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CHALLENGES IN MACRO-FINANCE MODELING

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ABSTRACT. This paper discusses various challenges in the specification and implementation of “macro-finance” models in which macroeconomic variables and term structure variables are modeled together in a no-arbitrage framework. I classify macro-finance models into pure latent-factor models (“internal basis models”) and models which have observed macroeconomic variables as state variables (“external basis models”), and examine the underlying assumptions behind these models. Particular attention is paid to the issue of unspanned short-run fluctuations in macro variables and their potentially adverse effect on the specification of external basis models. I also discuss the challenge of addressing features like structural breaks and time-varying inflation uncertainty. Empirical difficulties in the estimation and evaluation of macro-finance models are also discussed in detail.

1. INTRODUCTION

In recent years there has been much interest in developing “macro-finance models”, in which yields on nominal bonds are jointly modeled with one or more macroeconomic variables within a no-arbitrage framework. The need to go beyond “nominal yields only” no-arbitrage models (i.e., to include a description of the macroeconomy or other asset prices) has been felt for a long time by academic researchers and policy makers alike. Campbell, Lo, MacKinlay (1996), for example, have emphasized that, “as the term structure literature moves forward, it will be important to integrate it with the rest of the asset pricing literature.” Policy makers have often used traditional theories such as the expectations hypothesis and the Fisher hypothesis to extract an approximate measure of market expectations of interest rates and macroeconomic variables like inflation, but they are also aware that risk premiums and other factors might complicate the interpretation of the information in the yield curve,¹ and would welcome any progress in term structure modeling that would facilitate greater understanding of the messages in the yield curve.

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¹See, for example, Bernanke (2004a).

Despite a lot of exciting work in macro-finance modeling of late,² as a central bank economist who monitors markets regularly, I have found it difficult to bring current generation of models to bear on the practical analysis of bond market developments or to implement the models in real time to obtain a reliable measure of the market's expectation of key variables like inflation.³ In the academic literature there is not much evidence in this regard (either for or against macro-finance models). One exception is the recent paper of Ang, Bekaert, and Wei (2007a, henceforth ABW), which performed an extensive investigation of the out-of-sample inflation forecasting performance of various models and survey forecasts and found that the no-arbitrage models that they have used perform *worse* than not only survey forecasts but also other types of models.⁴

It thus seems useful at this juncture to review and discuss various challenges in the specification and implementation macro-finance models that might help shed light on the lack of documented practicality of macro-finance models in general and on the findings of ABW (2007a) in particular. To this end, in this paper I propose to take a closer look at what role the no-arbitrage principle is playing in macro-finance models and reconsider the assumptions that are often made in this literature. No-arbitrage itself is clearly a reasonable assumption, but the models also make *additional* assumptions whose validity may not have been discussed thoroughly in the existing literature. I also discuss "more advanced" issues (such as structural breaks and time-varying volatility) that require going beyond the standard affine-Gaussian framework of most macro-finance models and the challenges encountered in this regard. A big part of the challenge in macro-finance modeling is *empirical*, hence I shall also discuss at length the difficulties in the implementation stage (estimation and evaluation of models). Although the main focus of this paper is on the extraction of information from the yield curve (particularly inflation expectations), much of the discussion may be relevant for macro-finance models that were developed to address other issues, as they share some of the key assumptions discussed in this paper.

The state variables in the reduced-form no-arbitrage model framework (on which most macro-finance models are based) can be heuristically viewed as forming a *basis* onto which to project information in yields and other data. In this paper, I make a distinction between models that use (what I shall call) an "internal basis" versus models that use an "external basis". By an internal basis, I refer to a basis that is determined inside the

²Examples include Ang and Piazzesi (2003), Hoerdahl, Tristani, and Vestin (2006), Rudebusch and Wu (2003), and Ang, Bekaert, and Wei (2007a,b).

³I emphasize that I speak as one of many central bank economists and that my views in this paper do not necessarily represent the general consensus among economists at central banks.

⁴For example, the root-mean-square errors (RMSEs) for one-year CPI-inflation forecasts based on the two no-arbitrage models in ABW (2007a) (what they refer to as MDL1, MDL2) are larger than those of AR(1) and ARMA(1,1) models by more than 30 % for the post-1995 window. Furthermore, out of ABW (2007a)'s 11 regression models that involve term structure variables (what they refer to as TS1-TS11), all but one produce smaller RMSEs in forecasting the one-year CPI (PUNEW) inflation than the no-arbitrage models in the post-1995 sample.

estimation, hence unknown before the estimation. Latent factor models that describe inflation expectations and term structure jointly, such as Sangvinatsos and Wachter (2005) and D’Amico, Kim, and Wei (2007), are examples of internal basis models. By an external basis, I mean a basis that is *a priori* fixed completely or partially, as when a specific macroeconomic variable (such as inflation) is taken as a state variable. Note that no-arbitrage guarantees the existence of *some* pricing kernel, but it does not mean that the pricing kernel can be represented well by *a priori* selected variables. In this paper, I shall argue that external basis models involve strong assumptions, and discuss potential problems that they may give rise to in practice. All is not well with internal basis models either: the weaker assumptions of these models may come at the cost of the ability to give specific, intuitive interpretation of the yield curve movements. Most importantly, internal basis models face many empirical difficulties that are similar to those in the estimation of external basis models, in particular the overfitting and small-sample problems.

The remainder of this paper is organized as follows. Section 2 reviews the standard affine-Gaussian setup of macro-finance models, derives the affine bond pricing formula in a way that emphasizes the replicating portfolio intuition, and introduces a distinction between internal basis models and external basis models. Section 3 provides a critical examination of the assumptions in external basis models, both in the case of the “low-dimensional” and “high-dimensional” external basis models. Section 4 discusses the challenge of accommodating nonlinear/non-Gaussian effects such as structural breaks and time-varying uncertainties. Potential problems with empirical techniques commonly used in the estimation and evaluation of macro-finance models are discussed in Section 5. Section 6 comes back to ask *why* surveys perform better than models in inflation forecasting (as documented by ABW (2007a)), and Section 7 concludes.

2. BASIC MODEL

2.1. Affine-Gaussian framework. Most macro-finance models in the literature are based on the “affine-Gaussian” model, given by

$$(1) \quad \begin{aligned} m_{t+1} &\equiv \log M_t = -r(x_t) - \lambda(x_t)' \epsilon_{t+1} - \frac{1}{2} \lambda_t' \lambda_t \\ x_{t+1} &= \Phi x_t + (I - \Phi) \mu + \Sigma \epsilon_{t+1}, \\ r_t &= \rho_o + \rho' x_t \\ \lambda_t &= \lambda_a + \Lambda_b x_t \end{aligned}$$

where M_t is the pricing kernel, x_t is an n -dimensional vector of state variables, r_t is the nominal short rate (i.e., one-period yield), and λ_t is the market price of risk of the n -dimensional shocks ϵ_{t+1} . (Φ , Σ , and Λ_b are $n \times n$ constant matrices, ρ and λ_a are constant n -dimensional vectors, and ρ_o is a constant.) A well-known result in finance theory says

that no-arbitrage implies the existence of a pricing kernel (stochastic discount factor) of the form (1).⁵

There is freedom in choosing the specific functional form of r_t and λ_t and the dynamics of x_t . Having affine forms for r_t and λ_t and the Gaussian specification (VAR(1) specification) of x_t constitutes the affine-Gaussian model. This form has certain limitations (discussed in Section 4), but it is still quite general and capable of encompassing many of the known models in finance and macroeconomics.

Using the recursion relation for the price of a τ -period zero-coupon bond at time t

$$(2) \quad P_{\tau,t} = E_t(P_{\tau-1,t+1}M_{t+1}),$$

it is straightforward to show that bond prices in this model are given by

$$(3) \quad P_{\tau,t} = \exp(A_\tau + B'_\tau x_t)$$

where A_τ and B_τ are the solution of the difference equations

$$(4) \quad \begin{aligned} 0 &= \rho_o + A_\tau - A_{\tau-1} - \frac{1}{2}B'_{\tau-1}\Sigma\Sigma'B_{\tau-1} - B'_{\tau-1}((I - \Phi)\mu - \Sigma\lambda_a) \\ 0_{n \times 1} &= \rho + B_\tau - (\Phi - \Sigma\Lambda_b)'B_{\tau-1} \end{aligned}$$

with boundary condition $A_{\tau=0} = 0, B_{\tau=0} = 0_{n \times 1}$; see, for example, Ang and Piazzesi (2003). Hence the framework (1) leads to a tractable affine formula for bond yields $y_{t,\tau}$ ($= -\log(P_{\tau,t})/\tau$).

The original ‘‘finance term structure models’’ such as Dai and Singleton (2000) and Duffie (2002) were written for nominal bond yields only. For example, the model (1) could be estimated with just nominal yields data, with suitable (normalization) restrictions on the parameters Φ, μ, ρ, \dots to insure that the model be econometrically identified. The state variables in this case are ‘‘latent factors’’ without an explicit economic meaning.

In a seminal paper, Ang and Piazzesi (2003, henceforth AP) proposed to combine this setup with a description of macroeconomy. Their basic insight is that the well-known Taylor-rule specification of the short rate also has an affine form:

$$(5) \quad r_t = \rho_\pi \pi_t^Y + \rho_g \text{gap}_t + \text{const},$$

where π_t^Y is the annual inflation and gap_t is the GDP gap (log GDP minus log potential GDP).⁶ Therefore, taking variables like inflation and GDP gap to be part of the state vector in eq. (1), i.e.,

$$(6) \quad x_t = [\pi_t^Y, \text{gap}_t, \dots]'$$

one can have a system in which bond yields are linked to key macro variables. Some macroeconomic variables might not be well described by a simple VAR(1) dynamics, but this is in principle not a problem, as a higher-order VAR process (VAR(q) model)

⁵Duffie (2001) discusses this in the continuous-time formalism; see also Cochrane (2001).

⁶To be precise, AP (2003) use the GDP growth, instead of GDP gap in their formulation.

can be written as a VAR(1) process with an expanded state vector that includes lags of these variables (e.g., $[\pi_t^Y, \pi_{t-1}^Y, \dots, gap_t, gap_{t-1}, \dots]'$).

Various macro-finance models differ by the choice of the restrictions imposed on the matrices like Φ, ρ, \dots , etc. For example, AP (2003) adopt an atheoretical (statistical) approach, reminiscent of Sims (1980)'s original VAR proposal, while Hoerdahl, Tristani and Vestin (2006), henceforth HTV) imposed more structure based on a New-Keyesian model as in Clarida, Gali, Gertler (2000) though still remaining in the reduced-form framework.

These are an innovation from the earlier approach of handling long-term bond yields in macroeconomic models. In fact, most macroeconomic models have not dealt with long-term bond yields at all, despite their importance for savings and investment decisions in the economy. Pre-macro-finance models like Federal Reserve's FRB/US model do contain the 5-year and 10-year nominal yields, which are specified as the expectations-hypothesis-implied yield plus a term premium (the 5-year term premium and the 10-year term premium are modeled separately),⁷ but the framework (1) allows not just a few selected long-term yields but the *entire* yield curve information to be integrated with a description of the macroeconomy.

2.2. No-arbitrage and replicating portfolios. While the derivation of the affine bond pricing equation (3) using the recursion relation involving the pricing kernel is simple and elegant, it is useful to re-derive it using the hedging (spanning) argument,⁸ in order to get a better sense of the role that the no-arbitrage principle is playing in macro-finance models.

Suppose there are n -dimensional shocks underlying the term structure movements, denoted by a standard normal random vector ϵ_t . The change in the value of a bond with maturity τ can be expressed generally as

$$(7) \quad \frac{\delta P_{\tau,t+1}}{P_{\tau,t}} = \mu_{\tau,t} + \gamma'_{\tau,t} \epsilon_{t+1},$$

where I have used the notation $\delta P_{\tau,t+1}$ for $P_{\tau-1,t+1} - P_{\tau,t}$ (the change in the value of a bond which was of time-to-maturity τ at time t) to avoid confusion with simple time-differencing $\Delta P_{\tau,t+1} = P_{\tau,t+1} - P_{\tau,t}$, $\mu_{\tau,t}$ is the one-period expected return on a bond that has time-to-maturity τ at time t (i.e., $\mu_{\tau,t} = E_t(\delta P_{\tau,t+1}/P_{\tau,t})$), and the n -dimensional vector $\gamma_{\tau,t}$ is the loading on the shocks that determine the unexpected return.

