretical appeal, DNS fails on an important theoretical dimension: it does not impose the restrictions necessary to rule out opportunities for riskless arbitrage (e.g., Filipović, 1999, and Diebold, Piazzesi, and Rudebusch, 2005). This motivates us in this paper to introduce the class of arbitrage-free Nelson-Siegel (AFNS) models, which are affine AF term structure models that maintain the dynamic Nelson-Siegel factor-loading structure.

In short, the AFNS models proposed here combine the best of both the AF and DNS yield-curve modeling traditions. Approached from the AF side, they maintain the AF theoretical restrictions of the canonical affine models but can be easily and robustly estimated because the dynamic Nelson-Siegel structure helps identify the latent yield-curve factors.¹ Approached from the DNS side, they maintain the simplicity and empirical tractability of the popular DNS models, while simultaneously enforcing the theoretically (and practically, as we shall see) desirable property of absence of riskless arbitrage.

After deriving the new class of AFNS models, we examine their in-sample fit and out-of-sample forecast performance relative to standard DNS models. For both the DNS and the AFNS models, we estimate parsimonious and flexible versions (with both independent factors and more richly parameterized correlated factors). We find that the flexible versions of both models are preferred for in-sample fit, but that the parsimonious versions exhibit significantly better out-of-sample forecast performance. Most importantly, we find that the parsimonious AFNS model outperforms its DNS counterpart in forecasting, which supports the imposition of the AF restrictions. As a final comparison, we also show that the AFNS model can outperform the canonical affine AF model in forecasting.

We proceed as follows. In Section 2 we introduce the DNS model and derive the main theoretical result of the paper, which defines the AFNS class of models. In Section 3 we derive the relationship between the AFNS class and the canonical representation of affine AF models as detailed in Singleton (2006). For the four specific DNS and AFNS models used in our empirical analysis, we describe in Section 4 the estimation method, data, and in-sample fit, and we examine their out-of-sample forecast performance in Section 5. We conclude in Section 6, and we provide additional technical details in the Appendices.

¹In particular, empirical implementation of the AFNS models is facilitated by the fact that in those models zero-coupon bond prices have analytical solutions, which we provide.

2 Nelson-Siegel term structure models

In this section, we review the DNS model and introduce the AFNS class of arbitrage-free affine term structure models that maintain the Nelson-Siegel factor loading structure.

2.1 The dynamic Nelson-Siegel model

The original Nelson-Siegel model fits the yield curve with the simple functional form

$$y(\tau) = \beta_0 + \beta_1 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right), \quad (1)$$

where $y(\tau)$ is the zero-coupon yield with τ months to maturity, and β_0 , β_1 , β_2 , and λ are parameters.

As noted earlier, this representation is commonly used by financial market practitioners to fit the yield curve at a point in time. Although for some purposes such a static representation is useful, a dynamic version is required to understand the evolution of the bond market over time. Hence Diebold and Li (2006) suggest allowing the β coefficients to vary over time, resulting in

$$y(\tau) = \beta_{0t} + \beta_{1t} \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_{2t} \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right), \quad (2)$$

in which case they show that, given their Nelson-Siegel loadings, the coefficients may be interpreted as time-varying level, slope and curvature factors. To emphasize this we re-write the model as

$$y_t(\tau) = L_t + S_t \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + C_t \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right). \quad (3)$$

Diebold and Li assume an autoregressive structure for the factors, which yields the DNS model—a fully dynamic Nelson-Siegel specification.

Empirically, the DNS model is highly tractable and provides a good fit to the data. As a theoretical matter, however, it does not require that the dynamic evolution of yields cohere such that arbitrage opportunities are precluded. Indeed, the results of Filipović (1999) imply that *whatever* stochastic dynamics are chosen for the DNS factors, it is impossible to preclude arbitrage at the bond prices implicit in the resulting Nelson-Siegel yield curve. In the next subsection we show how to remedy this theoretical weakness.

2.2 The AFNS model

Our derivation of the AFNS model starts from the standard continuous-time affine AF structure (Duffie and Kan, 1996).² To represent an affine diffusion process, define a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t), Q)$, where the filtration $(\mathcal{F}_t) = \{\mathcal{F}_t : t \geq 0\}$ satisfies the usual conditions (Williams, 1997). The state variable X_t is assumed to be a Markov process defined on a set $M \subset \mathbf{R}^n$ that

²Krippner (2006) derives a special case of the AFNS model with constant risk premiums.

solves the following stochastic differential equation (SDE)³

$$dX_t = K^Q(t)[\theta^Q(t) - X_t]dt + \Sigma(t)D(X_t, t)dW_t^Q, \quad (4)$$

where W^Q is a standard Brownian motion in \mathbf{R}^n , the information of which is contained in the filtration (\mathcal{F}_t) . The drift terms $\theta^Q : [0, T] \rightarrow \mathbf{R}^n$ and $K^Q : [0, T] \rightarrow \mathbf{R}^{n \times n}$ are bounded, continuous functions.⁴ Similarly, the volatility matrix $\Sigma : [0, T] \rightarrow \mathbf{R}^{n \times n}$ is assumed to be a bounded, continuous function, while $D : M \times [0, T] \rightarrow \mathbf{R}^{n \times n}$ is assumed to have the following diagonal structure

$$\begin{pmatrix} \sqrt{\gamma^1(t) + \delta_1^1(t)X_t^1 + \dots + \delta_n^1(t)X_t^n} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sqrt{\gamma^n(t) + \delta_1^n(t)X_t^1 + \dots + \delta_n^n(t)X_t^n} \end{pmatrix}.$$

To simplify the notation, $\gamma(t)$ and $\delta(t)$ are defined as

$$\gamma(t) = \begin{pmatrix} \gamma^1(t) \\ \vdots \\ \gamma^n(t) \end{pmatrix} \quad \text{and} \quad \delta(t) = \begin{pmatrix} \delta_1^1(t) & \dots & \delta_n^1(t) \\ \vdots & \ddots & \vdots \\ \delta_1^n(t) & \dots & \delta_n^n(t) \end{pmatrix},$$

where $\gamma : [0, T] \rightarrow \mathbf{R}^n$ and $\delta : [0, T] \rightarrow \mathbf{R}^{n \times n}$ are bounded, continuous functions. Given this notation, the SDE of the state variables can be written as

$$dX_t = K^Q(t)[\theta^Q(t) - X_t]dt + \Sigma(t) \begin{pmatrix} \sqrt{\gamma^1(t) + \delta^1(t)X_t} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sqrt{\gamma^n(t) + \delta^n(t)X_t} \end{pmatrix} dW_t^Q,$$

where $\delta^i(t)$ denotes the i th row of the $\delta(t)$ -matrix. Finally, the instantaneous risk-free rate is assumed to be an affine function of the state variables

$$r_t = \rho_0(t) + \rho_1(t)'X_t,$$

where $\rho_0 : [0, T] \rightarrow \mathbf{R}$ and $\rho_1 : [0, T] \rightarrow \mathbf{R}^n$ are bounded, continuous functions.

Duffie and Kan (1996) prove that zero-coupon bond prices in this framework are exponential-affine functions of the state variables

$$P(t, T) = E_t^Q \left[\exp \left(- \int_t^T r_u du \right) \right] = \exp (B(t, T)'X_t + C(t, T)),$$

where $B(t, T)$ and $C(t, T)$ are the solutions to the following system of ordinary differential equa-

³The affine property applies to bond prices; therefore, affine models only impose structure on the factor dynamics under the pricing measure.

⁴Stationarity of the state variables is ensured if all the eigenvalues of $K^Q(t)$ are positive (if complex, the real component should be positive), see Ahn, Dittmar, and Gallant (2002). However, stationarity is not a necessary requirement for the process to be well defined.

tions (ODEs)

$$\frac{dB(t, T)}{dt} = \rho_1 + (K^Q)' B(t, T) - \frac{1}{2} \sum_{j=1}^n (\Sigma' B(t, T) B(t, T)' \Sigma)_{j,j} (\delta^j)', \quad B(T, T) = 0 \quad (5)$$

$$\frac{dC(t, T)}{dt} = \rho_0 - B(t, T)' K^Q \theta^Q - \frac{1}{2} \sum_{j=1}^n (\Sigma' B(t, T) B(t, T)' \Sigma)_{j,j} \gamma^j, \quad C(T, T) = 0, \quad (6)$$

and the possible time-dependence of the parameters is suppressed in the notation. These pricing functions imply that the zero-coupon yields are given by

$$y(t, T) = -\frac{1}{T-t} \log P(t, T) = -\frac{B(t, T)'}{T-t} X_t - \frac{C(t, T)}{T-t}.$$

Given these pricing functions, for a three-factor affine model with $X_t = (X_t^1, X_t^2, X_t^3)$, the closest match to the Nelson-Siegel yield function would be a yield function of the form

$$y(t, T) = X_t^1 + \frac{1 - e^{-\lambda(T-t)}}{\lambda(T-t)} X_t^2 + \left[\frac{1 - e^{-\lambda(T-t)}}{\lambda(T-t)} - e^{-\lambda(T-t)} \right] X_t^3 - \frac{C(t, T)}{T-t},$$

with ODEs for the $B(t, T)$ functions that have these solutions:

$$\begin{aligned} B^1(t, T) &= -(T-t), \\ B^2(t, T) &= -\frac{1 - e^{-\lambda(T-t)}}{\lambda}, \\ B^3(t, T) &= (T-t)e^{-\lambda(T-t)} - \frac{1 - e^{-\lambda(T-t)}}{\lambda}. \end{aligned}$$

In this case, the factor loadings exactly match the Nelson-Siegel ones, but there is an unavoidable additional term in the yield function $-\frac{C(t, T)}{T-t}$, which only depends on the maturity of the bond. As described in Proposition 1, there exists a unique class of affine AF models that satisfy the above ODEs.

Proposition 1:

Assume that the instantaneous risk-free rate is defined by

$$r_t = X_t^1 + X_t^2.$$

In addition, assume that the state variables $X_t = (X_t^1, X_t^2, X_t^3)$ are described by the following system of SDEs under the risk-neutral Q -measure

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & -\lambda \\ 0 & 0 & \lambda \end{pmatrix} \left[\begin{pmatrix} \theta_1^Q \\ \theta_2^Q \\ \theta_3^Q \end{pmatrix} - \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} \right] dt + \Sigma \begin{pmatrix} dW_t^{1,Q} \\ dW_t^{2,Q} \\ dW_t^{3,Q} \end{pmatrix}, \quad \lambda > 0.$$

Then, zero-coupon bond prices are given by

$$P(t, T) = E_t^Q \left[\exp \left(- \int_t^T r_u du \right) \right] = \exp \left(B^1(t, T)X_t^1 + B^2(t, T)X_t^2 + B^3(t, T)X_t^3 + C(t, T) \right),$$

where $B^1(t, T)$, $B^2(t, T)$, $B^3(t, T)$, and $C(t, T)$ are the unique solutions to the following system of ODEs:

$$\begin{pmatrix} \frac{dB^1(t, T)}{dt} \\ \frac{dB^2(t, T)}{dt} \\ \frac{dB^3(t, T)}{dt} \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & -\lambda & \lambda \end{pmatrix} \begin{pmatrix} B^1(t, T) \\ B^2(t, T) \\ B^3(t, T) \end{pmatrix} \quad (7)$$

and

$$\frac{dC(t, T)}{dt} = -B(t, T)' K^Q \theta^Q - \frac{1}{2} \sum_{j=1}^3 (\Sigma' B(t, T) B(t, T)' \Sigma)_{j,j}, \quad (8)$$

with boundary conditions $B^1(T, T) = B^2(T, T) = B^3(T, T) = C(T, T) = 0$. The unique solution for this system of ODEs is:

$$\begin{aligned} B^1(t, T) &= -(T-t), \\ B^2(t, T) &= -\frac{1 - e^{-\lambda(T-t)}}{\lambda}, \\ B^3(t, T) &= (T-t)e^{-\lambda(T-t)} - \frac{1 - e^{-\lambda(T-t)}}{\lambda}, \end{aligned}$$

and

$$C(t, T) = (K^Q \theta^Q)_2 \int_t^T B^2(s, T) ds + (K^Q \theta^Q)_3 \int_t^T B^3(s, T) ds + \frac{1}{2} \sum_{j=1}^3 \int_t^T (\Sigma' B(s, T) B(s, T)' \Sigma)_{j,j} ds.$$

Finally, zero-coupon bond yields are given by

$$y(t, T) = X_t^1 + \frac{1 - e^{-\lambda(T-t)}}{\lambda(T-t)} X_t^2 + \left[\frac{1 - e^{-\lambda(T-t)}}{\lambda(T-t)} - e^{-\lambda(T-t)} \right] X_t^3 - \frac{C(t, T)}{T-t}.$$

Proof: See Appendix A.

The existence of an AFNS model, as defined in this proposition, is not too surprising from a theoretical perspective. Following Trolle and Schwartz, 2007, the dynamics of a forward rate curve in a general m -dimensional Heath-Jarrow-Morton (HJM) model can always be represented by a finite-dimensional Markov process with time-homogeneous volatility structure if each volatility function is given by

$$\sigma_i(t, T) = p_{n,i}(T-t) e^{-\gamma_i(T-t)}, \quad i = 1, \dots, m,$$

where $p_{n,i}(\tau)$ is an n -order polynomial in τ . Since the forward rates in the DNS model satisfy this requirement, there exists such an arbitrage-free three-dimensional HJM model. However, the simplicity of the solution in the case of the Nelson-Siegel model presented in Proposition 1 is

striking.