⁷See, for example, Brayton et al (1997).

⁸The derivation here can be viewed as a discrete-time analogue of Cox, Ross, Ingersoll (1981)'s continuous-time derivation.

Consider a portfolio formed by taking positions in $n + 1$ bonds with maturities $\tau_1, \tau_2, \dots, \tau_{n+1}$, with portfolio weights $w_{1t}, \dots, w_{n+1,t}$. Denoting the value of this portfolio V , the return on the portfolio is given by

$$(8) \quad \frac{\delta V}{V} = w_1 \frac{\delta P_{\tau_1}}{P_{\tau_1}} + \dots + w_{n+1} \frac{\delta P_{\tau_{n+1}}}{P_{\tau_{n+1}}} = \sum_{i=1}^{n+1} w_i \mu_{\tau_i} + \left(\sum_{i=1}^{n+1} w_i \gamma_{\tau_i} \right)' \epsilon,$$

where the time index t has been suppressed for notational simplicity. If the portfolio is locally risk-free ($\sum_{i=1}^{n+1} w_i \gamma_{\tau_i} = 0$), then by no-arbitrage it should yield a risk free rate (one-period yield), thus

$$(9) \quad \sum_{i=1}^{n+1} w_{it} \mu_{\tau_i,t} = r_t.$$

Together with $\sum_i w_{it} = 1$, this implies, in matrix form,

$$(10) \quad \begin{bmatrix} \mu_{\tau_1,t} - r_t & \cdots & \mu_{\tau_{n+1},t} - r_t \\ \gamma_{\tau_1,t} & \cdots & \gamma_{\tau_{n+1},t} \end{bmatrix} w_t = 0_{(n+1) \times 1},$$

where $w_t = [w_{1t}, \dots, w_{n+1,t}]'$. In order for this matrix equation to have a nontrivial (i.e., nonzero) solution w_t for an arbitrary choice of τ_i 's, the expected excess return $\mu_{\tau,t} - r_t$ has to be a linear combination of $\gamma_{\tau,t}$, i.e.,

$$(11) \quad \mu_{\tau,t} - r_t = \gamma'_{\tau,t} \lambda_t,$$

where the n -dimensional vector λ_t ("market price of risk") expresses the linear-dependence between $\mu_{\tau,t} - r_t$ and $\gamma_{\tau,t}$.

It is often more convenient to deal with log prices and log returns on bonds, $\delta \log P_{\tau,t+1}$ ($= \log P_{\tau-1,t+1} - \log P_{\tau,t}$). From the discrete-time version of the Ito's lemma,⁹ one has

$$(12) \quad \delta \log P_{\tau,t+1} = \tilde{\mu}_{\tau,t} + \gamma'_{\tau,t} \epsilon_{t+1},$$

where

$$(13) \quad \tilde{\mu}_{\tau,t} = E_t \left(\frac{\delta P}{P} \right) - \text{var}_t \left(\frac{\delta P}{P} \right) = \mu_{\tau,t} - \frac{1}{2} \gamma'_{\tau,t} \gamma_{\tau,t}.$$

Thus, eq. (11) can be also written

$$(14) \quad \tilde{\mu}_{\tau,t} - r_t + \frac{1}{2} \gamma'_{\tau,t} \gamma_{\tau,t} = \gamma'_{\tau,t} \lambda_t.$$

Note that the derivation thus far has been quite general. If the short rate and market price of risk are affine in the state variables and if the state variables follow a VAR(1) process (i.e, eq (1)), one obtains a particularly simple result. Positing that the bond prices take the form $\log P_{\tau,t} = A_\tau + B'_\tau x_t$, one has (from eq. (12))

$$(15) \quad \tilde{\mu}_{\tau,t} = A_{\tau-1} - A_\tau + B'_{\tau-1} (I - \Phi) \mu + (B'_{\tau-1} \Phi - B'_\tau) x_t$$

$$(16) \quad \gamma'_{\tau,t} = B'_{\tau-1} \Sigma.$$

⁹See, for example, Campbell, Chan and Viceira (2003).

Substituting these (and the expressions for r_t and λ_t) into eq. (14) gives the same difference equation for bond prices as in eq. (4), hence the same bond prices, as promised earlier.

2.3. Internal basis models versus external basis models. The key formula in the above derivation of the bond pricing equation is eq. (11), or equivalently eq. (14). It states that the expected return on a bond of arbitrary maturity in excess of the short rate depends on the product of the bond-independent market price of risk, λ_t , and the bond's sensitivity to risk, $\gamma_{\tau,t}$. The basic intuition underlying eq. (11) is that *the yield curve is "smooth", so the risks to a bond can be hedged well by a portfolio of (a relatively small number of) other bonds*. This is well known from the factor analysis of Litterman and Scheinkman (1991) and other studies. One can also see this from the regression of the quarterly change in the 5-year yield on the changes in 6-month, 2-year, and 10-year yields, which gives very high R^2 s (e.g., 99%).

Note that eq. (11) itself is silent about the structure of the λ_t vector, except for the condition that it does not depend on bond specific information (like maturity). In fact, the early generation of affine-Gaussian models assumed a constant market price of risk vector λ , which in effect implied a version of the expectations hypothesis. Later studies recognized that λ_t can depend on the state of economy, thus a variable influencing the market price of risk would also influence bond prices.¹⁰ However, this creates, in a sense, too large a set of possibilities – any variable, e.g., coffee production in Brazil, could in principle enter the expression for market price of risk and, in turn, the expression for bond yields.

Latent-factor models of the term structure, such as the affine-Gaussian model of Duffee (2002) ($EA_0(n)$ model in Duffee's terminology), partly get around this problem by implicitly defining the model in statistical terms. A "maximally flexible" n -dimensional affine-Gaussian model (1) can be viewed as an answer to the question, "what is the most general n -dimensional representation of the yield dynamics in which yields are Gaussian, linear in some basis, and consistent with no-arbitrage?"¹¹ As the yield curve seems to be well described by a small number of risk sources, it stands to reason that there exists a suitable representation for a relatively small n . Thus, the no-arbitrage principle in this setting can help describe the rich variation of the yield curve in a tractable and relatively parsimonious way, while allowing for a general pricing of risk (as opposed to the expectations hypothesis).

Duffee (2002)'s affine-Gaussian model describes only the nominal yield curve, but it is straightforward to write down a "joint model" of nominal yields and inflation in the

¹⁰Thus, a shock that changes λ_t , say ξ_t , should be also included in the vector of shocks ϵ_t that moves bond prices.

¹¹Appendix A of the present paper gives two examples (eqs. (55) and (65)) of such maximally flexible affine-Gaussian models for $n = 3$; see also Dai and Singleton (2000) for a discussion of maximally flexible affine models.

same spirit by combining eq. (1) with the following specification of the inflation process,

$$(17) \quad \begin{aligned} \pi_{t+1} &= \chi(x_t) + \tilde{\sigma}'\tilde{\epsilon}_{t+1}, \\ \chi(x_t) &= \psi_o + \psi'x_t \end{aligned}$$

where the one-period inflation π_{t+1} ($= \log(Q_{t+1}/Q_t)$, Q_t being the price level) consists of the one-period *expected* inflation $\chi(x_t)$ and unforecastable inflation $\tilde{\sigma}'\tilde{\epsilon}_{t+1}$. As in the case of the nominal short rate r_t , the one-period inflation expectation is specified as an affine function of the state vector x_t . The disturbance vector $\tilde{\epsilon}_t$ includes the vector of shocks that move interest rates (ϵ_t in eq. (1)) and a shock (say ϵ_t^\perp) that is orthogonal to the interest rate shocks.¹² As in the nominal-yields-only model, the state vector x_t is a vector of statistical variables (latent variables), which is determined only up to normalization restrictions (on parameter matrices Φ , ρ_o , ρ , ψ_o , ψ ,...) that insure the (maximal) identification of the model. I shall refer to such a model as an “internal basis model,” as the state vector x_t is unknown before the estimation and is determined *inside* the estimation with yields, inflation, and possibly other data.¹³

Such a joint model makes only fairly weak assumptions: writing the one-period inflation as the sum of expected inflation and unexpected inflation in eq. (17) is quite general, and it makes intuitive sense to have the state vector x_t describe inflation expectations and bond yields together, as a variable that moves inflation expectation would be also expected to move nominal interest rates. At the same time, this formulation relaxes the assumptions implicit in the two traditional theories of nominal yields: it goes beyond the expectations hypothesis, as it now allows for time-varying term premia, and the Fisher hypothesis, as it now implicitly allows for a general correlation between real rates and inflation.

Note that the state vector x_t in the joint model has more economic meaning than the nominal-yields-only model in the sense that it is now (implicitly) related to objects like inflation expectations and inflation risk premia. However, the fact that x_{it} 's are still latent factors is potentially an unattractive feature, and makes it difficult to discuss bond market developments in a simple manner. One would not win an “effective communication award” by telling market participants that “bond yields moved x basis points because latent factors did this and that.”

Thus, many papers in the macro-finance literature take all or part of the state vector to be specific macroeconomic variables (or variables with clear macroeconomic interpretation) so as to make the connection between the yield curve and macroeconomy more explicit. These variables form an external basis, in the sense that they are *a priori* fixed, partially (“mixed” models) or completely (observables-only models). Simply speaking,

¹²This shock (ϵ_t^\perp) is introduced to allow for shocks to inflation that are not spanned by interest rate shocks. (One can also define the ϵ_t vector in eq. (1) to include this shock.)

¹³Perhaps the best known example of internal basis models is factor analysis (e.g., Litterman and Scheinkman (1991)). As in the no-arbitrage internal basis models, the factors in factor analysis are determined only up to an invariant transformation, thus normalization restrictions are needed to define them.

internal basis models try to project information in yields $y_{\tau,t}$ and “observable” macro variables f_{it}^o onto the state vector x_t consisting of unobservable variables f_{it}^u , while external basis models try to project information in yields onto “observable” macro variables f_{it}^o and latent variables (if there are any). Schematically,

$$\begin{aligned} \text{internal basis :} & \quad \{y_{\tau,t}\}, \{f_{it}^o\} \Rightarrow x_t = [f_{1t}^u, f_{2t}^u, \dots]' \\ \text{external basis :} & \quad \{y_{\tau,t}\} \Rightarrow x_t = [f_{1t}^o, f_{2t}^o, \dots, f_{1t}^u, f_{2t}^u, \dots]' \end{aligned}$$

As one moves on to external basis models, one might be also moving away from the relative comfort of the original intuition behind no-arbitrage (the smoothness of the yield curve); hence a close scrutiny of additional assumptions that they involve is warranted.

3. EXAMINING THE ASSUMPTIONS IN THE EXTERNAL BASIS MODELS

3.1. Unspanned short-run inflation. One implication of having a macroeconomic variable like inflation as a state variable in the setup of eq. (1) is that short-run inflation risk can be hedged by taking positions in nominal bonds.¹⁴ Many practitioners, however, would be skeptical about this claim. Policy makers are well aware of large short-run variations in price indices such as PPI and CPI that do not require a policy response, and they are careful to “smooth through the noise” in interpreting data on inflation. Blinder (1997) puts this clearly and strongly: “[The noise issue] was my principal concern as Vice-Chairman of the Federal Reserve. I think it is a principal concern of central bankers everywhere.”