Proposition 1 also has several interesting implications. First, the three state variables are Gaussian Ornstein-Uhlenbeck processes with a constant volatility matrix Σ .⁵ The instantaneous interest rate is the sum of level and slope factors (X_t^1 and X_t^2), while the curvature factor (X_t^3) is a truly latent factor in the sense that its sole role is as a stochastic time-varying mean for the slope factor under the Q -measure. Second, Proposition 1 only imposes structure on the dynamics of the AFNS model under the Q -measure and is silent about the dynamics under the P -measure. Still, the observation that curvature is a truly latent factor generally accords with the empirical literature where it has been difficult to find sensible interpretations of curvature under the P -measure (Diebold, Rudebusch, and Aruoba, 2006). Similarly, the level factor is a unit-root process under the Q -measure, which accords with the usual finding that one or more of the interest rate factors are close to being nonstationary processes under the P -measure.⁶ Third, Proposition 1 provides insight into the nature of the parameter λ . Although in principle λ could vary over time, starting with Nelson and Siegel (1987), implementations of the Nelson-Siegel model have almost always fixed λ over the sample. In the AFNS model, λ is indeed a constant, namely, the mean-reversion rate of the curvature and slope factors as well as the scale by which a deviation of the curvature factor from its mean affects the mean of the slope factor. Fourth, relative to the Nelson-Siegel model, the AFNS model contains an additional maturity-dependent term $-\frac{C(t,T)}{T-t}$ in the function for the zero-coupon bond yields. The nature of this “yield-adjustment” term is crucial in assessing differences between the AFNS and DNS models, and we now turn to a theoretical analysis of this term.

2.3 The AFNS yield-adjustment term

The only parameters in the system of ODEs for the AFNS $B(t,T)$ functions are ρ_1 and K^Q , i.e., the factor loadings of r_t and the mean-reversion structure for the state variables under the Q -measure. The drift term θ^Q and the volatility matrix Σ do not appear in the ODEs but in the yield-adjustment term $-\frac{C(t,T)}{T-t}$. Therefore, in the AFNS model, the choice of the volatility matrix Σ affects both the P -dynamics and the yield function through the yield-adjustment term. In contrast, the DNS model is silent about the real-world dynamics of the state variables, so the choice of P -dynamics is irrelevant for the yield function.

As discussed in the next section, we identify the AFNS models by fixing the mean levels of the state variables under the Q -measure at 0, i.e., $\theta^Q = 0$. This implies that the yield-adjustment

⁵Proposition 1 can be extended to include jumps in the state variables. As long as the jump arrival intensity is state-independent, the Nelson-Siegel factor loading structure in the yield function is maintained since only $C(t,T)$ is affected by the inclusion of such jumps. See Duffie, Pan, and Singleton (2000) for the needed modification of the ODEs for $C(t,T)$ in this case.

⁶With the unit root in the level factor, as maturity increases, $-\frac{C(t,T)}{T-t} \rightarrow -\infty$, which implies that, strictly speaking, this model is not arbitrage-free. However, if we modify the mean-reversion matrix K^Q to

$$K^Q(\varepsilon) = \begin{pmatrix} \varepsilon & 0 & 0 \\ 0 & \lambda & -\lambda \\ 0 & 0 & \lambda \end{pmatrix}$$

and consider a converging sequence $\varepsilon_n > 0$, $\varepsilon_n \downarrow 0$, then there is a converging sequence of AF models with a limit given by the result in Proposition 1. Thus, by choosing $\varepsilon > 0$ sufficiently small, we can obtain an AF model that is indistinguishable from the AFNS model in Proposition 1.

term will have the following form:

$$-\frac{C(t, T)}{T-t} = -\frac{1}{2} \frac{1}{T-t} \sum_{j=1}^3 \int_t^T (\Sigma' B(s, T) B(s, T)' \Sigma)_{j,j} ds.$$

Given a general volatility matrix

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix},$$

the yield-adjustment term can be derived in analytical form (see Appendix B) as

$$\begin{aligned} \frac{C(t, T)}{T-t} &= \frac{1}{2} \frac{1}{T-t} \int_t^T \sum_{j=1}^3 (\Sigma' B(s, T) B(s, T)' \Sigma)_{j,j} ds \\ &= \bar{A} \frac{(T-t)^2}{6} + \bar{B} \left[\frac{1}{2\lambda^2} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{1}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right] \\ &+ \bar{C} \left[\frac{1}{2\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{4\lambda} (T-t) e^{-2\lambda(T-t)} - \frac{3}{4\lambda^2} e^{-2\lambda(T-t)} - \frac{2}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{5}{8\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right] \\ &+ \bar{D} \left[\frac{1}{2\lambda} (T-t) + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} \right] \\ &+ \bar{E} \left[\frac{3}{\lambda^2} e^{-\lambda(T-t)} + \frac{1}{2\lambda} (T-t) + \frac{1}{\lambda} (T-t) e^{-\lambda(T-t)} - \frac{3}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} \right] \\ &+ \bar{F} \left[\frac{1}{\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{2\lambda^2} e^{-2\lambda(T-t)} - \frac{3}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{3}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right], \end{aligned}$$

where

- $\bar{A} = \sigma_{11}^2 + \sigma_{12}^2 + \sigma_{13}^2,$
- $\bar{B} = \sigma_{21}^2 + \sigma_{22}^2 + \sigma_{23}^2,$
- $\bar{C} = \sigma_{31}^2 + \sigma_{32}^2 + \sigma_{33}^2,$
- $\bar{D} = \sigma_{11}\sigma_{21} + \sigma_{12}\sigma_{22} + \sigma_{13}\sigma_{23},$
- $\bar{E} = \sigma_{11}\sigma_{31} + \sigma_{12}\sigma_{32} + \sigma_{13}\sigma_{33},$
- $\bar{F} = \sigma_{21}\sigma_{31} + \sigma_{22}\sigma_{32} + \sigma_{23}\sigma_{33}.$

This result has two implications. First, the fact that zero-coupon bond yields in the AFNS class of models are given by an analytical formula will greatly facilitate empirical implementation of these models. Second, the nine underlying volatility parameters are not identified. Indeed, only the six terms \bar{A} , \bar{B} , \bar{C} , \bar{D} , \bar{E} , and \bar{F} can be identified; thus, the maximally flexible AFNS specification that can be identified has a triangular volatility matrix given by⁷

$$\Sigma = \begin{pmatrix} \sigma_{11} & 0 & 0 \\ \sigma_{21} & \sigma_{22} & 0 \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix}.$$

⁷The choice of upper or lower triangular is irrelevant for the fit of the model.

In Section 4, we quantify the yield-adjustment term and examine how it affects the empirical performance of two specific AFNS models relative to their corresponding DNS models. These models are introduced next.

2.4 Four specific Nelson-Siegel models

In general, the DNS and AFNS models are silent about the P -dynamics, so there are an infinite number of possible specifications that could be used to match the data. However, for continuity with the existing literature, our econometric analysis focuses on two specific versions of the DNS model that have been estimated in recent studies, and, for consistency, we also examine the two corresponding versions of the AFNS model.

In the *independent-factor DNS model*, all three state variables are assumed to be independent first-order autoregressions, as in Diebold and Li (2006). Using their notation, the state equation is given by

$$\begin{pmatrix} L_t - \mu_L \\ S_t - \mu_S \\ C_t - \mu_C \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix} \begin{pmatrix} L_{t-1} - \mu_L \\ S_{t-1} - \mu_S \\ C_{t-1} - \mu_C \end{pmatrix} + \begin{pmatrix} \eta_t(L) \\ \eta_t(S) \\ \eta_t(C) \end{pmatrix},$$

where the error terms $\eta_t(L)$, $\eta_t(S)$, and $\eta_t(C)$ have a conditional covariance matrix given by

$$Q = \begin{pmatrix} q_{11}^2 & 0 & 0 \\ 0 & q_{22}^2 & 0 \\ 0 & 0 & q_{33}^2 \end{pmatrix}.$$

The *correlated-factor DNS model* has factor P -dynamics described by a first-order vector autoregression (VAR(1))

$$\begin{pmatrix} L_t - \mu_L \\ S_t - \mu_S \\ C_t - \mu_C \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} L_{t-1} - \mu_L \\ S_{t-1} - \mu_S \\ C_{t-1} - \mu_C \end{pmatrix} + \begin{pmatrix} \eta_t(L) \\ \eta_t(S) \\ \eta_t(C) \end{pmatrix},$$

as in Diebold, Rudebusch, and Aruoba (2006). The innovations $\eta_t(L)$, $\eta_t(S)$, and $\eta_t(C)$ are allowed to be correlated with a conditional covariance matrix given by $Q = qq'$, where the Cholesky factor q of the covariance matrix Q is

$$q = \begin{pmatrix} q_{11} & 0 & 0 \\ q_{21} & q_{22} & 0 \\ q_{31} & q_{32} & q_{33} \end{pmatrix}.$$

In both of these DNS models, the measurement equation takes the form

$$\begin{pmatrix} y_t(\tau_1) \\ y_t(\tau_2) \\ \vdots \\ y_t(\tau_N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} - e^{-\lambda\tau_1} \\ 1 & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} - e^{-\lambda\tau_2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} - e^{-\lambda\tau_N} \end{pmatrix} \begin{pmatrix} L_t \\ S_t \\ C_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t(\tau_1) \\ \varepsilon_t(\tau_2) \\ \vdots \\ \varepsilon_t(\tau_N) \end{pmatrix},$$

where the measurement errors $\varepsilon_t(\tau_i)$ are assumed to be i.i.d. white noise.

The corresponding AFNS models are formulated in continuous time and the relationship between the real-world dynamics under the P -measure and the risk-neutral dynamics under the Q -measure is given by the measure change

$$dW_t^Q = dW_t^P + \Gamma_t dt,$$

where Γ_t represents the risk premium specification. In order to preserve affine dynamics under the P -measure, we limit our focus to essentially affine risk premium specifications (see Duffee, 2002). Thus, Γ_t will take the form

$$\Gamma_t = \begin{pmatrix} \gamma_1^0 \\ \gamma_2^0 \\ \gamma_3^0 \end{pmatrix} + \begin{pmatrix} \gamma_{11}^1 & \gamma_{12}^1 & \gamma_{13}^1 \\ \gamma_{21}^1 & \gamma_{22}^1 & \gamma_{23}^1 \\ \gamma_{31}^1 & \gamma_{32}^1 & \gamma_{33}^1 \end{pmatrix} \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix}.$$

With this specification, the SDE for the state variables under the P -measure,

$$dX_t = K^P[\theta^P - X_t]dt + \Sigma dW_t^P, \quad (9)$$

remains affine. Due to the flexible specification of Γ_t , we are free to choose any mean vector θ^P and mean-reversion matrix K^P under the P -measure and still preserve the required Q -dynamic structure described in Proposition 1. Therefore, we focus on the two AFNS models that correspond to the specific two DNS models above.

In the *independent-factor AFNS model*, all three factors are assumed to be independent under the P -measure

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = \begin{pmatrix} \kappa_{11}^P & 0 & 0 \\ 0 & \kappa_{22}^P & 0 \\ 0 & 0 & \kappa_{33}^P \end{pmatrix} \left[\begin{pmatrix} \theta_1^P \\ \theta_2^P \\ \theta_3^P \end{pmatrix} - \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} \right] dt + \begin{pmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{pmatrix} \begin{pmatrix} dW_t^{1,P} \\ dW_t^{2,P} \\ dW_t^{3,P} \end{pmatrix}.$$

This model is the AF equivalent of our first DNS model.

In the *correlated-factor AFNS model*, the three shocks may be correlated, and there may be

full interaction among the factors as they adjust to the steady state

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = \begin{pmatrix} \kappa_{11}^P & \kappa_{12}^P & \kappa_{13}^P \\ \kappa_{21}^P & \kappa_{22}^P & \kappa_{23}^P \\ \kappa_{31}^P & \kappa_{32}^P & \kappa_{33}^P \end{pmatrix} \left[\begin{pmatrix} \theta_1^P \\ \theta_2^P \\ \theta_3^P \end{pmatrix} - \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} \right] dt + \begin{pmatrix} \sigma_{11} & 0 & 0 \\ \sigma_{21} & \sigma_{22} & 0 \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix} \begin{pmatrix} dW_t^{1,P} \\ dW_t^{2,P} \\ dW_t^{3,P} \end{pmatrix}.$$

This is the most flexible version of the AFNS models where all parameters are identified.

For both AFNS models, the measurement equation takes the form

$$\begin{pmatrix} y_t(\tau_1) \\ y_t(\tau_2) \\ \vdots \\ y_t(\tau_N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} & \frac{1-e^{-\lambda\tau_1}}{\lambda\tau_1} - e^{-\lambda\tau_1} \\ 1 & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} & \frac{1-e^{-\lambda\tau_2}}{\lambda\tau_2} - e^{-\lambda\tau_2} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} & \frac{1-e^{-\lambda\tau_N}}{\lambda\tau_N} - e^{-\lambda\tau_N} \end{pmatrix} \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} - \begin{pmatrix} \frac{C(\tau_1)}{\tau_1} \\ \frac{C(\tau_2)}{\tau_2} \\ \vdots \\ \frac{C(\tau_N)}{\tau_N} \end{pmatrix} + \begin{pmatrix} \varepsilon_t(\tau_1) \\ \varepsilon_t(\tau_2) \\ \vdots \\ \varepsilon_t(\tau_N) \end{pmatrix},$$

where, again, the measurement errors $\varepsilon_t(\tau_i)$ are assumed to be i.i.d. white noise.