Market participants are also (implicitly) cognizant of these issues. One striking evidence is the bond market’s reaction to the announcement of total CPI (also called “headline CPI”, or simply “CPI”) and core CPI. Core CPI is an inflation measure obtained by stripping out the volatile food and energy prices from total CPI. As can be seen in Figure 1a, monthly inflation based on total CPI is substantially more volatile than that of core CPI, and annual (year-on-year) inflations based on core CPI and total CPI can also differ significantly (Figure 1b). In the US, core CPI and total CPI for each month are announced in the following month (by the Bureau of Labor Statistics, typically in the second or third week). Before the release of the data, business economists partake in a survey about what the released numbers are going to be, from which “consensus expectations” are computed. The released number minus this consensus number can be viewed as a measure of the surprise component of the announcement.¹⁵

The regression of the change in the 2-year yield surrounding the data release (denoted $\Delta y_{2Y,t}$) on the surprise component of core CPI or total CPI (denoted $\Delta CORE_t$ and

¹⁴Let the first element of the state vector x_t in eq. (1) be inflation. The formalism (1) then implies that one can in general form a portfolio of bonds which replicates the inflation shock ϵ_{1t} .

¹⁵This measure has been frequently used to study bond market’s reaction to data announcements. See, e.g., Fleming and Remolona (1997).

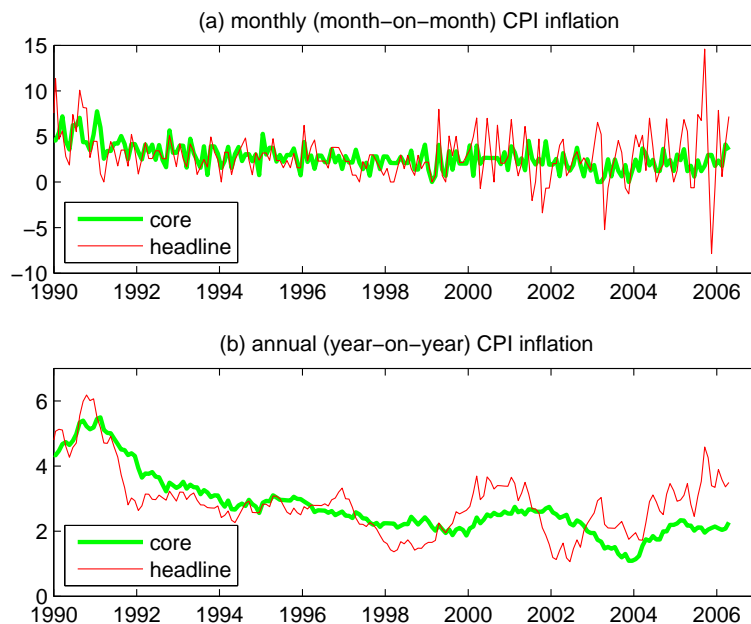


Figure 1: US monthly and annual inflation in core CPI and headline CPI (total CPI).

$\Delta TOTAL_t$, respectively) in the 1990-2006 period gives:¹⁶

$$(18) \quad \Delta y_{2Y,t} = 0.11_{(0.23)} + 18.41_{(2.39)} \Delta CORE_t + e_t,$$

$$(19) \quad \Delta y_{2Y,t} = 0.10_{(0.26)} + 6.97_{(2.07)} \Delta TOTAL_t + e_t,$$

where the standard errors are given in parentheses. The coefficients on the surprise component in both cases are positive, in line with intuition: a positive inflation surprise leads to an upward revision in yields.

The more interesting case, however, is when both surprise components are used as regressors:

$$(20) \quad \Delta y_{2Y,t} = 0.09_{(0.24)} + 19.49_{(2.88)} \Delta CORE_t - 1.49_{(2.22)} \Delta TOTAL_t + e_t.$$

Note that the coefficient on $\Delta TOTAL_t$ is now insignificant. In other words, once the information in the core CPI surprise is taken into account, the total CPI surprise has no explanatory power. There are also many instances of the total CPI and core CPI surprises having opposite signs to re-do the regression (19) for them only (about 40 in

¹⁶Here I present the results on the 2-year yield, as the 2-year maturity is often regarded as the most sensitive to policy expectations; other yields lead to similar conclusions. Intraday data on two-year benchmark Treasury yield are used to compute the yield change (5 minutes before the announcement and 25 minutes after the announcement).

1990-2006), which gives:

$$(21) \quad \Delta y_{2Y,t} = -0.03_{(0.35)} - 8.91_{(3.22)} \Delta TOTAL_t + e_t.$$

The coefficient on $\Delta TOTAL_t$ is now counterintuitive (negative) and significant.

These results do not necessarily mean that the “extra” components in the total CPI (food and energy prices) are completely irrelevant to the yield curve. They do, however, raise the question as to whether it is reasonable to treat the fluctuation in total CPI as risks that are spanned by the the yield curve factors (an implicit assumption in most external-basis macro-finance models).

In a more prosaic approach, one can also examine the spanning of short-run inflation risk by regressing the change in quarterly inflation π_t onto the changes in 6-month, 2-year, and 10-year yields.¹⁷ This regression gives an R^2 of at most 10% in the 1965-2006 period, in stark contrast to the aforementioned regression of the change in the 5-year yield (R^2 of 99%). Even when the lagged inflation terms are included, as in

$$(22) \quad \Delta \pi_t = a + b_1 \Delta \pi_{t-1} + b_2 \Delta \pi_{t-2} + b_3 \Delta \pi_{t-3} + b_4 \Delta y_{6M,t} + b_5 \Delta y_{2Y,t} + b_6 \Delta y_{10Y,t} + e_t,$$

the R^2 's do not exceed 40%.¹⁸ This exercise is similar in spirit to Collin-Dufresne and Goldstein (2002), who argue that the relatively low R^2 's in the regressions of the changes in interest rate derivative prices on the changes in interest rates indicate the presence of “unspanned stochastic volatility” in interest rates.

The evidence for poor spanning of short-run inflation risk raises questions as to whether external basis models are compatible with the no-arbitrage principle. Let us now address a related question — whether external basis models can properly describe inflation expectations, which, according to the Fisher hypothesis intuition, are an important determinant of the nominal term structure.

3.2. Do macro variables form a suitable basis for representing expectations?

To those who engage in inflation forecasting extensively, the poor inflation forecast performance of macro-finance models like those of ABW (2007a) might not be a surprise: a long line of research has explored the inflation forecasting performance of the yield curve information and generally obtained disappointing results. Stock and Watson (2003) summarize the situation thus: “With some notable exceptions, the papers in this literature generally find that there is little or no marginal information content in the nominal interest rate term structure for future inflation.”

¹⁷Let y_t denote a vector of n yields. In the affine model, one has $y_t = a + \mathcal{B}x_t$, where x_t is the n -dimensional vector of state variables, a is an n -dimensional constant vector, and \mathcal{B} is an $n \times n$ constant matrix. Inverting it gives $x_t = \mathcal{B}^{-1}a + \mathcal{B}^{-1}y_t$. Thus, if π_t is an element of x_t , this implies $\Delta \pi_t = c' \Delta y_t$, where c is a constant vector. This is in the linear regression form *without the residual error term* (and the intercept term).

¹⁸In the regression (22), I have tried both quarterly inflations based on the quarter-averaged CPI and the end-of-quarter (last month of the quarter) CPI. In the former and latter cases, the quarter-averaged yields and end-of-quarter yields were used, respectively.

One paper that does find evidence for the predictive information in the yield curve for future inflation is Mishkin (1990), so it is worth updating his results. Mishkin's regression takes the form

$$(23) \quad \pi_{t+\tau,t} - \pi_{t+u,t} = \alpha_{\tau,u} + \beta_{\tau,u}(y_{\tau,t} - y_{u,t}) + e_{t+\tau},$$

where $\pi_{t+\tau,t}$ is the inflation between time t and $t + \tau$, i.e., $\pi_{t+\tau,t} = (1/\tau) \log(Q_{t+\tau}/Q_t)$, and $\tau > u$. This regression is motivated by the Fisher hypothesis, which can be stated as

$$(24) \quad E_t(\pi_{t+u,t}) = y_{u,t} - \text{real yield}.$$

If the real yield were constant, subtracting this from the same equation with maturity τ would give eq. (23) with $\beta = 1$. Mishkin argued that his finding of statistically significant β s indicates the usefulness of the information in the yield curve for inflation forecasting.

With yield data from 1960 to 1983, I obtain a result similar to Mishkin: for example, running the regression (23) for $\tau = 2$ -year and $u = 1$ -year gives a $\beta_{\tau,u}$ of 2.32 (with standard error 0.28), which is indeed large and significant, and in fact larger than 1 (which is also the case in Mishkin (1990) with both his "full" sample and "pre-October 1979" sample). However, the same regression with the more recent 1984-2006 sample gives a much smaller $\beta_{\tau,u}$ of 0.17 (and standard error of 0.26). As discussed in Appendix B, the Mishkin regression coefficient probably has an upward bias, which may explain why the the coefficient in the earlier-period sample is substantially larger than 1. But this bias also suggests that the coefficient in the 1984-2006 sample, already small, may have been overstated. In sum, even the Mishkin regression provides little support for the usefulness of the yield curve information in the more recent sample period (which is presumably a more relevant period for current applications).

Most of the regression-based inflation forecasting models in the literature include current and lagged inflation as regressors in order to take into account the persistence of inflation. The expected inflation over the next year in these models takes the form

$$(25) \quad E_t(\pi_{t+1Y,t}) = a + b_0\pi_t^* + b_1\pi_{t-1}^* + \dots + c'z_t,$$

where π_t^* is either the one-period inflation or annual inflation, and the vector z_t denotes other regressors, which could include term structure variables.

Consider a macro-finance model (1) that has quarterly (one-period) inflation π_t as a state variable. In other words, $x_t = [\pi_t, \tilde{z}_t']'$, where $\tilde{z}_t (= [\tilde{z}_{1t}, \tilde{z}_{2t}, \dots]')$ denotes other state variables. The expected inflation over the next year is

$$(26) \quad \begin{aligned} E_t(\pi_{t+1Y,t}) &= [1, 0, \dots, 0] ((\Phi + \Phi^2 + \Phi^3 + \Phi^4)(x_t - \mu) + \mu) \\ &= \tilde{a} + \tilde{b}_0\pi_t + \tilde{b}_1\tilde{z}_{1t} + \tilde{b}_2\tilde{z}_{2t} + \dots, \end{aligned}$$

which is in the same form as eq. (25).¹⁹ (The case is similar with models that use annual inflation as a state variable.) As such, the difference between the macro-finance models formulated this way and the regression models is simply in the *coefficients*, not in the *basis*. There is a possibility of an “efficiency gain” with no-arbitrage models (through the imposition of useful constraints on the coefficients), but even this is not assured, if the results in ABW (2007a) are any indication. More fundamentally though, the frequently poor inflation forecast performance of regression models and macro-finance models like ABW(2007a) raises questions about the basis itself.

3.3. Lessons from simple models. Some of the key conceptual issues in the representation of the yield curve and inflation expectations may be explained through a comparison of two simple models of inflation, namely AR(1) and ARMA(1,1) models:

$$(27) \quad \pi_t = (1 - \phi)\mu + \phi\pi_{t-1} + \varepsilon_t, \quad (\text{AR})$$

$$(28) \quad \pi_t = (1 - \phi)\mu + \phi\pi_{t-1} + \varepsilon_t - \alpha\varepsilon_{t-1}. \quad (\text{ARMA})$$

The τ -period-ahead inflation expectations in both models take the form

$$(29) \quad E_t(\pi_{t+\tau}) = \phi^{\tau-1}(\chi_t - \mu) + \mu,$$

where the expected one-period inflation $\chi_t \equiv E_t(\pi_{t+1})$ for the AR(1) model is given by

$$(30) \quad \chi_t = \phi\pi_t + (1 - \phi)\mu$$

and χ_t for the ARMA(1,1) model is given by

$$(31) \quad \chi_t = \phi\pi_t - \alpha\varepsilon_t + (1 - \phi)\mu.$$

The estimate of ϕ in the AR(1) model, based on US quarterly CPI inflation data from 1960Q1 to 2005Q4, is $0.785_{(0.045)}$, while the estimates of ϕ and α in the ARMA(1,1) model are $0.935_{(0.031)}$ and $0.341_{(0.081)}$, respectively, standard errors being in parentheses. These numbers imply fairly similar one-quarter-ahead inflation expectations, as can be seen in Figure 2a. (There is somewhat more jaggedness in the AR(1) forecast.) The same parameter estimates, however, imply very different longer-horizon inflation expectations: the 5-year-ahead (20-quarter-ahead) inflation expectation from the AR(1) model is almost constant, while the 5-year-ahead inflation expectation from the ARMA(1,1) model is more variable. (This reflects the difference between $0.785^{20-1} = 0.01$ versus $0.935^{20-1} = 0.28$ in eq. (29).)