3 The AFNS subclass of canonical affine AF models

Before proceeding to an empirical analysis of the various DNS and AFNS models, we first answer a key theoretical question: What, precisely, are the restrictions that the AFNS model imposes on the canonical representation of three-factor affine AF models—the $A_0(3)$ representation (with three state variables and zero square-root processes) as detailed in Singleton (2006), Chap. 12. Denoting the state variables by Y_t , the canonical $A_0(3)$ model is given by

$$\begin{aligned} r_t &= \delta_0^Y + (\delta_1^Y)' Y_t \\ dY_t &= K_Y^P [\theta_Y^P - Y_t] dt + \Sigma_Y dW_t^P \\ dY_t &= K_Y^Q [\theta_Y^Q - Y_t] dt + \Sigma_Y dW_t^Q, \end{aligned}$$

with $\delta_0^Y \in \mathbf{R}$, $\delta_1^Y, \theta_Y^P, \theta_Y^Q \in \mathbf{R}^3$, and $K_Y^P, K_Y^Q, \Sigma_Y \in \mathbf{R}^{3 \times 3}$. If the essentially affine risk premium specification $\Gamma_t = \gamma_Y^0 + \gamma_Y^1 Y_t$ is imposed on the model, the drift terms under the P -measure (K_Y^P, θ_Y^P) can be chosen independently of the drift terms under the Q -measure (K_Y^Q, θ_Y^Q).

Because the latent state variables may rotate without changing the probability distribution of bond yields, not all parameters in the above model can be identified. Singleton (2006) imposes the identifying restrictions under the Q -measure. Specifically, he sets the mean $\theta_Y^Q = 0$, the volatility matrix Σ_Y equal to the identity matrix, and the mean-reversion matrix K_Y^Q equal to a triangular matrix.⁸ Thus, the canonical representation has Q -dynamics given by

$$\begin{pmatrix} dY_t^1 \\ dY_t^2 \\ dY_t^3 \end{pmatrix} = - \begin{pmatrix} \kappa_{11}^{Y,Q} & \kappa_{12}^{Y,Q} & \kappa_{13}^{Y,Q} \\ 0 & \kappa_{22}^{Y,Q} & \kappa_{23}^{Y,Q} \\ 0 & 0 & \kappa_{33}^{Y,Q} \end{pmatrix} \begin{pmatrix} Y_t^1 \\ Y_t^2 \\ Y_t^3 \end{pmatrix} dt + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} dW_t^{1,Q} \\ dW_t^{2,Q} \\ dW_t^{3,Q} \end{pmatrix},$$

⁸Without loss of generality, we will take it to be upper triangular in the following.

AFNS Model	δ_0^Y, δ_1^Y	κ_Y^Q	κ_Y^P	θ_Y^P	No. restrictions
Independent-factor	$\delta_0^Y = 0,$ $\delta_{1,3}^Y = 0$	$\kappa_{1,1}^{Y,Q} = \kappa_{1,2}^{Y,Q} = \kappa_{1,3}^{Y,Q} = 0,$ $\kappa_{2,2}^{Y,Q} = \kappa_{3,3}^{Y,Q}$	κ_Y^P is diagonal	No restriction	12
Correlated-factor	$\delta_0^Y = 0$	$\kappa_{1,1}^{Y,Q} = 0,$ $\kappa_{2,2}^{Y,Q} = \kappa_{3,3}^{Y,Q}$	No restriction	No restriction	3

Table 1: **AFNS Model Parameter Restrictions on the Canonical Representation**

These are the restrictions on the $A_0(3)$ model needed to obtain the independent-factor and correlated-factor AFNS specifications.

and P -dynamics given by

$$\begin{pmatrix} dY_t^1 \\ dY_t^2 \\ dY_t^3 \end{pmatrix} = \begin{pmatrix} \kappa_{11}^{Y,P} & \kappa_{12}^{Y,P} & \kappa_{13}^{Y,P} \\ \kappa_{21}^{Y,P} & \kappa_{22}^{Y,P} & \kappa_{23}^{Y,P} \\ \kappa_{31}^{Y,P} & \kappa_{32}^{Y,P} & \kappa_{33}^{Y,P} \end{pmatrix} \left[\begin{pmatrix} \theta_1^{Y,P} \\ \theta_2^{Y,P} \\ \theta_3^{Y,P} \end{pmatrix} - \begin{pmatrix} Y_t^1 \\ Y_t^2 \\ Y_t^3 \end{pmatrix} \right] dt + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} dW_t^{1,P} \\ dW_t^{2,P} \\ dW_t^{3,P} \end{pmatrix}.$$

The instantaneous risk-free rate is given by

$$r_t = \delta_0^Y + \delta_{1,1}^Y Y_t^1 + \delta_{1,2}^Y Y_t^2 + \delta_{1,3}^Y Y_t^3.$$

Thus, there is a total of 22 free parameters in the canonical representation of the $A_0(3)$ class of models. (Given this canonical representation, there is no loss of generality in fixing the AFNS model mean under the Q -measure at 0 and leaving the mean under the P -measure, θ^P , to be estimated.)

In the AFNS class of models, the mean-reversion matrix under the Q -measure is triangular, so it is straightforward to derive the restrictions that must be imposed on the canonical affine representation to obtain the class of AFNS models. The procedure through which the restrictions are identified is based on so-called *affine invariant transformations*. Appendix C describes such transformations and derives the restrictions associated with the AFNS models considered in this paper. The results are summarized in Table 1, which shows that for the correlated-factor AFNS model, there are three key parameter restrictions on the canonical affine model. First, $\delta_0^Y = 0$, so there is no constant in the equation for the instantaneous risk-free rate. There is no need for this constant because, with the second restriction $\kappa_{1,1}^{Y,Q} = 0$, the first factor must be a unit-root process under the Q -measure, which also implies that this factor can be identified as the level factor. Finally, $\kappa_{2,2}^{Y,Q} = \kappa_{3,3}^{Y,Q}$, so the own mean-reversion rates of the second and third factors under the Q -measure must be identical. The independent-factor AFNS model maintains these three parameter restrictions and adds nine others under both the P - and Q -measures. (For both specifications, there is a further modest restriction described in Appendix C: $\kappa_{2,3}^{Y,Q}$ must have the opposite sign of $\kappa_{2,2}^{Y,Q}$ and $\kappa_{3,3}^{Y,Q}$, but its absolute numerical size can vary freely.)

The Nelson-Siegel parameter restrictions on the canonical affine AF model greatly facilitate estimation.⁹ They allow a closed-form solution and, as described in the next section, eliminate in

⁹Note that in the AFNS model, the connection between the P -dynamics and the yield function is explicitly tied to the yield adjustment term through the specification of the volatility matrix, while in the canonical representation it is blurred by an interplay between the specifications of δ_1^Y and K_Y^Q .

an appealing way the surfeit of troublesome likelihood maxima in estimation.¹⁰

4 Estimation of the DNS and AFNS models

Here we describe estimation methods and results for the DNS and AFNS models.

4.1 Estimation methods

The Kalman filter is an efficient and consistent estimator for both the DNS and AFNS models. For the DNS models, the state equation is

$$X_t = (I - A)\mu + AX_{t-1} + \eta_t, \quad \eta_t \sim N(0, Q),$$

where $X_t = (L_t, S_t, C_t)$, while the measurement equation is given by

$$y_t = BX_t + \varepsilon_t.$$

Following Diebold, Rudebusch, and Aruoba (2006), we start the algorithm at the unconditional mean and variance of the state variables. This assumes the stationarity of the state variables, which is ensured by imposing that the eigenvalues of A are smaller than 1.

For the continuous-time AFNS models, the conditional mean vector and the conditional covariance matrix are given by

$$\begin{aligned} E^P[X_T|\mathcal{F}_t] &= (I - \exp(-K^P \Delta t))\mu^P + \exp(-K^P \Delta t)X_t \\ V^P[X_T|\mathcal{F}_t] &= \int_0^{\Delta t} e^{-K^P s} \Sigma \Sigma' e^{-(K^P)' s} ds, \end{aligned}$$

where $\Delta t = T - t$. By discretizing the continuous dynamics under the P -measure, we obtain the state equation

$$X_i = (I - \exp(-K^P \Delta t_i))\mu^P + \exp(-K^P \Delta t_i)X_{i-1} + \eta_t,$$

where $\Delta t_i = t_i - t_{i-1}$ is the time between observations. The conditional covariance matrix for the shock terms is given by

$$Q = \int_0^{\Delta t_i} e^{-K^P s} \Sigma \Sigma' e^{-(K^P)' s} ds.$$

Stationarity of the system under the P -measure is ensured by restricting the real component of each eigenvalue of K^P to be positive. The Kalman filter for these models is also started at the unconditional mean and covariance¹¹

$$\widehat{X}_0 = \mu^P \quad \text{and} \quad \widehat{\Sigma}_0 = \int_0^{\infty} e^{-K^P s} \Sigma \Sigma' e^{-(K^P)' s} ds.$$

¹⁰This contrasts with the common practice, mentioned earlier, of zeroing out an arbitrary set of individual coefficients.

¹¹In the estimation $\int_0^{\infty} e^{-K^P s} \Sigma \Sigma' e^{-(K^P)' s} ds$ is approximated by $\int_0^{10} e^{-K^P s} \Sigma \Sigma' e^{-(K^P)' s} ds$.

Finally, the AFNS measurement equation is given by

$$y_t = A + BX_t + \varepsilon_t.$$

For both types of models, the error structure is

$$\begin{pmatrix} \eta_t \\ \varepsilon_t \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Q & 0 \\ 0 & H \end{pmatrix} \right],$$

where H is a diagonal matrix

$$H = \begin{pmatrix} \sigma^2(\tau_1) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma^2(\tau_N) \end{pmatrix}.$$

The linear least-squares optimality of the Kalman filter requires that the transition and measurement errors are orthogonal to the initial state, i.e.,

$$E[f_0 \eta_t'] = 0, \quad E[f_0 \varepsilon_t'] = 0.$$

Finally, parameter standard deviations are calculated as

$$\Sigma(\hat{\psi}) = \frac{1}{T} \left[\frac{1}{T} \sum_{t=1}^T \frac{\partial \log l_t(\hat{\psi})}{\partial \psi} \frac{\partial \log l_t(\hat{\psi})'}{\partial \psi} \right]^{-1},$$

where $\hat{\psi}$ denotes the estimated model parameter set.

4.2 DNS model estimation results

In this subsection, we present estimation results for the two versions of the DNS model. These specifications, along with the two AFNS specifications described in the next subsection, are estimated using monthly data on U.S. Treasury security yields from January 1987 to December 2002. The data are end-of-month, unsmoothed Fama-Bliss (1987) zero-coupon yields at the following 16 maturities: 3, 6, 9, 12, 18, 24, 36, 48, 60, 84, 96, 108, 120, 180, 240, and 360 months.

The estimates of the DNS models with independent and correlated factors are shown in Tables 2 and 3, respectively. In both models, the level factor is the most persistent factor, while the curvature factor has the fastest rate of mean-reversion. Interestingly, for the correlated factors DNS model, the only significant off-diagonal element (the 0.0819) in the estimated A -matrix is $A_{S_t, C_{t-1}}$, which is the key non-zero off-diagonal element required in Proposition 1 for the AFNS specification.

Volatility parameters will be most easily compared by using the one-month conditional covari-

A	L_{t-1}	S_{t-1}	C_{t-1}	μ	q	1	2	3
L_t	0.9827 (0.0128)	0	0	0.06958 (0.0137)	1	0.002485 (0.000153)	0	0
S_t	0	0.9778 (0.0166)	0	-0.02487 (0.0151)	2	0	0.003329 (0.000194)	0
C_t	0	0	0.9189 (0.0284)	-0.01075 (0.00786)	3	0	0	0.007471 (0.000396)

Table 2: **Parameter Estimates of the Independent-Factor DNS Model.**

The left-hand panel contains the estimated A matrix and μ vector. The right-hand panel contains the estimated q matrix. Estimated standard deviations of the parameter estimates are given in parentheses. The associated estimated λ is 0.06040 (when yield maturities are measured in months) with a standard deviation of 0.00100. The maximized log-likelihood value is 16332.94.