An almost constant 5-year-ahead inflation expectation from the AR(1) model in the past 40 years is highly questionable. The main reason for the qualitative difference between the AR and ARMA models is that the ARMA(1,1) model tries to separate out the “unforecastable inflation” from the expected inflation, while the AR(1) model

¹⁹If the \tilde{z}_t vector includes latent factors, they can be “inverted” and expressed in terms of yields (because of the linear relationship between the yield and the factors), which again leads to the form (25). However, latent factors in these “mixed” models are partly defined by their relation to the macro-factors, and this may entail complications, as discussed later in Section 3.4.

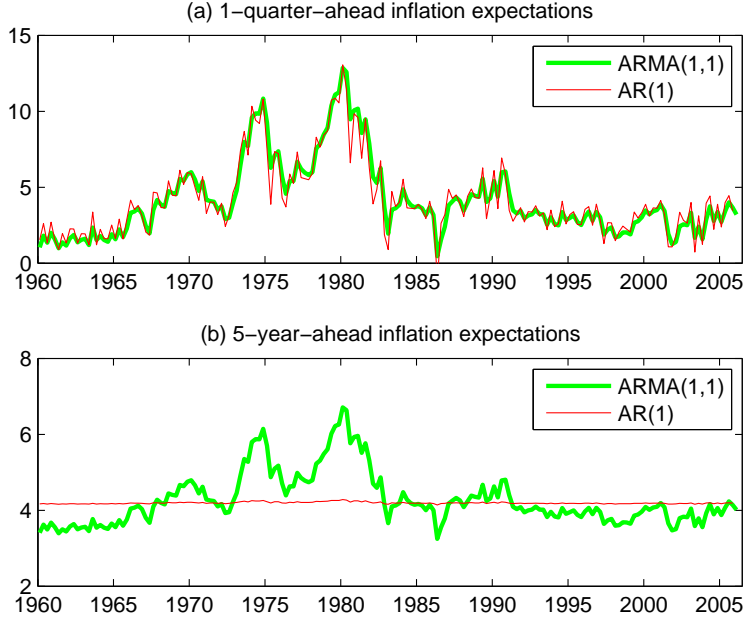


Figure 2: US inflation expectations based on AR(1) and ARMA(1,1) models.

does not. This can be seen from the fact that the ARMA(1,1) model is a univariate representation of the following “two-component model”:

$$(32) \quad \begin{aligned} \pi_t &= \chi_{t-1} + \eta_t \\ \chi_t &= (1 - \phi)\mu + \phi\chi_{t-1} + e_t, \\ \eta_t &\sim N(0, \sigma_\pi^2), \quad e_t \sim N(0, \sigma_x^2), \quad \text{corr}(\eta_t, e_t) = \rho, \end{aligned}$$

in which χ_t is an expected inflation process and η_t is an unforecastable inflation.²⁰ Though simple, this two-component model (of which the internal basis model (17) discussed in Section 2.3 can be viewed as an extension) is quite useful for illustrating some of the key points in this paper.²¹

The unforecastable inflation component η_t in eq. (32) can help explain several puzzling empirical results in the literature. Among them is the negative one-lag autocorrelation of the changes in quarterly inflation $\Delta\pi_t (= \pi_t - \pi_{t-1})$, which, according to Rudd and

²⁰The MA(1) coefficient in the ARMA(1,1) model is related to the two-component model parameters as $\alpha = c - \sqrt{c^2 - 1}$, where $c \equiv [(1 + \phi^2)\sigma_\pi^2 + \sigma_x^2 - 2\rho\phi\sigma_\pi\sigma_x] / [2(\phi\sigma_\pi^2 - \rho\sigma_\pi\sigma_x)]$. See, for a derivation, Cochrane (2001, pp418-20).

²¹This model of inflation has an interesting parallel with the consumption-based asset pricing model of Bansal and Yaron (2004), who argue that writing the consumption growth Δc_t as the sum of expected component and unexpected component ($\Delta c_{t+1} = \chi_t + \eta_{t+1}$) can help resolve the equity premium puzzle.

Whelan (2006, Sec III.C), is an evidence against the new-Keynesian Phillips curve models (which generate positive one-lag autocorrelation). In the case of the two-component model (32), one has

$$(33) \quad cov(\Delta\pi_t, \Delta\pi_{t-1}) = cov(\Delta\eta_t, \Delta\eta_{t-1}) + cov(\Delta\chi_{t-1}, \Delta\chi_{t-2}) + cov(\Delta\chi_{t-1}, \Delta\eta_{t-1}).$$

The obviously negative first term dominates the second and third terms at appropriate parameter values, resulting in a negative $cov(\Delta\pi_t, \Delta\pi_{t-1})$. The unforecastable component η_t also plays the role of putting an upper bound on the predictability of inflation.

Economically, the η_t term represents the very-short-run effects in total CPI inflation, including part of the food and energy prices that create the wedge between total CPI and core CPI (as seen in Section 3.2), as well as the unforecastable components of the core CPI inflation and potential errors in the measurement of CPI. A large part of η_t is beyond the control of monetary policy makers (or economic agents, for that matter); thus, in some sense, the presence of a substantial amount of unforecastable inflation is a “fact of life”.

The importance of the η_t -term in the two-component model (32) has a parallel implication for no-arbitrage macro-finance models: the failure to separate out the “unspanned macro shocks” in macro-finance models may produce problems that mirror those of the AR(1) inflation model. It is worth mentioning here that Stock and Watson (2007) have also recently emphasized that separating inflation into a trend component and a serially uncorrelated shock (like η_t in eq. (32)) is useful for explaining key features of the US inflation dynamics,²² though they do not discuss the ramifications for macro-finance (no-arbitrage) models.

It is instructive to ask about the basic variable underlying the term structure of inflation expectations in the ARMA(1,1) model. As is clear from eq. (29), the basic variable is χ_t , not the realized inflation π_t . Note that in the case of the AR(1) model, χ_t is π_t (up to a prefactor and an intercept), as can be seen from eq. (30). This is not the case for the ARMA(1,1) model: it is straightforward to show (by solving for ε_t in eq. (28) and recursively substituting into eq. (31)) that χ_t in the ARMA(1,1) model can be expressed as

$$(34) \quad \chi_t = (\phi - \alpha) \sum_{j=0}^{\infty} \alpha^j (\pi_{t-j} - \mu) + \mu.$$

This is in the exponential smoothing form, which has been familiar at least since the work of Muth (1960).

The expression (34) suggests that the connection between realized macro variables and state variables in no-arbitrage term structure models could be complicated, and that the poor inflation forecasting performance of regression models and no-arbitrage

²²Stock and Watson (2007) write the US inflation process for the last half century as $\pi_t = \tau_t + \eta_t$, where η_t is a serially uncorrelated disturbance term. The τ_t term (what they refer to as the trend component) can be identified as χ_{t-1} in eq. (32). Stock and Watson (2007)’s τ_t and η_t have time-varying volatilities, a feature which, they argue, is important in the inflation persistence debate.

models with macro variables may be a more complex issue than being just a matter of having “efficient” coefficients (with conventional basis). To be sure, the state variables in nominal term structure models are not simply those that underlie the variation of inflation expectations. Factors that affect the real term structure and inflation risk premia should also be included in the nominal term structure model. However, it is not clear that these additional aspects would be any better described by macro variables.

Note that the expression for χ_t in eq. (34), although useful for conceptual illustration, is still deficient as a description of inflation expectations for both subtle and fundamental reasons. The subtle reason concerns the conditioning information: if the two-component model (32) is the data generating process for inflation, the “true” inflation expectation cannot be expressed simply in terms of the past inflations (except when $\varrho = \pm 1$ in eq. (32)). Mathematically,

$$(35) \quad E_t(\pi_{t+1} | \eta_t, e_t, \eta_{t-1}, e_{t-1}, \dots) \neq E_t(\pi_{t+1} | \pi_t, \pi_{t-1}, \dots).$$

In other words, the one-period inflation expectation based on the past history of inflation (as computed from the ARMA(1,1) model) is not the same as the one-period inflation expectation χ_t in eq. (32) computed using more information than just the inflation data.

More fundamentally, the ARMA model and even the two-component model are deficient, as both models imply that the one-period inflation expectation is an AR(1) process, which means that inflation expectations for all horizons are given by a single factor χ_t , with the term structure of inflation expectations monotonically sloping up when χ_t is below its long-run mean and monotonically sloping down when χ_t is above its long-run mean. This stiffness (lack of flexibility) of the model makes it difficult to describe the inflation environment of the past decades, during which people’s perception of Federal Reserve’s inflation target is believed to have changed appreciably. Thus, the model’s results depend materially on how long the estimation sample is. Figure 2b, based on the estimation with a “long sample” that includes the 1970s, indicates the current (circa 2006) five-year-ahead CPI inflation expectation of about 4%, which is too high to be believed. More generally, one can view the level to which inflation mean-reverts itself as varying over time.²³

3.4. Low-dimensional external basis models. Let us now consider some specific issues that arise in external basis models with a “low-dimensional” state vector.

Suppose that one has a three-factor macro-finance model in the setup of eq. (1), with the state vector x_t consisting of all “observable” macro variables, say, the quarterly

²³Note that if χ_t is highly persistent or nonstationary (as in Stock and Watson (2007)), the one-period inflation expectation χ_t itself can be interpreted as a time-varying (perceived) inflation target, but in this case χ_t would miss shorter-run predictable variation in inflation. Multi-factor internal basis models discussed in Section 2.3 can help address this problem, as the state vector x_t therein can be viewed as including a time-varying inflation target (or people’s perception of the target) as well as factors related to shorter-horizon inflation expectations. Note also that external basis models like HTV (2006) have time-varying inflation target in the state vector.

inflation π_t , quarterly GDP growth g_t , and the effective federal funds rate ff_t . The inflation expectations in this model are then linear functions of contemporaneous variables π_t, g_t, ff_t . (To see this, simply substitute $\tilde{z}_{1t} = g_t, \tilde{z}_{2t} = ff_t$ in eq. (26).) This type of forecast (VAR(1)) has more qualitative similarity to the AR(1) model than the ARMA(1,1) model; in particular, despite its multi-factor nature, it still mixes “signal” with “noise” and can therefore be expected to inherit many of the problems with the AR(1) model.

Some of the macro-finance models in the literature, including Ang, Dong, and Piazzesi (2005, henceforth ADP) and ABW (2007a), remain in a relatively low-dimensional framework but use a mix of latent factors and macroeconomic variables, but these “mixed models” may still have difficulties. Consider, for example, the ABW (2007a)’s affine model (their MDL1 model) with quarterly inflation and two latent factors, i.e., $x_t = [\pi_t, f_{1t}, f_{2t}]'$. If the latent factors f_{1t}, f_{2t} are interpreted as π_{t-1}, π_{t-2} , eq. (26) takes a form similar to the smoothing form (34). However, besides the issue that two lags might not be enough, one may not have the freedom to interpret f_t ’s this way, as that would deprive the ability to describe other aspects of the nominal term structure (e.g., real interest rates, time-varying risk premium, time-varying perceived inflation target).

In the mixed models, having a macro variable like π_t as a part of the state vector may cause a distortion in the inference, as the latent factors can end up absorbing the “unspanned” variation in π_t . To illustrate this schematically, suppose that the true model of the short rate is

$$(36) \quad r_t = \rho \tilde{\pi}_t + f_t,$$

where $\tilde{\pi}_t$ is the “spanned” part of the one-period inflation π_t , i.e.,

$$(37) \quad \pi_t = \tilde{\pi}_t + e_t,$$

with e_t denoting the unspanned component. If one uses realized inflation π_t in place of $\tilde{\pi}_t$, then

$$(38) \quad r_t = \rho(\pi_t - e_t) + f_t = \rho\pi_t + (f_t - \rho e_t).$$

Thus the latent factor f_t would be distorted by an amount ρe_t . Although this was illustrated with an affine model, the same problem can occur in the non-affine models.

3.5. High-dimensional external basis models. Some of the external basis macro-finance models in the literature use a fairly large number of state variables that include lagged macro variables. Many such models (including those of AP (2003) and HTV (2006)) use annual inflation $\pi_t^Y (= \pi_{t,t-1Y})$ as a state variable instead of the one-period inflation. This may help alleviate concerns about the problem with the use of the one-period inflation, since the year-on-year inflation partly “smooths out” the noise in quarterly inflation: π_t^Y can be written

$$(39) \quad \pi_t^Y = \sum_i w_i \pi_{t-i},$$

where the weights w_i are $\frac{1}{4}$ for $i = 0, 1, 2, 3$, and 0 for $i > 3$.

Note, however, that the construction (39) automatically implies a moving average structure in π_t^Y , which suggests that the simple VAR(1) description would not be a good description of its dynamics. Thus, macro-finance models that use annual inflation as a state variable typically include additional lags, e.g., AP (2003) use 12 monthly lags, in effect having a VAR(12) model. Bond yields in this case depend on a “large” set of state variables that include lagged macroeconomic variables.²⁴

A problem with this type of “high-dimensional” specification is that it inherits the well-known problems of the the unrestricted VAR models. In fact, AP (2003)’s inflation dynamics *is* a conventional VAR. They separate the vector of relevant variables into an “observable” macro vector f_t^o and an unobservable (latent) vector f_t^u , i.e., $\tilde{x}_t = [f_t^o, f_t^u]'$,²⁵ and impose the restriction that the latent factors do not affect the expectation of macroeconomic variables. Their macro vector dynamics is given by the VAR(q):

$$(40) \quad f_t^o = \Phi_1^o f_{t-1}^o + \Phi_2^o f_{t-2}^o + \cdots + \Phi_q^o f_{t-q}^o + c^o + \Sigma^o \epsilon_t^o,$$

where $q = 12$. Although the parameters in the matrices $\Phi_1^o, \dots, \Phi_q^o$ are in principle identified and can be estimated by OLS, this kind of unrestricted VAR is well known to suffer from overparametrization problems (which will be discussed further in Section 5.1).

By having only the macro variables describe inflation dynamics, AP (2003) turned off the possibility of the yield curve saying something about future inflation. Unfortunately, it is difficult to lift that restriction. The overparametrization problem would get worse, as the full (maximally-identified) model would have an even larger number of parameters: in the specification of the state vector dynamics

$$(41) \quad \begin{bmatrix} f_t^o \\ f_t^u \end{bmatrix} = \begin{bmatrix} \Phi_1^o & \Phi_1^{ou} \\ \Phi_1^{uo} & \Phi_1^u \end{bmatrix} \begin{bmatrix} f_{t-1}^o \\ f_{t-1}^u \end{bmatrix} + \begin{bmatrix} \Phi_2^o & \Phi_2^{ou} \\ \Phi_2^{uo} & \Phi_2^u \end{bmatrix} \begin{bmatrix} f_{t-2}^o \\ f_{t-2}^u \end{bmatrix} + \cdots + c + \Sigma \epsilon_t,$$

the matrices $\Phi_1^{ou}, \Phi_2^{ou}, \dots$ are now nonzero and have to be estimated. Furthermore, the two-step estimation procedure that AP (2003) used is no longer applicable, hence the estimation now involves a “one-step” optimization of a very-high-dimensional likelihood function.

Models like HTV (2006) have more structure (in the form of the new-Keynesian Phillips curve and IS equations), which may help alleviate overparametrization concerns, but at a possibly greater misspecification risk: various aspects of the new-Keynesian specification are still under debate, e.g., the presence or absence of the interest rate

²⁴Since an invertable ARMA(1,1) model can be written as an AR model with infinite lags, the use of lagged macro variables in an external basis model may partly address the deficiency of the AR(1) model (relative to the ARMA(1,1) model) discussed in Section 3.4. However, identifying inflation as a state variable may be still problematic conceptually (especially in the case of the one-period inflation π_t), in view of our earlier discussion regarding the difference between χ_t and π_t .

²⁵Here I have attached a tilde to x_t to clarify that this is not the full state vector. The full state vector (on which bond yields depend) in AP (2003) is larger: $x_t = [f_t^o, f_{t-1}^o, \dots, f_t^u]'$.

smoothing term (e.g., English et al (2003), Rudebusch (2006)) and the strength of the backward-looking inflation terms (e.g., Rudd and Whelan (2006)).

A common practice in the specification of external basis models that contain lags of macroeconomic variables in the state vector is to set the coefficients of the market price of risk (Λ_b matrix in eq. (1)) that load on lagged macro variables to zero (e.g., AP (2003) and HTV (2006)). Even with this restriction, the number of remaining market price risk parameters is large, and modelers often make additional *ad hoc* restrictions on the Λ_b matrices to reduce the number of parameters further.²⁶ Unfortunately, the practice of setting the Λ_b coefficients on lagged macro variables to zero is not as innocuous as it might appear. It implies that the expected excess return on a bond, $\mu_{\tau,t} - r_t$, is completely spanned by *contemporaneous* macroeconomic variables (and latent factors, if there are any). Recall, from eqs. (11) and (16), that

$$(42) \quad \mu_{\tau,t} - r_t = B'_\tau \Sigma \lambda_t.$$

Therefore, if λ_t does not depend on lagged macro variables, neither does the bond return premium. This means that while one has

$$(43) \quad y_{\tau,t} = a_\tau + b_{\tau,1}\pi_t + b_{\tau,2}\pi_{t-1} + b_{\tau,3}\pi_{t-2} \cdots,$$

one cannot have

$$(44) \quad \mu_{\tau,t} - r_t = \alpha_\tau + \beta_{\tau,1}\pi_t + \beta_{\tau,2}\pi_{t-1} + \beta_{\tau,3}\pi_{t-2} + \cdots.$$

This asymmetry in the way yields and bond risk premia depend on lagged macro variables has nothing to do with no-arbitrage, and has little empirical basis. In other words, in order to cast the model in a “no-arbitrage” framework, many external basis macro-finance models are introducing arbitrary and nontrivial assumptions about the market price of risk. This raises the question of whether the no-arbitrage principle can play its intended role.²⁷

3.6. Would composite factors help? Several recent studies have explored the use of composite variables created from a large array of macroeconomic variables in modeling the term premia (e.g., Ludvigson and Ng, 2006) or the yield curve (e.g., Moench, 2006).

The composite factors may be appealing because they utilize a much bigger information set and also because they may be *cross-sectionally* smoothing out some of the idiosyncratic noise in quantities like CPI, hence one can expect them to reflect more of the systematic variation than the individual macro variables.

²⁶For example, AP (2003) and HTV (2006) assume that Λ_b is a block-diagonal matrix (a block matrix for macro factors and a block matrix for latent factors).

²⁷Duffee (2006) has also recently questioned the modeling of term premium in the macro-finance literature, more specifically, the finding in some macro-finance papers of a strong relationship between term premium and macroeconomy. His point is that these studies often do not provide alternatives other than the “expectations hypothesis” (zero or constant return premium) and the term premium that depends on macro variables, leading to an exaggerated role of macro variables in term premium variation.

However, since these models do not address expectations concerning specific macroeconomic variables of potential interest, one cannot tackle issues such as the expectation of the CPI inflation implicit in the yield curve; thus macro-finance models based on purely composite factors would not have much to say about TIPS pricing, as TIPS are specifically indexed to the CPI.

More fundamentally, it is unclear whether composite factors can be valid state variables in no-arbitrage term structure models, as they may still face many of the aforementioned problems with external basis models. In particular, the way the composite factors in Moench (2006) and Ludvigson and Ng (2006) are constructed is such that they are not very persistent variables.²⁸ For example, Ludvigson and Ng (2006) report that their most persistent factor has a monthly AR(1) coefficient of 0.77 (the half-life is less than a quarter). In order for such a variable to describe yields in the setup of (1) even just qualitatively (e.g., producing the kind of persistence that yields have), one needs long lags, which again raise overparametrization concerns. In addition, even if principal components analysis indicates that a small number, say n , of factors describe the bulk of yield curve movements, it is not clear whether the proper truncation number for *cross-sectional* composite factors should be also small or is related to n .

4. AFFINE GAUSSIAN MODELS VERSUS NON-AFFINE/NON-GAUSSIAN MODELS

4.1. Structural stability. One potential limitation of the general framework (1) is structural stability. To be sure, the debate about the structural stability of macroeconomic relationships is not new (see, e.g., Rudebusch (1998) and Sims (1998)). However, it may have different ramifications for internal basis models and external basis models, and hence merits a discussion here.

Several well-known structural instabilities are of direct relevance to macro-finance models. Many have noted that in the 1990s a large part of the term structure variation seemed to be due to the variation of real rates, while in the 1970s the variation in inflation expectations seemed to be a more dominant factor. The stark difference between the Mishkin regression coefficients in the 1960-83 and 1984-2006 periods discussed in Section 3.2 lends support to the claim of a change in the relative importance of inflation for explaining yield curve movements. Another instability is that of the Taylor rule coefficients, as argued by Clarida, Gali, and Gertler (2000) and others. Since the Taylor rule underpins the short-rate specification of many macro-finance models, this instability is a serious concern for the macro-finance models that are estimated with a “long” sample that includes the pre-Volcker disinflation period. Note also that the dynamics of many

²⁸Models like Moench (2006) use only the composite factors and the short rate as state variables for the term structure model (i.e., without “latent” factors). Together with the restriction that the market price of risk does not depend on lagged variables, this implies that the expected excess return on a bond is a linear function of the *contemporaneous* composite factors and the short rate (recall eq. (42)). The lack of persistence of the composite factors may then imply a bond return premium that has a lot of short-run variability by design.

macro-finance models is similar to conventional VARs, but low-dimensional macro-VARs were often found to be unstable (e.g., Stock and Watson (1996)).

The traditional specification may also face difficulty in accommodating relatively new developments. For example, in recent years there has been an increased discussion of the effects of global forces on domestic bond markets. Increased “global liquidity” has been often cited as a potential factor pressing down inflation expectations or bond risk premia, and interest rates movements in various countries, including the United States, Euro area, and Japan, have lately become more highly correlated.²⁹ Whether structurally stable Taylor-rule type specifications are consistent with these developments is an open question.

One may hope that concerns about structural instability would be alleviated if latent factors are also included in external basis models. For example, a macro-finance model with a Taylor-rule-like mixed specification of the short rate (similar to ADP (2005))

$$(45) \quad r_t = \text{const} + \rho_\pi \pi_t^Y + \rho_g \text{gap}_t + f_t,$$

where f_t is a latent factor, can be written as

$$(46) \quad r_t = \text{const} + \pi_t^Y + (1 - \rho_\pi)(\pi_t^Y - \pi_t^*) + \rho_g \text{gap}_t,$$

where π_t^* ($= -f_t/(1 - \rho_\pi)$) is the time-varying inflation target. However, the factor f_t may have to play a number of other roles in the model, for instance, the interest rate smoothing term, time-varying risk premium, and so on (analogously to an earlier discussion in Section 3.4 regarding ABW (2007a)’s affine model). Thus a model written with f_t as a time-varying inflation target in mind might have some difficulty capturing the intended effect.