A	L_{t-1}	S_{t-1}	C_{t-1}	μ	q	1	2	3
L_t	0.9874 (0.0165)	0.0050 (0.0183)	-0.0097 (0.0157)	0.0723 (0.0145)	1	0.002457 (0.000147)	0	0
S_t	0.0066 (0.0228)	0.9332 (0.0229)	0.0819 (0.0202)	-0.0294 (0.0159)	2	-0.002227 (0.000255)	0.002265 (0.000110)	0
C_t	0.0152 (0.0526)	0.0401 (0.0418)	0.9011 (0.0377)	-0.0120 (0.0126)	3	0.002752 (0.000706)	0.000618 (0.000610)	0.006554 (0.000441)

Table 3: **Parameter Estimates of the Correlated-Factor DNS Model.**

The left-hand panel contains the estimated A matrix and μ vector. The right-hand panel contains the estimated q matrix. Estimated standard deviations of the parameter estimates are given in parentheses. The associated estimated λ is 0.06248 (when yield maturities are measured in months) with a standard deviation of 0.00109. The maximum log-likelihood value is 16415.36.

ance matrices for the independent-factor model

$$Q_{indep}^{DNS} = qq' = \begin{pmatrix} 6.17 \times 10^{-6} & 0 & 0 \\ 0 & 1.11 \times 10^{-5} & 0 \\ 0 & 0 & 5.58 \times 10^{-5} \end{pmatrix} \quad (10)$$

and the correlated-factor model

$$Q_{corr}^{DNS} = qq' = \begin{pmatrix} 6.03 \times 10^{-6} & -5.47 \times 10^{-6} & 6.76 \times 10^{-6} \\ -5.47 \times 10^{-6} & 1.01 \times 10^{-5} & -4.73 \times 10^{-6} \\ 6.76 \times 10^{-6} & -4.73 \times 10^{-6} & 5.09 \times 10^{-5} \end{pmatrix}. \quad (11)$$

Across the two models, the variances of each state variable are similar, with the level factor the least volatile and the curvature factor the most volatile. The covariance estimates obtained in the correlated-factor DNS model translate into a correlation of -0.701 for innovations to the level and slope factor, a correlation of 0.385 for innovations to the level and curvature factor, and a correlation of -0.208 for innovations to the slope and curvature factor.

The two DNS models are nested, so we can test the independent-factor restricted parameter set θ_{indep} versus the correlated-factor unrestricted parameter set θ_{corr} with a likelihood ratio test

$$LR = 2[\log L(\theta_{corr}) - \log L(\theta_{indep})] = 164.8 \sim \chi^2(q),$$

Maturity in months	DNS		DNS		AFNS		AFNS	
	indep.-factor		corr.-factor		indep.-factor		corr.-factor	
	Mean	RMSE	Mean	RMSE	Mean	RMSE	Mean	RMSE
3	-1.64	12.26	-1.84	11.96	-2.85	18.54	-2.47	11.53
6	-0.24	1.09	-0.29	1.34	-1.19	7.12	-0.04	0.75
9	-0.54	7.13	-0.51	6.92	-1.24	3.44	-0.35	6.86
12	4.04	11.19	4.11	10.86	3.58	9.60	3.69	10.11
18	7.22	10.76	7.28	10.42	7.15	10.44	5.49	8.31
24	1.18	5.83	1.19	5.29	1.37	5.94	-1.20	4.37
36	-0.07	1.51	-0.19	2.09	0.31	1.98	-1.10	3.16
48	-0.67	3.92	-0.85	4.03	-0.39	3.72	0.94	4.14
60	-5.33	7.13	-5.51	7.31	-5.27	6.82	-1.99	5.20
84	-1.22	4.25	-1.30	4.25	-1.50	4.29	0.90	3.83
96	1.31	2.10	1.29	2.02	1.02	2.11	1.05	1.83
108	0.03	2.94	0.07	3.11	-0.11	3.02	-3.24	5.28
120	-5.11	8.51	-5.01	8.53	-4.96	8.23	-11.67	14.02
180	24.11	29.44	24.40	29.66	27.86	32.66	3.76	16.50
240	25.61	34.99	26.00	35.33	35.95	42.61	4.20	23.93
360	-29.62	37.61	-29.12	37.18	1.37	22.04	-0.81	23.02

Table 4: **Summary Statistics of In-Sample Fit.**

The means and the root mean squared errors for 16 different maturities. All numbers are measured in basis points.

where q , the number of parameter restrictions, equals nine. The associated p -value is less than .0001, so the restrictions imposed in the independent-factor DNS model are not supported by the data.¹² Still, the increased flexibility of the correlated-factor DNS model provides little advantage in fitting the observed yields.¹³ Table 4 reports summary statistics for the fitted errors for each of the four models considered in this study. For the two DNS models, the differences in RMSEs at any maturity are not large (less than 0.58 basis points), and there is no consistent advantage for the correlated factors model. Interestingly, both models have difficulty fitting yields beyond the 10-year maturity, which suggests that a maturity-dependent yield adjustment term, as in the AFNS models that we turn to next, could improve fit.

4.3 AFNS model estimation results

As many have noted, estimation of the canonical affine $A_0(3)$ term structure model is very difficult and time-consuming and effectively prevents the kind of repetitive re-estimation required in a comprehensive simulation study or out-of-sample forecast exercise, which we pursue with the AFNS model in the next section.¹⁴ By comparison, the estimation of the AFNS model is straightforward

¹²This rejection reflects an elevated negative correlation between the innovations to the level and slope factor and a significant positive correlation through the mean-reversion matrix between changes in the slope factor and deviations of the curvature factor from its mean.

¹³The similarity in fit is not too surprising, since there is no direct connection in these DNS models between the yield function and the assumed P -dynamics of the state variables. Indeed, across the two models, the level, slope, and curvature factors are very highly correlated.

¹⁴For example, Rudebusch, Swanson, and Wu (2006) report being unable to replicate the published estimates of a no-arbitrage model even though they use the same data and programs that generated the model's parameter estimates.

K^P	$K_{:,1}^P$	$K_{:,2}^P$	$K_{:,3}^P$	μ^P	Σ	$\Sigma_{:,1}$	$\Sigma_{:,2}$	$\Sigma_{:,3}$
$K_{1,\cdot}^P$	0.06734 (0.0623)	0	0	0.07243 (0.0148)	$\Sigma_{1,\cdot}$	0.005095 (0.000139)	0	0
$K_{2,\cdot}^P$	0	0.2083 (0.179)	0	-0.02825 (0.0173)	$\Sigma_{2,\cdot}$	0	0.01103 (0.000580)	0
$K_{3,\cdot}^P$	0	0	1.230 (0.423)	-0.009266 (0.00609)	$\Sigma_{3,\cdot}$	0	0	0.02647 (0.00137)

Table 5: **Parameter Estimates of the Independent-Factor AFNS Model.**

The left-hand panel contains the estimated K^P matrix and μ vector. The right-hand panel contains the estimated Σ matrix. Estimated standard deviations of the parameter estimates are given in parentheses. The associated estimated λ is 0.5971 with a standard deviation of 0.0115. The maximum log-likelihood value is 16279.55.

and robust in large part because the role of each latent factor is not left unidentified as in the maximally flexible $A_0(3)$ model. Even though the factors are latent in the AFNS model, with the Nelson-Siegel factor loading structure, they can be clearly identified as level, slope, and curvature. This identification eliminates the troublesome local maxima reported by Kim and Orphanides (2005), i.e. maxima with likelihood values very close to the global maximum but with very different interpretations of the three factors and their dynamics.¹⁵

The estimated parameters of the independent-factor AFNS model are reported in Table 5. The factor means are close to those of the DNS model. To compare the mean-reversion parameters, we translate the continuous-time matrix in Table 5 into the one-month conditional mean-reversion matrix

$$\exp\left(-K^P \frac{1}{12}\right) = \begin{pmatrix} 0.994 & 0 & 0 \\ 0 & 0.983 & 0 \\ 0 & 0 & 0.903 \end{pmatrix}. \quad (12)$$

We also convert the volatility matrix into a one-month conditional covariance matrix

$$Q_{indep}^{AFNS} = \int_0^{\frac{1}{12}} e^{-K^P s} \Sigma \Sigma' - (K^P)' s ds = \begin{pmatrix} 2.15 \times 10^{-6} & 0 & 0 \\ 0 & 9.97 \times 10^{-6} & 0 \\ 0 & 0 & 5.28 \times 10^{-5} \end{pmatrix}. \quad (13)$$

These too appear little different from the ones reported for the independent-factor DNS model. Still, although the two independent-factor models are non-nested, they contain the same number of parameters, and the lower log-likelihood value obtained for the AFNS model (16279 vs. 16332) suggests a slightly weaker in-sample performance for that model, which appears consistent with the RMSEs in Table 4.

Similar fit to the data by the two models is not too surprising because they make identical assumptions about the P -dynamics, so the only difference between the two models is the inclusion of the yield-adjustment term in the AFNS model yield function. For the independent-factor AFNS model, this term is given by

¹⁵Other strategies to facilitate estimation include adding survey information (Kim and Orphanides, 2005) or assuming the latent yield-curve factors are observable (Ang, Piazzesi, and Wei, 2006).

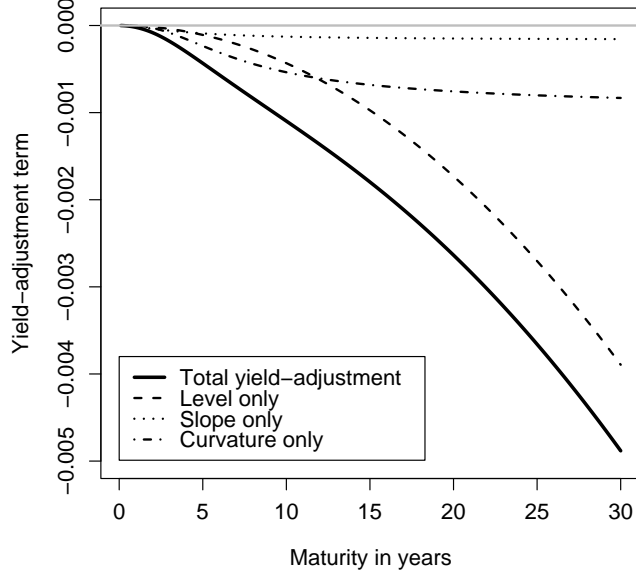


Figure 1: **The Yield-Adjustment Term for the Independent-Factor AFNS Model.**
The yield-adjustment term $-\frac{C(\tau)}{\tau}$ and its three components.

$$\begin{aligned}
-\frac{C(t, T)}{T-t} &= -\frac{\sigma_{11}^2}{2} \frac{1}{T-t} \int_t^T B^1(s, T)^2 ds - \frac{\sigma_{22}^2}{2} \frac{1}{T-t} \int_t^T B^2(s, T)^2 ds - \frac{\sigma_{33}^2}{2} \frac{1}{T-t} \int_t^T B^3(s, T)^2 ds \\
&= -\sigma_{11}^2 \frac{(T-t)^2}{6} - \sigma_{22}^2 \left[\frac{1}{2\lambda^2} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{1}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right] \\
&\quad - \sigma_{33}^2 \left[\frac{1}{2\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{4\lambda} (T-t) e^{-2\lambda(T-t)} - \frac{3}{4\lambda^2} e^{-2\lambda(T-t)} - \frac{2}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{5}{8\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right].
\end{aligned}$$

The estimated yield-adjustment term and its three components associated with the variances of the three state variables are shown in Figure 1. All three components are negative, regardless of the size of the volatility parameters. In general, the rather simple functional form of the yield-adjustment term suggests that the lack of improvement in fit of this model is not too surprising.

Greater flexibility is allowed in the correlated-factor AFNS model, and the estimated parameters of this model are reported in Table 6. Since this model nests the independent-factor version, a standard likelihood ratio test can be performed,

$$LR = 2[\log L(\theta_{corr}) - \log L(\theta_{indep})] = 424.9 \sim \chi^2(q),$$

where q , the number of parameter restrictions, equals nine. The associated p -value is again minuscule, so the independent factor restrictions are not supported by the data in sample.

The greater flexibility is apparent in the complexity of the yield-adjustment term for this model:

K^P	$K_{\cdot,1}^P$	$K_{\cdot,2}^P$	$K_{\cdot,3}^P$	μ^P	Σ	$\Sigma_{\cdot,1}$	$\Sigma_{\cdot,2}$	$\Sigma_{\cdot,3}$
$K_{1,\cdot}^P$	4.729 (1.14)	8.046 (1.19)	-9.730 (1.23)	0.07982 (0.00738)	$\Sigma_{1,\cdot}$	0.01542 (0.000364)	0	0
$K_{2,\cdot}^P$	-0.8584 (1.12)	-0.3617 (1.96)	0.5775 (2.38)	-0.03798 (0.0200)	$\Sigma_{2,\cdot}$	-0.003763 (0.00480)	0.01088 (0.00174)	0
$K_{3,\cdot}^P$	-32.89 (9.68)	-59.34 (1.01)	72.49 (1.02)	-0.02636 (0.0189)	$\Sigma_{3,\cdot}$	-0.1615 (0.00658)	-0.05981 (0.0102)	0.01457 (0.0430)

Table 6: **Parameter Estimates of the Correlated-Factor AFNS Model.**

The left-hand panel contains the estimated K^P matrix and μ vector. The right-hand panel contains the estimated Σ matrix. Estimated standard deviations of the parameter estimates are given in parentheses. The associated estimated λ is 0.8219 with a standard deviation of 0.0122. The maximum log-likelihood value is 16492.00.

$$\begin{aligned}
-\frac{C(t,T)}{T-t} &= -\sigma_{11}^2 \frac{(T-t)^2}{6} - (\sigma_{21}^2 + \sigma_{22}^2) \left[\frac{1}{2\lambda^2} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{1}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right] \\
&- (\sigma_{31}^2 + \sigma_{32}^2 + \sigma_{33}^2) \\
&\times \left[\frac{1}{2\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{4\lambda} (T-t) e^{-2\lambda(T-t)} - \frac{3}{4\lambda^2} e^{-2\lambda(T-t)} - \frac{2}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{5}{8\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right] \\
&- \sigma_{11}\sigma_{21} \left[\frac{1}{2\lambda} (T-t) + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} \right] \\
&- \sigma_{11}\sigma_{31} \left[\frac{3}{\lambda^2} e^{-\lambda(T-t)} + \frac{1}{2\lambda} (T-t) + \frac{1}{\lambda} (T-t) e^{-\lambda(T-t)} - \frac{3}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} \right] \\
&- (\sigma_{21}\sigma_{31} + \sigma_{22}\sigma_{32}) \left[\frac{1}{\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{2\lambda^2} e^{-2\lambda(T-t)} - \frac{3}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{3}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right].
\end{aligned}$$

Figure 2 displays this yield-adjustment term and its various components. This term has an interesting hump with a peak in the 15- to 20-year maturity range, which appears to improve the fit of those long-term yields in particular, but also of yields with fairly short maturities. This added flexibility allows the level factor to become less persistent, as is evident in the estimated one-month conditional mean-reversion matrix

$$\exp\left(-K^P \frac{1}{12}\right) = \begin{pmatrix} 0.915 & -0.170 & 0.124 \\ 0.0499 & 0.992 & -0.00222 \\ 0.451 & 0.765 & 0.0556 \end{pmatrix}. \quad (14)$$

It appears that to the extent long-term yields are fit through the yield-adjustment term, the level factor becomes less persistent because it blends with slope and curvature in an effort to provide an improved fit for maturities up to nine years.

The one-month conditional covariance matrix is given by

$$Q_{corr}^{AFNS} = \int_0^{\frac{1}{12}} e^{-K^P s} \Sigma \Sigma' - (K^P)' s ds = \begin{pmatrix} 7.44 \times 10^{-6} & -6.37 \times 10^{-6} & -8.35 \times 10^{-6} \\ -6.37 \times 10^{-6} & 1.09 \times 10^{-5} & 2.80 \times 10^{-6} \\ -8.35 \times 10^{-6} & 2.80 \times 10^{-6} & 2.04 \times 10^{-4} \end{pmatrix}. \quad (15)$$

The conditional variances in the diagonal are about the same for the level and slope factors as

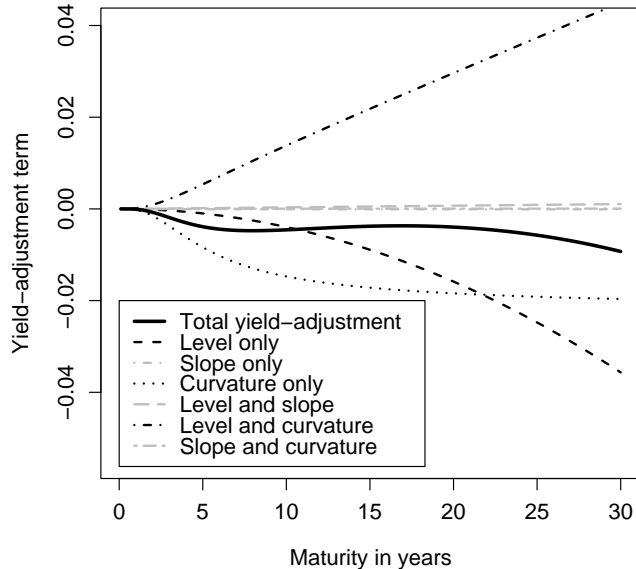


Figure 2: **The Yield-Adjustment Term for the Correlated-Factor AFNS Model.**
The yield adjustment term $-\frac{C(\tau)}{\tau}$ and its six components.

those obtained in the correlated-factor DNS model, but the conditional variance for curvature is much larger. In terms of covariances, the negative correlation between the innovations to level and slope is maintained. For the correlations between shocks to curvature and shocks to level and slope, the signs have changed relative to the unconstrained correlated-factor DNS model. This suggests that the off-diagonal elements of Σ are heavily influenced by the required shape of the yield-adjustment term rather than the dynamics of the state variables. This interpretation will be supported by our out-of-sample forecast exercise in the next section.

5 Forecast performance

In this section, we investigate whether the in-sample superiority of the flexible correlated-factor models carries over to out-of-sample forecast accuracy. We first describe the recursive estimation and forecasting procedure employed, and then we proceed to the results.

5.1 Construction of out-of-sample forecasts

We construct one-, six-, and twelve-month-ahead forecasts from the four DNS and AFNS models for six yields with maturities of 3 months and 1, 3, 5, 10, and 30 years. We use a recursive procedure. For the first set of forecasts, the model is estimated from January 1987 to December 1996; then, one month of data is added, the models are reestimated, and another set of forecasts is constructed. The largest estimation sample for the one-month-ahead forecasts ends in November

2002 (72 forecasts in all). For the six- and 12-month horizons, the largest samples end in June 2002 and December 2001 (67 and 61 forecasts), respectively. This recursive estimation strategy is greatly facilitated for the AF model by the addition of the Nelson-Siegel factor loadings. For the usual method of estimating the canonical $A_0(3)$ model, each additional month requires reexamination of the zero exclusion restrictions, which is prohibitively time consuming.

For the DNS models, the period- t forecast of the τ -maturity yield h periods ahead is simply the conditional expectation

$$\hat{y}_{t+h}^{DNS}(\tau) \equiv E_t^P[y_{t+h}(\tau)] = E_t^P[L_{t+h}] + E_t^P[S_{t+h}]\left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau}\right) + E_t^P[C_{t+h}]\left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right).$$

Given parameter estimates for A and μ from a sample that ends in period t , the discrete-time state equation for the DNS model can be written

$$X_t = (I - A)\mu + AX_{t-1} + \eta_t,$$

where $X_t = (L_t, S_t, C_t)$. Recursive iteration (and i.i.d. innovations) imply that the conditional expectation of the state variables in period $t + h$ are

$$E_t^P[X_{t+h}] = \left(\sum_{i=0}^{h-1} A^i\right)(I - A)\mu + A^h X_t,$$

so it is straightforward to calculate forecasted yields.

For the AFNS models, the forecast of the τ -maturity yield in period $t + h$ based on information available at time t is simply the conditional expectation

$$\hat{y}_{t+h}^{AFNS}(\tau) \equiv E_t^P[y_{t+h}(\tau)] = E_t^P[X_{t+h}^1] + E_t^P[X_{t+h}^2]\left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau}\right) + E_t^P[X_{t+h}^3]\left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) - \frac{C(\tau)}{\tau}.$$

In this case, the requisite conditional expectations are given by

$$E_0^P[X_t] = (I - \exp(-K^P t))\theta^P + \exp(-K^P t)X_0,$$

where $X_t = (X_t^1, X_t^2, X_t^3)$. Thus, with estimates for K^P , θ^P , λ , and Σ along with the optimally filtered paths of the three factors, it is easy to calculate future factor expected values and yields.

5.2 Evaluation of out-of-sample forecasts

Out-of-sample forecast accuracy has been a key metric to evaluate the adequacy of AF yield-curve models.¹⁶ The forecast performances of the four models are compared using the root mean squared error (RMSE) of the forecast error $\varepsilon_t(\tau, h) = \hat{y}_{t+h}(\tau) - y_{t+h}(\tau)$, for $\tau = 3, 12, 36, 60, 120, 360$, and $h = 1, 6, 12$ (in months). These RMSEs are shown in Table 7. For each of the 18 combinations of yield maturity and forecast horizon, the most accurate model's RMSE is underlined. The results

¹⁶Recent analyses of the forecast performance of AF models include Ang and Piazzesi (2003), Hördaahl, Tristani, and Vestin (2005), Mönch (2006), De Pooter, Ravazzolo, and van Dijk (2007).

are quite striking. In 14 of the 18 combinations, the most accurate model is the independent-factor AFNS model. In particular, the in-sample advantage of the correlated-factor AFNS model disappears out of sample. Evidently, the correlated-factor AFNS model is prone to in-sample overfitting, due to its complex yield-adjustment term and rich P -dynamics. Furthermore, the cases in which the independent-factor AFNS model is not the most accurate all pertain to shorter-maturity yields. Specifically, it is only for the 3-month yield, that the correlated-factor models have lower RMSEs. This advantage likely reflects idiosyncratic fluctuations in short-term Treasury bill yields from institutional factors that are unrelated to yields on longer-maturity Treasuries, as described by Duffee (1996). The more flexible models appear to have a slight advantage in fitting these idiosyncratic movements.

In examining forecast performance, we are interested in two broad comparisons. First, how do the correlated-factor models do against the independent-factor models, and second, how does the imposition of the AF structure affect forecast performance. Table 8 brings these two questions into sharper focus by showing the ratios of the forecast RMSEs of various models. The two columns on the left divide the DNS and AFNS independent-factor model RMSEs by their respective correlated-factor model RMSEs. These are almost uniformly below one (outside of the 3-month yield noted above), which supports the parsimonious versions of these models. These differences in forecast accuracy are also generally statistically significant. For each maturity and horizon combination, we use the Diebold-Mariano (1995) test to compare model performance.¹⁷ The asterisks in Table 8 denote significant differences in out-of-sample model performance at the 1, 5, and 10 percent levels. For both the DNS and AFNS models, the preponderance of evidence supports the parsimonious models.¹⁸

The two columns on the right divide the RMSEs of the AF versions of the independent- and correlated-factor models by their non-AF counterparts. Here the story is more mixed, but for the independent-factor case, which is arguably the one of interest given the generally poor performance and overparameterization of the correlated-factor models, the AF version dominates. The bottom line is that out-of-sample forecast performance is improved by imposing the AF restrictions—especially at longer horizons and for longer maturities.

5.3 Forecast comparison with Duffee (2002)

A key remaining question is what is the relative forecasting performance of an AFNS model compared to the unrestricted $A_0(3)$ model, which could provide some guidance as to the benefits of imposing the Nelson-Siegel restrictions. Of course, as we have stressed above, there are clear computational benefits to imposing these restrictions. Indeed, without them, the out-of-sample forecasting exercise pursued above with rolling re-estimation of the model for each new forecast is very difficult, if not impossible, to conduct for the maximally flexible $A_0(3)$ model. Accordingly,

¹⁷We implement this test by regressing the differences between the squared forecast errors for two models on an intercept and examining the significance of that intercept using standard errors that are corrected for possibly heteroskedastic and autocorrelated residuals.

¹⁸We also examined model accuracy using the generalized Diebold-Mariano test proposed by Christensen et al. (2007), which can pool observations across all maturities or horizons simultaneously. This test supported our conclusions from the individual comparisons.

Model	Forecast horizon		
	One month	Six months	Twelve months
3-month yield			
DNS _{indep}	22.93	96.87	173.39
DNS _{corr}	<u>20.43</u>	<u>87.43</u>	166.91
AFNS _{indep}	22.84	91.60	164.97
AFNS _{corr}	20.56	88.67	<u>162.33</u>
1-year yield			
DNS _{indep}	29.41	103.25	170.85
DNS _{corr}	<u>27.06</u>	102.71	173.14
AFNS _{indep}	29.12	<u>98.58</u>	<u>164.01</u>
AFNS _{corr}	33.89	98.87	165.99
3-year yield			
DNS _{indep}	30.64	92.22	135.24
DNS _{corr}	30.59	99.55	145.82
AFNS _{indep}	<u>30.29</u>	<u>87.23</u>	<u>127.78</u>
AFNS _{corr}	36.95	91.00	136.44
5-year yield			
DNS _{indep}	30.77	87.87	122.09
DNS _{corr}	31.23	94.95	132.40
AFNS _{indep}	<u>30.13</u>	<u>82.68</u>	<u>113.83</u>
AFNS _{corr}	32.37	88.46	125.42
10-year yield			
DNS _{indep}	28.35	74.71	105.02
DNS _{corr}	29.06	79.48	112.37
AFNS _{indep}	<u>27.18</u>	<u>67.72</u>	<u>93.36</u>
AFNS _{corr}	35.08	90.42	124.28
30-year yield			
DNS _{indep}	38.42	71.35	96.90
DNS _{corr}	38.73	72.71	99.68
AFNS _{indep}	<u>30.42</u>	<u>48.82</u>	<u>63.50</u>
AFNS _{corr}	38.30	71.35	96.86

Table 7: **Out-of-Sample Forecast RMSE for Four Models.**

For each maturity and horizon, the most accurate model's RMSE is underlined. All numbers are measured in basis points.