Furthermore, there may be instabilities other than time-varying intercept, for instance, changes in the conditional correlation of various macroeconomic variables, changes in the persistence of the macroeconomic variables, and so on. Imagine, heuristically, a situation in which the “true” model is

$$(47) \quad r_t = c + \rho_{\pi,t} \pi_t^Y + \rho_{g,t} \text{gap}_t,$$

i.e, a Taylor-rule-like short-rate with time-varying loadings on the macroeconomic variables. In this case, the 2-factor affine model in which the state variables are $[\pi_t^Y, \text{gap}_t]'$ is obviously misspecified. For another example, consider a “time-varying inflation-persistence model”

$$(48) \quad \pi_t^Y = \phi_{t-1} \pi_{t-1}^Y + c + \varepsilon_t.$$

Again, identifying π_t^Y as a state variable in an affine setting would be a misspecification.

One way to address this problem is to model these effects explicitly in non-affine/non-Gaussian models. However, these models, being richer than affine-Gaussian models, may be even more susceptible to overfitting concerns and may incur a greater risk of misspecification. The disappointing inflation forecasting performance of the vector

²⁹See, for example, Backus and Wright (2007).

regime-switching model and the no-arbitrage “regime-switching” model in ABW (2007a) (referred to by them as RGMVAR and MDL2, respectively) may serve as a reminder in this regard.

Alternatively, the use of an internal basis (while still remaining in the affine-Gaussian setup) may allay structural instability concerns to some extent: internal basis models are agnostic as regards the definition of the factors; thus a model that is obviously unstable from the point of view of an external basis may not necessarily be so from the point of view of an internal basis. For example, going back to eq. (47), choosing the state variable as $x_t = [\rho_{\pi,t} \pi_t^Y, \rho_{g,t} gap_t]'$ may be more effective than having $x_t = [\pi_t^Y, gap_t]'$, although there may be an even better internal basis for the problem (depending on how the rest of the model is defined).³⁰

Of course, no-arbitrage models with an internal basis should not be expected to answer all structural stability concerns. A strong structural instability may be difficult to capture even with an internal basis model, in which case it might be better to use a shorter, structurally more homogeneous sample.

4.2. Time-varying uncertainty. Another limitation of the affine-Gaussian models (both internal and external basis models) is that they imply homoskedastic yields, while there is copious evidence for time-varying volatility of interest rates, e.g., from interest rate derivatives as well as the stochastic-volatility models and GARCH-type models. However, it is not clear whether a no-arbitrage model that allows for time-varying volatility would produce better results. Again, the concern is that such a model may incur greater specification errors and implementation errors.

Theoretically and intuitively, one *should* expect a relation between term structure variables and time-varying uncertainty about interest rates: to the extent that bond market term premia arise from risk, the changing amount of interest rate risk should translate to a changing term premium. It also stands to reason that at least a part of the variation in interest rate volatility is linked to the variation in the uncertainties about key macro variables. Various studies have noted that macroeconomic uncertainties (inflation, GDP, monetary policy) have declined since the Volcker disinflation, a phenomenon often dubbed the “Great Moderation”.³¹ One can expect this effect to be accompanied by a corresponding reduction in term premia in the bond market. Kim and Orphanides (2007) indeed report positive relationships between the term premium in the 10-year forward rate and proxies for uncertainties about monetary policy and inflation based on the dispersion of long-horizon survey forecasts.³²

However, much work remains to be done to properly address the relationship between term premia and macroeconomic uncertainties, in particular inflation uncertainty. For

³⁰If π_t^Y and $\rho_{\pi,t}$ are Gaussian processes, the process $\rho_{\pi,t} \pi_t^Y$ would be non-Gaussian (with time-varying volatility). However, one can still think of the affine version as an approximation of the non-Gaussian process.

³¹Bernanke (2004b) discusses this phenomenon from a policy maker’s perspective.

³²See also Backus and Wright (2007).

instance, one can debate as to whether the survey dispersion measure used in Kim and Orphanides (2007) is a good proxy for uncertainty. Furthermore, their evidence is mainly about the low-frequency relation; whether there is a relation at shorter time scales remains unclear. A key difficulty addressing this question is measuring the relevant uncertainty. For example, the uncertainty measures from GARCH-type models of inflation do not seem promising for making a connection with bond market term premia, as those models imply a tight relation between short-term inflation uncertainty and long-term inflation uncertainty.³³

Recall from the discussion in Section 3 that much of high-frequency variation in inflation is not spanned by interest rates. This, in turn, suggests that the changing amount of this unspanned risk might not have much connection with bond market term premia either. Furthermore, the relevant inflation uncertainty is over the life of the bond, which could be qualitatively different from short-run uncertainty about inflation.

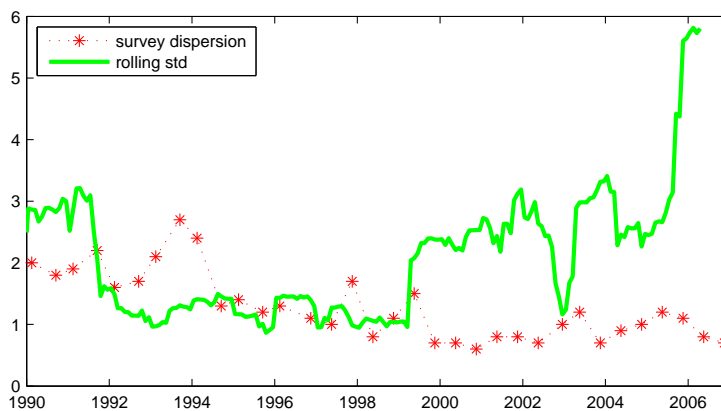


Figure 3: The dispersion of long-horizon US inflation forecasts in the Blue Chip Financial Forecasts and the 1-year rolling standard deviation of monthly CPI inflation.

The increase in the volatility of monthly inflation in total CPI from about 1999 and on (which can be clearly seen in Figure 1a) is a case in point. This increase in the near-term uncertainty does not seem to have translated to an increase in the *perception of longer-term uncertainty*. Indeed, as shown in Figure 3, a proxy for the long-horizon inflation uncertainty based on a survey forecast dispersion has been subdued in this period, contrasting with an elevated level of one-year rolling standard derivation of monthly inflation (a simple proxy for short-run inflation uncertainty) in the same period. Even

³³Consider a GARCH specification of the one-period inflation, $\pi_{t+1} = f(\pi_t, \pi_{t-1}, \dots) + \epsilon_{t+1}$, $\epsilon_{t+1} \sim N(0, \sigma_t^2)$, $\sigma_t^2 = \alpha + \beta\sigma_{t-1}^2 + \gamma\epsilon_t^2$. It is straightforward to show that the the uncertainty about multi-period inflation $\pi_{t+\tau, t} = (\pi_{t+1} + \pi_{t+2} + \dots + \pi_{t+\tau})/\tau$ has similar qualitative time-variation as σ_t (short-run inflation uncertainty).

granting the imperfection of the long-horizon inflation uncertainty measure, this lack of relation bears noting.³⁴

The complexity of inflation dynamics can thus create considerable challenge for attempts to go beyond homoskedastic models: it may be that a nonlinear model with time-varying inflation uncertainty can lead to *poorer* results if the model's inflation uncertainty is misspecified, as when a model that does not make a qualitative distinction between short- and long-run inflation uncertainties tries to link the rise in the volatility of short-run inflation of the recent several years (as seen in Figure 3) to bond market term premia.³⁵

5. EMPIRICAL ISSUES

5.1. Overfitting problems. Flexibly specified no-arbitrage models tend to entail much estimation difficulty due to a large number of parameters to be estimated and due to the nonlinear relationship between the parameters and yields that necessitates a nonlinear optimization. Even if one finds the parameter vector that corresponds to the global optimum of the criterion function, not all may be fine with the resulting estimate.

The experience with the unrestricted VARs explored in the 1980s macroeconomics literature is an important reminder in this regard. Unrestricted VARs can be estimated via the OLS regression, thus the estimation itself is straightforward; however, it is well known that unrestricted VARs often lead to poor results.³⁶ The main problem is that these models get easily overparameterized, and there is little structure in the model to prevent estimations from generating unreasonable outcomes. This problem can be expected to be shared by flexibly specified macro-finance models (both internal basis models and external basis models), which are, like the unrestricted VARs, an “atheoretical” representation with a large number of parameters.

The key innovation of the macro-finance models like AP (2003), as compared to the traditional macro models, is that they link not only the short rate r_t ($= y_{1,t}$) but also the rest of the term structure ($\{y_{\tau,t}\}_{\tau>1}$) to the macroeconomy by casting the problem in the no-arbitrage framework (1), introducing the market price of risk λ_t for the shocks in the model. However, it does not seem to have been seriously questioned as to whether the amount of additional information thus introduced is large enough to compensate for the large increase in the number of parameters of the model.

Note that the no-arbitrage principle tells the existence of a pricing kernel such as eq. (1), but the principle by itself does not constrain the parameters of the market price of

³⁴Interestingly, an earlier literature including Ball and Cecchetti (1990) and Evans (1991) has also emphasized in another context the need to distinguish between the short-run and long-run inflation uncertainties.

³⁵There has been much discussion about the low level of term premia in recent years (see, e.g., Backus and Wright (2007)). Trying to explain the *low* term premium and *high* uncertainty would be a daunting prospect.

³⁶See, e.g., Todd (1984) and Stock and Watson (2001).

risk (Λ_b matrix). Suppose, as in AP (2003), that one has in the state vector p observable variables, its $q - 1$ lags, and m unobservable (latent) variables, in other words,

$$(49) \quad x_t = [f_{1t}^o, \dots, f_{pt}^o, f_{1t}^u, \dots, f_{mt}^u, f_{1,t-1}^o, \dots, f_{p,t-1}^o, \dots, f_{1,t-q+1}^o, \dots, f_{p,t-q+1}^o]'$$

In that case the Λ_b matrix in eq. (1) can have as many as $(p+m) \cdot (p \cdot q + m)$ parameters.³⁷ For $p = 2$, $q = 12$, $m = 3$ (as in AP (2003)), there are 135 parameters for Λ_b to be determined; even if one chooses a smaller q , the number of parameters is still quite large.

Empirically, yields of various maturities tend to be highly correlated, giving rise to the finding in factor analysis and principal components analysis that there is a single dominant factor. But this also means that the pure additional information in longer-term yields (beyond what is in the short rate) may be modest in amount and perhaps too delicate to capture with a specification of the market price of risk that is liable to be overfitted; the relation that one might see between yields and macro variables in macro-finance models may be more of a statement of the Taylor rule (macro description of the short rate) rather than no-arbitrage. Thus, it is not clear whether the reduced-form no-arbitrage framework (1) can do an effective job of incorporating the information in the entire yield curve.³⁸

Though the overparametrization problem may be particularly severe with external basis models that contain lags of macroeconomic variables, internal basis models (which tend to be implemented with comparatively smaller number of factors, e.g., 3 factors) may also face serious overfitting concerns; they may be more easily overfitted than external basis models because of the especially flexible nature (the definitional freedom) of the latent-factor models. In particular, latent factor models could fit very well *data that it is asked to fit*, even if the data or the model were a poor one. For example, because yield fitting errors are minimized as a part of the estimation process, internal basis models with 3 ~ 4 factors can fit the cross-section of the yield curve quite well (with much smaller fitting errors than external basis models), but that by itself might not be a sufficient reason to recommend internal basis models.

As another example, I find that estimating the 3-factor internal basis model in D'Amico et al (2007) with yields and inflation data in the 2000-2006 period *and* with supplementary data on the SPF survey forecast of 10-year inflation (assuming that survey expectation is the model expectation plus a measurement error whose size is also estimated) can fit very closely the survey forecast, which has hardly moved from the level of 2.5%. Such an outcome is likely due to the richness and flexibility of the model rather than a genuine feature of market expectations. The problem is that although the latent factor

³⁷The lagged macro variables do not have market price of risk, but the market price of risk of contemporaneous variables and latent variables can still depend on them, as discussed in Section 3.5.

³⁸It may be useful here to compare with the way long-term yields are included in the FRB/US model (mentioned in Section 2.1). The FRB/US model takes in only a few yields (besides the short rate) using a fairly simple specification for term premia, but in that case it is introducing only a relatively small number of additional parameters.

model is identified in principle (with suitable normalization conditions), there may be not enough discipline in the model and not enough information in other data in the sample to prevent “too close” fit of the SPF survey data.³⁹

5.2. Small sample problems. The implementation of macro-finance models is also complicated by small sample problems that arise from the highly persistent nature of the data. Both interest rates and inflation are known to be persistent; unit-root tests often fail to reject nonstationarity (unit-root) null for them.⁴⁰

In light of this, many practitioners often use nonstationary models to forecast inflation. For example, many of the inflation forecasting models used by the Federal Reserve staff impose the unit root condition.⁴¹ By the Fisher-hypothesis intuition, unit root inflation dynamics implies a unit-root interest rate dynamics.

By contrast, most of the estimated macro-finance models (or nominal term structure models) in the literature assume stationarity. This may be due in large part to tradition, but there is also an intuitive justification as well: being “rates”, interest rates and inflation do not grow unboundedly, and experience tells us that these variables typically stay within the range of, say, 0% and 20%; this has been the case for modern economies (excluding special episodes like hyperinflation and deflation) as well as in ancient economies such as the Babylonian economy. The implication of unit root models that the unconditional means of inflation and interest rates are undefined and their unconditional variances are infinite is objectionable.

It thus seems more reasonable that the “true model” of yields is a stationary one, perhaps with many factors to describe the complex dynamics of yields and expectations, schematically,

$$(50) \quad y_{\tau,t} = f_{\tau}(x_{1t}, x_{2t}, x_{3t}, \dots, x_{Nt}).$$

In practice, however, one is forced to deal with relatively low-dimensional models, because limited amount of data make it impossible to pin down the parameters of such a model, or because one does not have enough knowledge to write down a very detailed model. In this case, it is not clear whether the “best” *low-dimensional approximation*

$$(51) \quad y_{\tau,t} \approx \tilde{f}_{\tau}(\tilde{x}_{1t}, \dots, \tilde{x}_{nt}), \quad (n \ll N)$$

of the model (50) should be a stationary or nonstationary (unit-root) model.

The distinction between stationary and nonstationary models could be semantic in the sense that a stationary model that is close to the unit-root boundary is almost

³⁹For this reason, the estimations in D’Amico et al (2007) use a longer sample going back to 1990 and do not consider models beyond the 3-factor case.

⁴⁰Though there have been claims that inflation dynamics has become less persistent in recent decades, this may be due to a shift in the relative weights of the variance of the short-run disturbance in inflation and the variance of the persistent component (as discussed by Stock and Watson (2007) and Sims (2002)), rather than the weakening of the persistence of inflation expectations.

⁴¹Federal Reserve staff make inflation forecast judgmentally, but they do look at a variety of models to inform their judgments. The staff’s forecasting procedure is discussed, for example, in Kohn (2005).

indistinguishable from unit-root models. But whether to assume stationarity or not can make a big difference operationally, as conventional estimations have tendency to *bias down* the persistence of stationary time series, the bias being stronger the smaller the sample. This makes the expectations appear converging to a long-run level faster than they actually do; thus longer-horizon expectations of inflation and interest rates in (estimated) stationary models are often artificially stable, varying little from the sample-mean of these variables.

Another manifestation of the small sample problem (besides bias) is *imprecision*: highly persistent interest rates effectively make the size of the sample “small”; no matter how frequently the data are sampled, some of the key aspects of the term structure model (those pertaining to expectations in the physical measure, as opposed to the risk-neutral measure) are difficult to estimate, as stressed in Kim and Orphanides (2005). In a conventional estimation of term structure model with the last 10 ~ 15 years’ yield data, one often finds that many of the parameters of the model are estimated very imprecisely and the confidence intervals for quantities of interest like the model-implied short-rate forecast are too wide (i.e., includes almost any scenarios).

5.3. Are classical procedures applicable? Most implementation of macro-finance models have relied on classical methods such as the maximum likelihood estimation (ML) and generalized method of moments (GMM), but these methods may be less effective in this context than is often presumed.

At the heart of the matter is the point that reduced-form macro-finance models are obviously an *approximate representation* of data, and hence not very compatible with the classical premise of having the “true model.” Though it goes without saying that all models in economics and finance are approximate, this point is particularly relevant here in view of the atheoretical (statistical) nature of many of the macro-finance models and the large number of parameters. For instance, it is not clear that the ML or GMM criterion function of these models should contain a unique meaningful maximum; there might be different maxima which capture different aspects of data with differing degree of emphasis. The small sample problems discussed above adds to the difficulty, as they make asymptotic statistics a poor guide to finite sample properties.

Let us now consider specific difficulties with certain classical procedures. In some implementations the fit of certain unconditional moments are used either as an estimation condition (e.g., Brandt and Chapman (2003)) or as a diagnostic check (ABW (2007b)), for example,

$$(52) \quad \begin{aligned} E(y_{\tau,t}) &= \frac{1}{T} \sum_{t=1}^T y_{\tau,t} \\ E(y_{\tau,t} y_{\tau',t-j}) &= \frac{1}{T} \sum_{t=1}^T y_{\tau,t} y_{\tau',t-j}, \end{aligned}$$

and so on. As discussed above, nonstationary (unit-root) scenario cannot be dismissed easily for the “approximate model”, but trying to match the moment conditions (52) in this case is pointless: the right-hand side numbers are finite, while the left-hand side numbers infinite (or indefinite). In the case of near-nonstationarity, the left-hand side numbers are finite, but the proximity to the unit root boundary means that they are likely to be very inaccurate estimates, so that “how close the unconditional moments are to sample moments” could be a poor guide to a model estimation or evaluation.⁴²

Many of the classical estimation approaches implicitly minimize fitting errors for the one-period-ahead conditional moments. For example, the ML estimation can be viewed as minimizing the one-period prediction errors or the errors in the fit of the “likelihood score moments” ($\frac{\partial}{\partial \theta} \log f(y_t|y_{t-1}, \theta)$) in a GMM framework. While in theory this could yield an asymptotically correct estimate of the true model (if the true model exists), the inherently approximate nature of model means that fitting the one-period moments as closely as possible might come at the expense of other aspects of the model. Cochrane and Piazzesi (2006) in effect make this point when they note that conventionally estimated affine models may have difficulty producing the kind of term premia that they find based on regressing multi-period (one-year) excess returns on a set of forward rates.

In macro-finance models, the reliance on the one-period-ahead conditional moments could be further compromised by the complexity of relatively high-frequency macro data. A rather striking demonstration is provided by a comparison of the “quarterly inflation” measured in two ways: quarterly inflation based on the CPI values in the middle month of each quarter, π_t^{mid} (e.g., log CPI difference between May and February) and in the last month of each quarter, π_t^{last} (e.g., log CPI difference between June and March). The sample one-lag autocorrelations $corr(\pi_t^{mid}, \pi_{t-1}^{mid})$, $corr(\pi_t^{last}, \pi_{t-1}^{last})$ based on the 1960-2006 sample are 0.79 and 0.67, respectively. Considering that the only difference between π_t^{mid} and π_t^{last} is the one-month shift in the definition, this is a large discrepancy. This effect is even more pronounced in the 1984-2006 sample, which gives $corr(\pi_t^{mid}, \pi_{t-1}^{mid}) = 0.33$ and $corr(\pi_t^{last}, \pi_{t-1}^{last}) = -0.04$. This is largely due to a very sharp rise and reversal in the one-month total CPI inflation in 2005 (as can be seen in Figure 1a); one version of the quarterly CPI inflation (π_t^{last}) is picking this up and the other (π_t^{mid}) is not. Ang, Bekaert, and Wei (2007b) look at lagged autocovariance terms based on π_t^{last} as a part of their diagnostic check, but nothing in theory says that π_t^{last} is more valid than π_t^{mid} . Thus it is difficult to take either $corr(\pi_t^{mid}, \pi_{t-1}^{mid})$ or $corr(\pi_t^{last}, \pi_{t-1}^{last})$ too seriously.⁴³

⁴²One indication of the problem may be the occurrence in Brandt and Chapman (2003) of *no-solution* cases in the inversion of state variables from yields (quadratic equation) in the quadratic-Gaussian model estimated by fitting “economic” unconditional moments (despite the good fit of these moments).

⁴³Incidentally, $corr(\pi_t, \pi_{t-1})$ is the persistence coefficient of the AR(1) model. It can be seen that even the value of the higher of the two ($corr(\pi_t^{mid}, \pi_{t-1}^{mid}) = 0.33$) is quite low, but this does not necessarily imply a reduced persistence of inflation expectations (as discussed in a footnote in Section 5.2).

5.4. How can we evaluate models? The above discussion suggests that looking at the fit of the moments that are often used in the classical estimation might not necessarily be a good criterion for model evaluation.

Some papers *do* look directly at practical implications of the model, such as the multi-period forecasts of inflation and interest rates. Indeed, in view of the fact that the second moment aspects of affine-Gaussian models are trivial, much attention has focused on these conditional first moments (the forecasting performance) as a part of diagnostic criteria, as in Ang and Piazzesi (2003), HTV (2006), and Moench (2006).

However, it is unclear to what extent summary measures of forecasting performance examined in these papers can help with model evaluation/selection. To be sure, looking at the forecasting performance can be useful for detecting problematic models. In Duffee (2002), for example, interest rate forecast RMSEs that are substantially larger than the random-walk benchmark were used to highlight problems with certain stochastic-volatility no-arbitrage models (e.g., the $EA_2(3)$ specification). Similarly, the inflation forecast RMSEs based on ABW (2007a)'s no-arbitrage models that are substantially larger than the univariate inflation model benchmark may signal problems with the no-arbitrage models that they have used.

Nonetheless, the RMSE measures for in-sample or out-of-sample forecasts are often ineffective in discriminating between models. For instance, ABW (2007a) obtain very similar RMSEs for the one-year out-of-sample inflation forecasts from the AR(1) and the ARMA(1,1) models, although the AR(1) model implies qualitatively quite different inflation expectations than the ARMA(1,1) model as discussed in Sec 3.3.

Furthermore, because a large part of the inflation and interest rate variations are an unforecastable variation, the RMSEs themselves may have substantial uncertainty (sampling variability).⁴⁴ Thus, it may happen that the “true model” generates a RMSE that is no smaller than some other models. In this sense, it may be actually misleading to focus on the RMSE as a criterion for selecting the model that best describes the reality. In the case of in-sample forecasts, this problem is exacerbated by the possibility that RMSEs are artificially pushed down due to the use of “future information” in the generating the forecast, making interest rates and inflation look more forecastable than they actually are.

Often there are cases in which classical criteria cannot easily tell if a model's output is unreasonable, while practitioners can do so using “judgmental information.” For instance, many macro-finance models estimated with data going back to 1970s generate current (circa 2006) long-horizon inflation expectation that exceeds 4%. (Recall also the AR and ARMA model outputs in Figure 2b.) Though long-horizon expectations are difficult to evaluate on purely econometric grounds as there are not many non-overlapping observations, most policy makers and market participants would immediately say that

⁴⁴Clark and McCracken (2006) emphasize that out-of-sample inflation forecast RMSEs may have weak power.

4% long-horizon CPI inflation expectation is too high; hence models with such an output may fail the test of relevance, before any statistical tests.⁴⁵

Note also that even if two models generated similar forecast RMSEs, practitioners could have a very different assessment of them, depending on the details of the forecast errors from the models (such as the direction of the errors). In the 1990s inflation data often came in on the “low” side, and it is widely believed that not all of this had been predicted by market participants, i.e., the “true” market forecast of inflation in this period likely contained a mild upward bias.⁴⁶ Even if there existed a model that generated an unbiased forecast or a forecast with bias in the opposite direction (which would have forecasted inflation better), I doubt whether policy makers would view such a forecast as a realistic description of the market expectation.⁴⁷

These discussions highlight the role of the larger information set of practitioners (as compared to academic researchers). Unfortunately, much of this extra information is difficult to cast in the formal language of statistical tests, and the proper evaluation of models remains a challenge for macro-finance modeling.