Forecast horizon (in months)	Ratios of out-of-sample forecast RMSEs			
	$\frac{DNS_{indep}}{DNS_{corr}}$	$\frac{AFNS_{indep}}{AFNS_{corr}}$	$\frac{AFNS_{indep}}{DNS_{indep}}$	$\frac{AFNS_{corr}}{DNS_{corr}}$
	3-month yield			
1	1.12*	1.11**	1.00	1.01
6	1.11	1.03**	0.95*	1.01
12	1.04	1.02	0.95*	0.97
	12-month yield			
1	1.09**	0.86**	0.99	1.25**
6	1.01	1.00	0.95	0.96
12	0.99	0.99	0.96	0.96
	36-month yield			
1	1.00	0.82***	0.99	1.21**
6	0.93**	0.96	0.95	0.91
12	0.93**	0.94	0.94	0.94**
	60-month yield			
1	0.99	0.93*	0.98**	1.04
6	0.93***	0.93	0.94*	0.93**
12	0.92**	0.91	0.93	0.95***
	120-month yield			
1	0.98***	0.77***	0.96***	1.21***
6	0.94***	0.75***	0.91**	1.14***
12	0.93***	0.75***	0.89*	1.11***
	360-month yield			
1	0.99	0.79*	0.79	0.99
6	0.98**	0.68***	0.68***	0.98
12	0.97***	0.66***	0.66***	0.97

Table 8: **RMSE Ratios for Out-of-Sample Forecast Errors.**

The ratios of the RMSEs for two different models are shown for each forecast horizon and yield maturity. The statistical significance of these forecast comparisons (based on tests of equal forecast accuracy using quadratic loss) are denoted by * at the 10% level, ** at the 5% level, and *** at the 1% level.

Maturity	Horizon		
	3 months	6 months	12 months
<i>6-month yield</i>	RMSE	RMSE	RMSE
Random walk	29.79	40.02	48.39
Duffee (2002), preferred $A_0(3)$	28.1	36.5	42.1
AFNS, independent factors	26.62	34.46	42.83
<i>2-year yield</i>	RMSE	RMSE	RMSE
Random walk	49.89	65.21	76.23
Duffee (2002), preferred $A_0(3)$	45.7	56.6	60.0
AFNS, independent factors	44.35	54.73	60.13
<i>10-year yield</i>	RMSE	RMSE	RMSE
Random walk	48.45	66.90	81.46
Duffee (2002), preferred $A_0(3)$	46.9	63.6	73.8
AFNS, independent factors	45.64	61.12	72.98

Table 9: **Out-of-Sample Forecast Performance of AFNS and $A_0(3)$ Models.**

Out-of-sample forecast RMSEs are shown for the $A_0(3)$ model, as estimated by Duffee (2002, Table 8), and the random walk forecast and the independent-factor AFNS model, as estimated by the authors using the Duffee (2002) data set. The estimated parameters for both models are kept fixed at the optimal set obtained for the sample covering January 1952 to December 1994. For each forecasting procedure, there are 45 three-month-ahead forecasts from January 1995 to September 1998, 42 6-month-ahead forecasts from January 1995 to June 1998, and 36 12-month-ahead forecasts from January 1995 to December 1997. All numbers are reported in basis points.

instead of estimating a somewhat arbitrary $A_0(3)$ model for our data set, we take an existing optimized empirical $A_0(3)$ model from the literature, specifically, Duffee (2002), and compare it to an AFNS model estimated on the same data.

Duffee (2002) examines the empirical performance of the $A_i(3)$ model classes for $i = 0, 1, 2$, and 3 (where i denotes the number of square-root processes). He estimates both the maximally flexible version (given essentially affine risk premium structure) and more parsimonious “preferred” specifications within each class. These various specifications are estimated on a single sample from January 1952 to December 1994.¹⁹ Holding the parameters fixed at those estimated values, Duffee updates the values of the three state variables by adding one month of data sequentially and produces yield forecasts three months, six months, and twelve months ahead. Across all models, Duffee judges that his preferred Gaussian $A_0(3)$ model is superior when it comes to forecasting yields and the RMSEs for the forecasts from this preferred Gaussian $A_0(3)$ specification are reported in Table 9. (The estimation method used by Duffee (2002) differs from ours in that he avoids filtering by assuming that the six-month, two-year, and ten-year yields are observed without error; therefore, he also only provides data on the out-of-sample forecast performance at these three maturities.)

We redo the analysis of Duffee (2002) using an independent-factor AFNS model. In our estimation of the AFNS model on the Duffee data, we use the Kalman filter to estimate the optimal parameters from the January 1952 to December 1994 sample (using three-month, six-month, one-year, two-year, five-year, and ten-year yields). The estimated parameters that maximize the log

¹⁹The data used are available on Duffee’s website <http://faculty.haas.berkeley.edu/duffee/>.

K^P	$K_{\cdot,1}^P$	$K_{\cdot,2}^P$	$K_{\cdot,3}^P$	μ^P	Σ	$\Sigma_{\cdot,1}$	$\Sigma_{\cdot,2}$	$\Sigma_{\cdot,3}$
$K_{1,\cdot}^P$	0.0008886 (0.0161)	0	0	0.03038 (0.538)	$\Sigma_{1,\cdot}$	0.006919 (0.000174)	0	0
$K_{2,\cdot}^P$	0	0.7450 (0.155)	0	-0.01616 (0.00538)	$\Sigma_{2,\cdot}$	0	0.02081 (0.000361)	0
$K_{3,\cdot}^P$	0	0	2.526 (0.353)	-0.004326 (0.00257)	$\Sigma_{3,\cdot}$	0	0	0.03641 (0.000901)

Table 10: **Parameter Estimates of the AFNS Model on the Duffee Data.**

The left-hand panel contains the estimated K^P matrix and μ vector. The right-hand panel contains the estimated Σ matrix. Estimated standard deviations of the parameter estimates are given in parentheses. The associated estimated λ is 0.8130 with a standard deviation of 0.0182. The maximum log-likelihood value is 14948.85.

likelihood function for the independent-factor AFNS model are reported in Table 10.²⁰ Fixing the parameters at this optimal parameter set throughout, we then add one month of data to the sample sequentially and use the Kalman filter to update the values of the state variables. Based on the updated state variables we produce yield forecasts at the three-month, six-months, and twelve-month horizon as above, with RMSEs as shown in Table 9.

In Table 9, the best performing model for each yield and at each forecast horizon is given in bold typeface. In seven of the nine yield and horizon combinations, the independent-factor AFNS model gives the most accurate forecasts. It comes in a close second in the remaining two, and it consistently outperforms the random walk. This superior out-of-sample forecast performance suggests that the AFNS class is a strong and, not least, well-identified representative of the general $A_0(3)$ class of models.

6 Concluding Remarks

Asset pricing, portfolio allocation, and risk management are the fundamental tasks in financial asset markets. For fixed income securities, superior yield-curve modeling translates into superior pricing, portfolio returns, and risk management. Accordingly, we have focused on two important and successful yield curve literatures: the Nelson-Siegel empirically based one and the no-arbitrage theoretically based one. Yield-curve models in both of these traditions are impressive successes, albeit for very different reasons. Ironically, both approaches are equally impressive failures, and for the same reasons, swapped. That is, models in the Nelson-Siegel tradition fit and forecast well, but they lack theoretical rigor insofar as they admit arbitrage possibilities. Conversely, models in the arbitrage-free tradition are theoretically rigorous insofar as they enforce absence of arbitrage, but they fit and forecast poorly.

In this paper we have bridged this divide, proposing Nelson-Siegel-inspired models that enforce absence of arbitrage. We analyzed our models theoretically and empirically, relating them to the canonical Dai-Singleton representation of three-factor arbitrage-free affine models and documenting that predictive gains may be achieved by imposing absence of arbitrage, particularly

²⁰There are 21 parameters estimated in Duffee's preferred $A_0(3)$ model and 16 parameters estimated in our AFNS model, including the six measurement error standard deviations.

for moderate to long maturities and forecast horizons.²¹ Going forward, this new AFNS structure appears likely to be a very useful representation for term structure research. For example, Christensen, Lopez, and Rudebusch (2008) have used it to provide a tractable and robust joint empirical model of nominal and real yield curves.

²¹In a related but distinct development, Chua et al. (2008) propose an arbitrage-free model with forward rates formulated as exponential-affine functions of the state variables, and they find that it performs well for forecasting.

Appendix A: Proof of Proposition 1

Start the analysis by limiting the volatility to be constant. Then the system of ODEs for $B(t, T)$ is given by

$$\frac{dB(t, T)}{dt} = \rho_1 + (K^Q)'B(t, T), \quad B(T, T) = 0.$$

Because

$$\frac{d}{dt} \left[e^{(K^Q)'(T-t)} B(t, T) \right] = e^{(K^Q)'(T-t)} \frac{dB(t, T)}{dt} - (K^Q)' e^{(K^Q)'(T-t)} B(t, T),$$

it follows from the system of ODEs that

$$\int_t^T \frac{d}{ds} \left[e^{(K^Q)'(T-s)} B(s, T) \right] ds = \int_t^T e^{(K^Q)'(T-s)} \rho_1 ds$$

or, equivalently, using the boundary conditions

$$B(t, T) = -e^{-(K^Q)'(T-t)} \int_t^T e^{(K^Q)'(T-s)} \rho_1 ds.$$

Now impose the following structure on $(K^Q)'$ and ρ_1 :

$$(K^Q)' = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & -\lambda & \lambda \end{pmatrix} \quad \text{and} \quad \rho_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}.$$

It is then easy to show that

$$e^{(K^Q)'(T-t)} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{\lambda(T-t)} & 0 \\ 0 & -\lambda(T-t)e^{\lambda(T-t)} & e^{\lambda(T-t)} \end{pmatrix} \quad \text{and} \quad e^{-(K^Q)'(T-t)} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\lambda(T-t)} & 0 \\ 0 & \lambda(T-t)e^{-\lambda(T-t)} & e^{-\lambda(T-t)} \end{pmatrix}.$$

Inserting this in the ODE, we obtain

$$\begin{aligned} B(t, T) &= - \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\lambda(T-t)} & 0 \\ 0 & \lambda(T-t)e^{-\lambda(T-t)} & e^{-\lambda(T-t)} \end{pmatrix} \int_t^T \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{\lambda(T-s)} & 0 \\ 0 & -\lambda(T-s)e^{\lambda(T-s)} & e^{\lambda(T-s)} \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} ds \\ &= - \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\lambda(T-t)} & 0 \\ 0 & \lambda(T-t)e^{-\lambda(T-t)} & e^{-\lambda(T-t)} \end{pmatrix} \int_t^T \begin{pmatrix} 1 \\ e^{\lambda(T-s)} \\ -\lambda(T-s)e^{\lambda(T-s)} \end{pmatrix} ds. \end{aligned}$$

Because

$$\int_t^T ds = T - t,$$

and

$$\int_t^T e^{\lambda(T-s)} ds = \left[\frac{-1}{\lambda} e^{\lambda(T-s)} \right]_t^T = -\frac{1 - e^{\lambda(T-t)}}{\lambda},$$

and

$$\int_t^T -\lambda(T-s)e^{\lambda(T-s)} ds = \frac{1}{\lambda} \int_{\lambda(T-t)}^0 xe^x dx = \frac{1}{\lambda} [xe^x]_{\lambda(T-t)}^0 - \frac{1}{\lambda} \int_{\lambda(T-t)}^0 e^x dx = -(T-t)e^{\lambda(T-t)} - \frac{1-e^{\lambda(T-t)}}{\lambda},$$

the system of ODEs can be reduced to

$$B(t, T) = - \begin{pmatrix} 1 & 0 & 0 \\ 0 & e^{-\lambda(T-t)} & 0 \\ 0 & \lambda(T-t)e^{-\lambda(T-t)} & e^{-\lambda(T-t)} \end{pmatrix} \begin{pmatrix} T-t \\ -\frac{1-e^{\lambda(T-t)}}{\lambda} \\ -(T-t)e^{\lambda(T-t)} - \frac{1-e^{\lambda(T-t)}}{\lambda} \end{pmatrix} = \begin{pmatrix} -(T-t) \\ -\frac{1-e^{-\lambda(T-t)}}{\lambda} \\ (T-t)e^{-\lambda(T-t)} - \frac{1-e^{-\lambda(T-t)}}{\lambda} \end{pmatrix},$$

which is identical to the claim in Proposition 1. **QED**

Appendix B: The AFNS yield-adjustment term

In the AFNS models the yield-adjustment term is in general given by

$$\begin{aligned} \frac{C(t, T)}{T-t} &= \frac{1}{2} \frac{1}{T-t} \int_t^T \sum_{j=1}^3 (\Sigma' B(s, T) B(s, T)' \Sigma)_{j,j} ds \\ &= \frac{1}{2} \frac{1}{T-t} \int_t^T \sum_{j=1}^3 \left[\begin{pmatrix} \sigma_{11} & \sigma_{21} & \sigma_{31} \\ \sigma_{12} & \sigma_{22} & \sigma_{32} \\ \sigma_{13} & \sigma_{23} & \sigma_{33} \end{pmatrix} \begin{pmatrix} B^1(t, T) \\ B^2(t, T) \\ B^3(t, T) \end{pmatrix} \begin{pmatrix} B^1(t, T) & B^2(t, T) & B^3(t, T) \end{pmatrix} \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix} \right]_{j,j} ds \\ &= \frac{\bar{A}}{2} \frac{1}{T-t} \int_t^T B^1(s, T)^2 ds + \frac{\bar{B}}{2} \frac{1}{T-t} \int_t^T B^2(s, T)^2 ds + \frac{\bar{C}}{2} \frac{1}{T-t} \int_t^T B^3(s, T)^2 ds \\ &\quad + \frac{\bar{D}}{T-t} \int_t^T B^1(s, T) B^2(s, T) ds + \frac{\bar{E}}{T-t} \int_t^T B^1(s, T) B^3(s, T) ds + \frac{\bar{F}}{T-t} \int_t^T B^2(s, T) B^3(s, T) ds, \end{aligned}$$

where

- $\bar{A} = \sigma_{11}^2 + \sigma_{12}^2 + \sigma_{13}^2,$
- $\bar{B} = \sigma_{21}^2 + \sigma_{22}^2 + \sigma_{23}^2,$
- $\bar{C} = \sigma_{31}^2 + \sigma_{32}^2 + \sigma_{33}^2,$
- $\bar{D} = \sigma_{11}\sigma_{21} + \sigma_{12}\sigma_{22} + \sigma_{13}\sigma_{23},$
- $\bar{E} = \sigma_{11}\sigma_{31} + \sigma_{12}\sigma_{32} + \sigma_{13}\sigma_{33},$
- $\bar{F} = \sigma_{21}\sigma_{31} + \sigma_{22}\sigma_{32} + \sigma_{23}\sigma_{33}.$

To derive the analytical formula for $\frac{C(t, T)}{T-t}$, six integrals need to be solved:

$$I_1 = \frac{\bar{A}}{2} \frac{1}{T-t} \int_t^T B^1(s, T)^2 ds = \frac{\bar{A}}{2} \frac{1}{T-t} \int_t^T (T-s)^2 ds = \frac{\bar{A}}{6} (T-t)^2.$$

$$I_2 = \frac{\bar{B}}{2} \frac{1}{T-t} \int_t^T B^2(s, T)^2 ds = \frac{\bar{B}}{2} \frac{1}{T-t} \int_t^T \left[-\frac{1-e^{-\lambda(T-s)}}{\lambda} \right]^2 ds = \bar{B} \left[\frac{1}{2\lambda^2} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{1}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right].$$

$$\begin{aligned}
I_3 &= \frac{\overline{C}}{2} \frac{1}{T-t} \int_t^T B^3(s, T) ds = \frac{\overline{C}}{2} \frac{1}{T-t} \int_t^T \left\{ (T-s)e^{-\lambda(T-s)} - \frac{1-e^{-\lambda(T-s)}}{\lambda} \right\}^2 ds \\
&= \overline{C} \left[\frac{1}{2\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{4\lambda} (T-t) e^{-2\lambda(T-t)} - \frac{3}{4\lambda^2} e^{-2\lambda(T-t)} - \frac{2}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{5}{8\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right].
\end{aligned}$$

$$I_4 = \frac{\overline{D}}{T-t} \int_t^T B^1(s, T) B^2(s, T) ds = \frac{\overline{D}}{T-t} \int_t^T [-(T-s)] \left[-\frac{1-e^{-\lambda(T-s)}}{\lambda} \right] ds = \overline{D} \left[\frac{1}{2\lambda} (T-t) + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} \right].$$

$$\begin{aligned}
I_5 &= \frac{\overline{E}}{T-t} \int_t^T B^1(s, T) B^3(s, T) ds = \frac{\overline{E}}{T-t} \int_t^T [-(T-s)] \left[(T-s)e^{-\lambda(T-s)} - \frac{1-e^{-\lambda(T-s)}}{\lambda} \right] ds \\
&= \overline{E} \left[\frac{3}{\lambda^2} e^{-\lambda(T-t)} + \frac{1}{2\lambda} (T-t) + \frac{1}{\lambda} (T-t) e^{-\lambda(T-t)} - \frac{3}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} \right].
\end{aligned}$$

$$\begin{aligned}
I_6 &= \frac{\overline{F}}{T-t} \int_t^T B^2(s, T) B^3(s, T) ds = \frac{\overline{F}}{T-t} \int_t^T \left[-\frac{1-e^{-\lambda(T-s)}}{\lambda} \right] \left[(T-s)e^{-\lambda(T-s)} - \frac{1-e^{-\lambda(T-s)}}{\lambda} \right] ds \\
&= \overline{F} \left[\frac{1}{\lambda^2} + \frac{1}{\lambda^2} e^{-\lambda(T-t)} - \frac{1}{2\lambda^2} e^{-2\lambda(T-t)} - \frac{3}{\lambda^3} \frac{1-e^{-\lambda(T-t)}}{T-t} + \frac{3}{4\lambda^3} \frac{1-e^{-2\lambda(T-t)}}{T-t} \right].
\end{aligned}$$

Combining the six integrals, the analytical formula reported in subsection 2.3 is obtained.

Appendix C: Parameter restrictions imposed in AFNS

Before we can turn to the derivation of the restrictions that need to be imposed on the canonical representation of the $A_0(3)$ class of affine models to arrive at the models equivalent to the AFNS model, we need to introduce the concept of so-called *affine invariant transformations*.

Consider an arbitrary affine diffusion process represented by

$$dY_t = K_Y^Q [\theta_Y^Q - Y_t] dt + \Sigma_Y dW_t^Q.$$

Now consider the affine transformation $\mathcal{T}_Y : AY_t + \eta$, where A is a nonsingular square matrix of the same dimension as Y_t while η is a vector of constants of the same dimension as Y_t . Denote the transformed process by $X_t = AY_t + \eta$. By Ito's lemma it follows that

$$\begin{aligned}
dX_t &= AdY_t = [AK_Y^Q \theta_Y^Q - AK_Y^Q Y_t] dt + A\Sigma_Y dW_t^Q = AK_Y^Q A^{-1} [A\theta_Y^Q - AY_t - \eta + \eta] dt + A\Sigma_Y dW_t^Q \\
&= AK_Y^Q A^{-1} [A\theta_Y^Q + \eta - X_t] dt + A\Sigma_Y dW_t^Q = K_X^Q [\theta_X^Q - X_t] dt + \Sigma_X dW_t^Q.
\end{aligned}$$

Thus, X_t is itself an affine diffusion process with the following parameter specification:

$$K_X^Q = AK_Y^Q A^{-1}, \quad \theta_X^Q = A\theta_Y^Q + \eta, \quad \text{and} \quad \Sigma_X = A\Sigma_Y.$$

A similar result holds for the dynamics under the P -measure.

In terms of the short rate process there exists the following relationship:

$$\begin{aligned} r_t &= \delta_0^Y + (\delta_1^Y)' Y_t = \delta_0^Y + (\delta_1^Y)' A^{-1} A Y_t = \delta_0^Y + (\delta_1^Y)' A^{-1} [A Y_t + \eta - \eta] \\ &= \delta_0^Y - (\delta_1^Y)' A^{-1} \eta + (\delta_1^Y)' A^{-1} X_t. \end{aligned}$$

Thus, defining $\delta_0^X = \delta_0^Y - (\delta_1^Y)' A^{-1} \eta$ and $\delta_1^X = (\delta_1^Y)' A^{-1}$, the short rate process is left unchanged and may be represented in either way

$$r_t = \delta_0^Y + (\delta_1^Y)' Y_t = \delta_0^X + (\delta_1^X)' X_t.$$

Because both Y_t and X_t are affine latent factor processes that deliver the same distribution for the short rate process r_t , they are equivalent representations of the same fundamental model.

The upshot is that the canonical representation detailed in Singleton (2006) is just one way of representing this model. There are an infinite number of representations of the same model that all share the property that the risk-free short rate process and, by consequence, all bond yields will have the same distribution independent of the choice of representation. Hence \mathcal{T}_X is called an affine invariant transformation.

We now turn to the derivation of the connection between the AFNS models and the canonical representation of the $A_0(3)$ class of affine term structure models. In the canonical representation of the subset of $A_0(3)$ affine term structure models considered here, the dynamics under the Q -measure are given by

$$\begin{pmatrix} dY_t^1 \\ dY_t^2 \\ dY_t^3 \end{pmatrix} = - \begin{pmatrix} \kappa_{11}^{Y,Q} & \kappa_{12}^{Y,Q} & \kappa_{13}^{Y,Q} \\ 0 & \kappa_{22}^{Y,Q} & \kappa_{23}^{Y,Q} \\ 0 & 0 & \kappa_{33}^{Y,Q} \end{pmatrix} \begin{pmatrix} Y_t^1 \\ Y_t^2 \\ Y_t^3 \end{pmatrix} dt + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} dW_t^{1,Q} \\ dW_t^{2,Q} \\ dW_t^{3,Q} \end{pmatrix},$$

and the P -dynamics are given by

$$\begin{pmatrix} dY_t^1 \\ dY_t^2 \\ dY_t^3 \end{pmatrix} = \begin{pmatrix} \kappa_{11}^{Y,P} & \kappa_{12}^{Y,P} & \kappa_{13}^{Y,P} \\ \kappa_{21}^{Y,P} & \kappa_{22}^{Y,P} & \kappa_{23}^{Y,P} \\ \kappa_{31}^{Y,P} & \kappa_{32}^{Y,P} & \kappa_{33}^{Y,P} \end{pmatrix} \left[\begin{pmatrix} \theta_1^{Y,P} \\ \theta_2^{Y,P} \\ \theta_3^{Y,P} \end{pmatrix} - \begin{pmatrix} Y_t^1 \\ Y_t^2 \\ Y_t^3 \end{pmatrix} \right] dt + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} dW_t^{1,P} \\ dW_t^{2,P} \\ dW_t^{3,P} \end{pmatrix}.$$

Finally, the instantaneous risk-free rate is given by

$$r_t = \delta_0^Y + \delta_{1,1}^Y Y_t^1 + \delta_{1,2}^Y Y_t^2 + \delta_{1,3}^Y Y_t^3.$$

There are 22 parameters in this maximally flexible canonical representation of the $A_3(0)$ class of models. We seek to find the parameter restrictions that need to be imposed on the canonical representation of this maximally flexible $A_0(3)$ model to arrive at a model equivalent to the affine AFNS models considered in this paper. We first consider the independent-factor case, and then we examine correlated factors.

(1) The AFNS model with independent factors

The independent-factor AFNS model has P -dynamics given by

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = \begin{pmatrix} \kappa_{11}^{X,P} & 0 & 0 \\ 0 & \kappa_{22}^{X,P} & 0 \\ 0 & 0 & \kappa_{33}^{X,P} \end{pmatrix} \left[\begin{pmatrix} \theta_1^{X,P} \\ \theta_2^{X,P} \\ \theta_3^{X,P} \end{pmatrix} - \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} \right] dt + \begin{pmatrix} \sigma_{11}^X & 0 & 0 \\ 0 & \sigma_{22}^X & 0 \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \begin{pmatrix} dW_t^{1,P} \\ dW_t^{2,P} \\ dW_t^{3,P} \end{pmatrix},$$

and the Q -dynamics are given by Proposition 1 as

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = - \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & -\lambda \\ 0 & 0 & \lambda \end{pmatrix} \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} dt + \begin{pmatrix} \sigma_{11}^X & 0 & 0 \\ 0 & \sigma_{22}^X & 0 \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \begin{pmatrix} dW_t^{1,Q} \\ dW_t^{2,Q} \\ dW_t^{3,Q} \end{pmatrix}.$$

Finally, the short rate process is $r_t = X_t^1 + X_t^2$. This model has a total of 10 parameters. Thus, the task is to determine the 12 parameter restrictions that need to be imposed on the canonical $A_0(3)$ model to arrive at this model.

It is easy to verify that the affine invariant transformation $\mathcal{T}_A(Y_t) = AY_t + \eta$ with

$$A = \begin{pmatrix} \sigma_{11}^X & 0 & 0 \\ 0 & \sigma_{22}^X & 0 \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \quad \eta = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

will convert the canonical representation into the independent-factor AFNS model. For the mean-reversion matrices, the relationship between the two representations is

$$\begin{aligned} K_X^P &= AK_Y^P A^{-1} & \iff & K_Y^P = A^{-1} K_X^P A \\ K_X^Q &= AK_Y^Q A^{-1} & \iff & K_Y^Q = A^{-1} K_X^Q A. \end{aligned}$$

The equivalent mean-reversion matrix under the Q -measure is then given by

$$K_Y^Q = \begin{pmatrix} \frac{1}{\sigma_{11}^X} & 0 & 0 \\ 0 & \frac{1}{\sigma_{22}^X} & 0 \\ 0 & 0 & \frac{1}{\sigma_{33}^X} \end{pmatrix} \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & -\lambda \\ 0 & 0 & \lambda \end{pmatrix} \begin{pmatrix} \sigma_{11}^X & 0 & 0 \\ 0 & \sigma_{22}^X & 0 \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & -\lambda \frac{\sigma_{33}^X}{\sigma_{22}^X} \\ 0 & 0 & \lambda \end{pmatrix}.$$

Thus, four restrictions need to be imposed on the upper triangular mean-reversion matrix K_Y^Q :

$$K_{11}^{Y,Q} = 0, \quad K_{12}^{Y,Q} = 0, \quad K_{13}^{Y,Q} = 0 \quad \text{and} \quad K_{33}^{Y,Q} = K_{22}^Y.$$

Furthermore, notice that $K_{23}^{Y,Q}$ will always have the opposite sign of $K_{22}^{Y,Q}$ and $K_{33}^{Y,Q}$, but its absolute size can vary independently of these two parameters. Since K_X^P , A , and A^{-1} are all diagonal matrices, K_Y^P is a diagonal matrix, too. This gives another six restrictions.

Finally, we can study the factor loadings in the affine function for the short rate process. In

all AFNS models, $r_t = X_t^1 + X_t^2$, which is equivalent to fixing

$$\delta_0^X = 0, \quad \delta_1^X = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}.$$

From the relation $(\delta_1^X)' = (\delta_1^Y)'A^{-1}$ it follows that

$$(\delta_1^Y)' = (\delta_1^X)'A = \begin{pmatrix} 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \sigma_{11}^X & 0 & 0 \\ 0 & \sigma_{22}^X & 0 \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} = \begin{pmatrix} \sigma_{11}^X & \sigma_{22}^X & 0 \end{pmatrix}.$$

For the constant term it holds that

$$\delta_0^X = \delta_0^Y - (\delta_1^Y)'A^{-1}\eta \iff \delta_0^Y = \delta_0^X = 0.$$

Thus, we have obtained two additional parameter restrictions

$$\delta_0^Y = 0 \quad \text{and} \quad \delta_{1,3}^Y = 0.$$

(2) The AFNS model with correlated factors

In the correlated-factor AFNS model, the P -dynamics are given by

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = \begin{pmatrix} \kappa_{11}^{X,P} & \kappa_{12}^{X,P} & \kappa_{13}^{X,P} \\ \kappa_{21}^{X,P} & \kappa_{22}^{X,P} & \kappa_{23}^{X,P} \\ \kappa_{31}^{X,P} & \kappa_{32}^{X,P} & \kappa_{33}^{X,P} \end{pmatrix} \left[\begin{pmatrix} \theta_1^{X,P} \\ \theta_2^{X,P} \\ \theta_3^{X,P} \end{pmatrix} - \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} \right] dt + \begin{pmatrix} \sigma_{11}^X & \sigma_{12}^X & \sigma_{13}^X \\ 0 & \sigma_{22}^X & \sigma_{23}^X \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \begin{pmatrix} dW_t^{1,P} \\ dW_t^{2,P} \\ dW_t^{3,P} \end{pmatrix},$$

and the Q -dynamics are given by Proposition 1 as

$$\begin{pmatrix} dX_t^1 \\ dX_t^2 \\ dX_t^3 \end{pmatrix} = - \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & -\lambda \\ 0 & 0 & \lambda \end{pmatrix} \begin{pmatrix} X_t^1 \\ X_t^2 \\ X_t^3 \end{pmatrix} dt + \begin{pmatrix} \sigma_{11}^X & \sigma_{12}^X & \sigma_{13}^X \\ 0 & \sigma_{22}^X & \sigma_{23}^X \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \begin{pmatrix} dW_t^{1,Q} \\ dW_t^{2,Q} \\ dW_t^{3,Q} \end{pmatrix}.$$

This model has a total of 19 parameters. Thus, there are three parameter restrictions to be determined as compared to the maximally flexible canonical representation of the $A_0(3)$ class.

It is easy to verify that the affine invariant transformation $\mathcal{T}_A(Y_t) = AY_t + \eta$ with

$$A = \begin{pmatrix} \sigma_{11}^X & \sigma_{12}^X & \sigma_{13}^X \\ 0 & \sigma_{22}^X & \sigma_{23}^X \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \quad \text{and} \quad \eta = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

will convert the canonical representation into the correlated-factor AFNS model. For the mean-

reversion matrices the relationship between the two representations is

$$\begin{aligned} K_X^P &= AK_Y^P A^{-1} \iff K_Y^P = A^{-1} K_X^P A \\ K_X^Q &= AK_Y^Q A^{-1} \iff K_Y^Q = A^{-1} K_X^Q A. \end{aligned}$$

The equivalent mean-reversion matrix under the Q -measure is then given by

$$\begin{aligned} K_Y^Q &= \begin{pmatrix} \frac{1}{\sigma_{11}^X} & -\frac{\sigma_{12}^X}{\sigma_{11}^X \sigma_{22}^X} & -\left(\frac{\sigma_{13}^X}{\sigma_{11}^X \sigma_{33}^X} - \frac{\sigma_{12}^X \sigma_{23}^X}{\sigma_{11}^X \sigma_{22}^X \sigma_{33}^X}\right) \\ 0 & \frac{1}{\sigma_{22}^X} & -\frac{\sigma_{23}^X}{\sigma_{22}^X \sigma_{33}^X} \\ 0 & 0 & \frac{1}{\sigma_{33}^X} \end{pmatrix} \begin{pmatrix} 0 & 0 & 0 \\ 0 & \lambda & -\lambda \\ 0 & 0 & \lambda \end{pmatrix} \begin{pmatrix} \sigma_{11}^X & \sigma_{12}^X & \sigma_{13}^X \\ 0 & \sigma_{22}^X & \sigma_{23}^X \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} \\ &= \begin{pmatrix} 0 & -\lambda \frac{\sigma_{12}^X}{\sigma_{11}^X} & \lambda \frac{\sigma_{12}^X \sigma_{33}^X - \sigma_{22}^X \sigma_{13}^X}{\sigma_{11}^X \sigma_{22}^X} \\ 0 & \lambda & -\lambda \frac{\sigma_{23}^X}{\sigma_{22}^X} \\ 0 & 0 & \lambda \end{pmatrix}. \end{aligned}$$

Thus, two restrictions need to be imposed on the upper triangular mean-reversion matrix K_Y^Q :

$$K_{11}^{Y,Q} = 0, \quad K_{33}^{Y,Q} = K_{22}^{Y,Q}.$$

Furthermore, notice that $K_{23}^{Y,Q}$ will always have the opposite sign of $K_{22}^{Y,Q}$ and $K_{33}^{Y,Q}$, but its absolute size can vary independently of the two other parameters.

Next we study the factor loadings in the affine function for the short rate process. In the AFNS models, $r_t = X_t^1 + X_t^2$, which is equivalent to fixing

$$\delta_0^X = 0, \quad \delta_1^X = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}.$$

From the relation $(\delta_1^X)' = (\delta_1^Y)' A^{-1}$, it follows that

$$(\delta_1^Y)' = (\delta_1^X)' A = \begin{pmatrix} 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \sigma_{11}^X & \sigma_{12}^X & \sigma_{13}^X \\ 0 & \sigma_{22}^X & \sigma_{23}^X \\ 0 & 0 & \sigma_{33}^X \end{pmatrix} = \begin{pmatrix} \sigma_{11}^X & \sigma_{21}^X + \sigma_{22}^X & \sigma_{13}^X + \sigma_{23}^X \end{pmatrix}.$$

This shows that there are no restrictions on δ_1^Y . For the constant term, we have

$$\delta_0^X = \delta_0^Y - (\delta_1^Y)' A^{-1} \eta \iff \delta_0^Y = \delta_0^X = 0.$$

Thus, we have obtained one additional parameter restriction,

$$\delta_0^Y = 0.$$

Finally, for the mean-reversion matrix under the P -measure, we have

$$K_X^P = AK_Y^P A^{-1} \iff K_Y^P = A^{-1}K_X^P A.$$

Since K_X^P is a free 3×3 matrix, K_Y^P is also a free 3×3 matrix. Thus, no restrictions are imposed on the P -dynamics in the equivalent canonical representation of this model.

References

- Ahn, Dong-Hyun, Robert F. Dittmar, and A. Ronald Gallant, 2002, "Quadratic Term Structure Models: Theory and Evidence," *Review of Financial Studies*, Vol. 15, No. 1, 243-288.
- Ang, Andrew and Monika Piazzesi, 2003, "A No-Arbitrage Vector Autoregression of Term Structure Dynamics with Macroeconomic and Latent Variables," *Journal of Monetary Economics*, Vol. 50, 745-787.
- Ang, Andrew, Monika Piazzesi, and Min Wei, 2006, "What Does the Yield Curve Tell Us About GDP Growth?," *Journal of Econometrics*, Vol. 131, 359-403.
- Bank for International Settlements, 2005, "Zero-Coupon Yield Curves: Technical Documentation," BIS papers, No. 25.
- Chua, Choong Tze, Dean Foster, Krishna Ramaswamy, and Robert Stine, 2008, "A Dynamic Model for the Forward Curve," *Review of Financial Studies*, Vol. 21, No. 1, 265-310.
- Christensen, Jens H., Francis X. Diebold, Glenn Rudebusch, and Georg Strasser, 2007, "Multivariate Comparisons of Predictive Accuracy," manuscript, University of Pennsylvania.
- Christensen, Jens H., Jose A. Lopez, and Glenn D. Rudebusch, 2008, "Inflation Expectations and Risk Premiums in an Arbitrage-Free Model of Nominal and Real Bond Yields," Unpublished manuscript, Federal Reserve Bank of San Francisco.
- Cox, John C., Jonathan E. Ingersoll, and Stephen A. Ross, 1985, "A Theory of the Term Structure of Interest Rates," *Econometrica*, Vol. 53, No. 2, 385-407.
- Dai, Qiang and Kenneth J. Singleton, 2000, "Specification Analysis of Affine Term Structure Models," *Journal of Finance*, Vol. 55, 1943-1978.
- Dai, Qiang and Kenneth J. Singleton, 2002, "Expectations Puzzles, Time-Varying Risk Premia, and Affine Models of the Term Structure," *Journal of Financial Economics*, Vol. 63, No. 3, 415-441.
- De Pooter, Michiel, Francesco Ravazzolo, and Dick van Dijk, 2007, "Predicting the Term Structure of Interest Rates: Incorporating Parameter Uncertainty and Macroeconomic Information," Tinbergen Institute Discussion Papers.
- Diebold, Francis X. and Canlin Li, 2006, "Forecasting the Term Structure of Government Bond Yields," *Journal of Econometrics*, Vol. 130, 337-364.
- Diebold, Francis X. and Roberto S. Mariano, 1995, "Comparing Predictive Accuracy," *Journal of Business and Economic Statistics*, Vol. 13, 253-265.
- Diebold, Francis X., Monika Piazzesi, and Glenn D. Rudebusch, 2005, "Modeling Bond Yields in Finance and Macroeconomics," *American Economic Review*, Vol. 95, 415-420.

- Diebold, Francis X., Glenn D. Rudebusch and S. Boragan Aruoba, 2006, "The Macroeconomy and the Yield Curve: a Dynamic Latent Factor Approach," *Journal of Econometrics*, Vol. 131, 309-338.
- Duffee, Gregory R., 1996, "Idiosyncratic Variation of Treasury Bill Yields," *Journal of Finance*, Vol. 51, 527-552.
- Duffee, Gregory R., 2002, "Term Premia and Interest Rate Forecasts in Affine Models," *Journal of Finance*, Vol. 57, 405-443.
- Duffie, Darrell and Rui Kan, 1996, "A Yield-factor Model of Interest Rates," *Mathematical Finance*, Vol. 6, 379-406.
- Duffie, Darrell, Jun Pan, and Kenneth J. Singleton, 2000, "Transform Analysis and Asset Pricing for Affine Jump-Diffusions," *Econometrica*, Vol. 68, 1343-1376.
- Fama, Eugene F. and Robert R. Bliss, 1987, "The Information in Long-Maturity Forward Rates," *American Economic Review*, Vol. 77, 680-692.
- Filipović, Damir, 1999, "A Note on the Nelson-Siegel Family," *Mathematical Finance*, Vol. 9, 349-359.
- Gürkaynak, Refet S., Brian Sack, and Jonathan H. Wright, 2007, "The U.S. Treasury Yield Curve: 1961 to the Present," *Journal of Monetary Economics*, Vol. 54, 2291-2304.
- Hördahl, Peter, Oreste Tristani, and David Vestin, 2005, "A Joint Econometric Model of Macroeconomic and Term-Structure Dynamics," *Journal of Econometrics*, Vol. 131, 406-436.
- Kim, Don H. and Athanasios Orphanides, 2005, "Term Structure Estimation with Survey Data on Interest Rate Forecasts," *Finance and Economics Discussion Series*, No. 48, Board of Governors of the Federal Reserve System.
- Krippner, Leo, 2006, "A Theoretically Consistent Version of the Nelson and Siegel Class of Yield Curve Models," *Applied Mathematical Finance*, Vol. 13, No. 1 (March), 39-59.
- Mönch, Emanuel, 2006, "Forecasting the Yield Curve in a Data-Rich Environment: A No-Arbitrage Factor-Augmented VAR Approach," manuscript, Humboldt University.
- Nelson, Charles R. and Andrew F. Siegel, 1987, "Parsimonious Modeling of Yield Curves," *Journal of Business*, Vol. 60, 473-489.
- Rudebusch, Glenn D., Eric Swanson, and Tao Wu, 2006, "The Bond Yield 'Conundrum' from a Macro-Finance Perspective," *Monetary and Economic Studies*, Vol. 24 (December), 83-128.
- Singleton, Kenneth J., 2006, *Empirical Dynamic Asset Pricing*, Princeton University Press.
- Svensson, Lars E. O., 1995, "Estimating Forward Interest Rates with the Extended Nelson-Siegel Method," *Quarterly Review*, No. 3, Sveriges Riksbank, 13-26.

Trolle, Anders B. and Eduardo S. Schwartz, 2007, "A general stochastic volatility model for the pricing of interest rate derivatives," forthcoming *Review of Financial Studies*.

Vasiček, Oldrich, 1977, "An Equilibrium Characterization of the Term Structure," *Journal of Financial Economics*, Vol. 5, 177-188.

Williams, David, 1997, *Probability with Martingales*, Cambridge University Press.