5.5. Would a Bayesian approach help? The use of the Bayesian techniques to address problems with conventional (classical) estimation has a long history, but a particularly relevant early example is the Bayesian approach to the VAR forecasting. As discussed in Sections 3.5 and 5.1, unrestricted VARs share some of the key problems encountered in flexibly specified macro-finance models, in particular, the statistical (atheoretical) nature of the specification and the tendency for overparametrization. Litterman

⁴⁵The financial press has often noted that the upper boundary of Fed’s “comfort zone” of inflation is currently (circa 2006) 2% for the PCE inflation. Persistent differential between annual PCE and CPI inflation of 30~40 b.p. then puts the upper boundary for the CPI inflation comfort zone at about 2.4%. In September 2006, annual core CPI inflation locally peaked at 2.9%. Most policy makers’ speeches at the time gave an the impression that they viewed this number as high, suggesting that the trend inflation should be lower. In this environment it seems difficult to justify a long-term CPI inflation expectation that is substantially higher than 3%. (Incidentally, the Michigan survey of consumers gives inflation expectation in excess of 3%, but there are problems in interpreting the Michigan survey as a forecast of the CPI inflation. See, e.g., D’Amico, Kim and Wei (2007).) A number like 4% for a long-horizon inflation expectation is likely due that fact that sample mean of inflation (for samples going back to the 70s) is in that neighborhood; recall the discussion of small sample problems in Section 5.2.

⁴⁶Kohn (1999) provides an account of the fact that the FOMC’s forecasts (in the semiannual report to the Congress) as well as the Fed staff’s forecasts overpredicted inflation. Private sector economists also did the same, as can be seen from survey forecasts; see, for example, Croushore (1998).

⁴⁷Though an “unbiased” multi-period forecast is often viewed as a consequence of rational expectations, to obtain it one needs tight assumptions that are difficult to justify in reality, in particular, the assumptions that there is a relatively simple, structurally stable model of the economy and that the agents fully know this structure. More realistic rational expectations hypotheses that relax these restrictions, e.g., models that allow for learning and time-varying structure, are consistent with biased expectations in “small” samples.

(1986) and others have documented that a Bayesian implementation with an informative prior (“random walk prior”) can generate better results than the classical implementation. This gives an encouragement to take up a Bayesian strategy to address the empirical difficulties with macro-finance models.

In the macro-finance context, Ang, Dong, and Piazzesi (2005) have in fact already proposed a Bayesian approach, but it is not clear that the particular priors that they use would help overcome the problems with classical estimation discussed above. ADP state that except for the condition that the model be stationary their priors are *uninformative*. However, to the extent that the main problem with the classical estimation of macro-finance models is that the data by themselves are not fully informative about the model (especially as regards the overfitting and small-sample problems), it is difficult to see how uninformative priors would solve the problem. Recall that the superior performance of the Bayesian VARs (over the conventionally estimated unrestricted VARs) came from having an *informative* prior.

When ADP (2005) tried to estimate their model using a classical method (maximum likelihood estimation), they found that the estimated model explained most of the term structure movements in terms of the latent factor, leaving little role for macro variables to explain yield curve movements,⁴⁸ an outcome that is unappealing from the viewpoint of making a connection between the macroeconomy and the yield curve. However, even granting the problems with classical methods, there may be a reason for this, namely that the estimation marginalizes the macro variables to avoid the counterfactual implication that shocks to inflation have a tight relation to the yield curve movements. This is a specification issue, i.e, one has to deal with “unspanned” variation in macro variables in the model. Addressing the problem purely as an estimation issue may lead to problems elsewhere in the model.

In my view, the main challenge for a Bayesian implementation is in coming up with suitable *informative* priors. This is particularly the case when there are latent factors in the model (external basis models with latent factors or internal basis models): because the economic meaning of many of the individual parameters related to the latent factors is unclear, it is difficult to provide sensible priors for them.

For illustration, consider a 3-factor internal-basis nominal-yields-only version of the affine-Gaussian model (1). This model can be normalized in different ways, as discussed in Appendix A. Suppose one has chosen certain normalization. To “simplify” the model, one could try to impose a prior that Λ_b is a diagonal matrix:

$$(53) \quad \Lambda_{b,i \neq j} \sim \mathcal{D}(0, \sigma^2).$$

where \mathcal{D} stands for some *a priori* distribution. However, this diagonal structure is no longer preserved when the model is converted to another normalization.⁴⁹ Because there

⁴⁸Private conversation with Andrew Ang. ADP’s paper (2005) itself does not describe the specifics of the outcome from the classical estimation of their model.

⁴⁹To be concrete, suppose that one is using the normalization given by eq. (65) in Appendix A. The model can be expressed in another normalization, eq. (55), using the invariant transformation (64).

is no special reason to choose one normalization over another, the parsimony implied by priors like (53) is partly illusory.⁵⁰

By stating priors about the variables that have direct economic meaning, like inflation expectations, interest rate expectations, and expected bond returns, one can get around this problem of normalization dependence: surely these variables must be normalization independent. Recall also that the source of the small sample problem is the difficulty of estimating the parameters related to expectations (in the physical measure), thus imposing priors on these variables would help alleviate the problem. A prior about the 10-year inflation expectation, for example, can be expressed as

$$(54) \quad i_{10Y,t}^e = a_{10Y}(\theta) + b(\theta)'_{10Y} x_t(\theta) \quad \sim N(\mu_t, \sigma_t^2),$$

θ denoting the model parameters collectively. For μ_t , one can use a survey median forecast. Setting $\sigma_t = \infty$ corresponds to having no priors on i_{10Y}^e . Setting σ_t at a value that is large, but not large enough to be irrelevant, can be viewed as a quasi-informative prior. Other Bayesian priors that are based on economic concepts and mechanisms may be also utilizable.⁵¹

A statement like (54) can be conveniently incorporated within a Kalman-filter setting. Running a Kalman-filter-based ML estimation with with survey median (or mean) forecast (of interest rates and/or inflation) as a noisy proxy, as in D’Amico et al (2007), can be viewed as a “poor man’s Bayesian” implementation, the point estimate serving as the mode of the Bayesian posterior.

6. UNDERSTANDING THE SUPERIOR PERFORMANCE OF SURVEY FORECAST

The specification and implementation problems discussed so far may help explain why macro-finance models, which use *more* information than the past inflation data, could generate *poorer* results than simple univariate inflation models. But is the yield curve information useful at all for inflation forecasting? Why do survey forecasts perform better than univariate models (and other models)?

One reason ABW (2007a) offer for the superior performance of survey forecasts is that survey participants have more information about the economy than econometricians. This is in line with the point made in Sec 5.4 that informational differences may create a wedge between a practitioner’s and an academic researcher’s evaluation of a model. But it is worth exploring this issue further.

One could plausibly expect that survey forecasts may have advantages at least at short horizons, in that a potentially vast amount of information that is relevant for forecasting the near-term inflation might not be easily summarizable in terms of a small number of

⁵⁰Note that if *all* the parameters of the Λ_b matrix are set to 0 (an “expectations hypothesis prior”), this *is* invariant under different normalizations. However, specifying this prior as $\Lambda_{b,ij} \sim \mathcal{D}(0, \sigma^2)$ may still be problematic, in the sense that the information about σ might not be normalization independent.

⁵¹“Structural” priors can be also imposed in a Bayesian setting, as in the dynamic stochastic general equilibrium (DSGE) modeling literature.

variables.⁵² It may be thus instructive to examine the near-term expectations in surveys and how they are linked to longer-term expectations (i.e., the *term structure* of survey inflation forecasts).

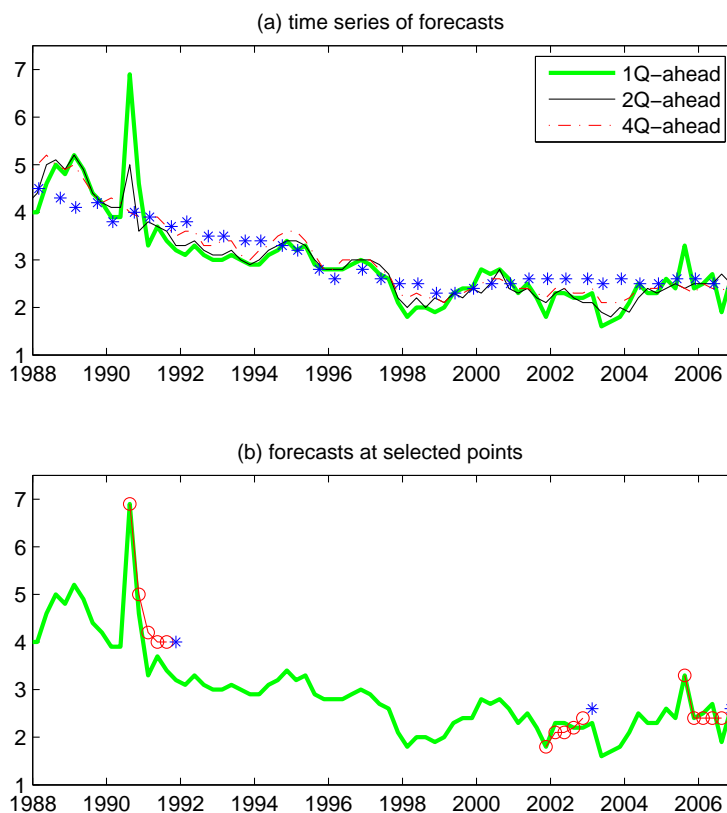


Figure 4: Forecast of US quarterly CPI inflation from the Blue Chip Financial Forecasts (BCFF). The * symbol in Figures (a) and (b) denotes the long-horizon BCFF survey. (In Figure (b) it is plotted at the 6-quarter-ahead position.)

Fortunately, fairly detailed information about the near-term term structure of survey inflation expectations can be obtained, as survey forecasts like SPF and BCFF surveys provide CPI inflation forecasts up to the next four or more quarters. Figure 4a shows the one-quarter-ahead, two-quarters-ahead, and four-quarters-ahead CPI inflation forecasts from the Blue Chip Financial Forecasts (BCFF) survey, based on the surveys published

⁵²It may be useful to recall here that in the ARMA(1,1) model and the two-component model in Section 3.3, the one-period inflation forecast based on $E_t(\pi_{t+1}|\pi_t, \pi_{t-1}, \dots)$ can be different from and less efficient than a forecast based on a larger information set.

in January, April, July, and October (taken at the end of December, March, June, and September), from 1988 to 2006. The BCFF long-horizon forecast (inflation expected between the next five to ten years), available twice a year, is also shown. It is notable that this long-horizon forecast, which can be viewed as a “quasi-long-run” mean of inflation, has moved about (shifted down) significantly. It is also notable how quickly the multi-period forecasts approach the quasi-long-run value. Not only is the 4-quarters-ahead forecast already quite similar to the long-horizon forecast, but also the 2-quarters-ahead forecast is.

Figure 4b further visualizes this point by showing the term structure of inflation expectations out to the next four quarters at several moments when the one-quarter-ahead forecasts were at their local peaks or troughs. Particularly interesting is the case of 1990Q3, when the one-quarter-ahead inflation expectation peaked. The expectations for longer horizons show that even then the survey participants expected inflation to come down quickly to the quasi-long-run level. A more recent example is 2005Q3, in which one-quarter-ahead expectation had risen amid rising oil prices and other near-term inflation pressures. Again, however, this was viewed as a temporary rise that would dissipate quickly. Thus one comes to a somewhat paradoxical conclusion that “the long-term is quite near.”

To get further insights into the survey forecasts, it is useful to compare them with *ex post* realized inflation and the real-time forecasts from the ARMA(1,1) model. Figure 5a shows the one-quarter-ahead inflation forecasts based on the BCFF survey and the ARMA(1,1) model (20-year rolling sample forecast), as well as the realized one-quarter inflation (π_t plotted at $t - 1$). The one-quarter-ahead survey forecast is seen to be less jagged than the ARMA(1,1) forecast. The ARMA forecast’s jaggedness comes from the fact that ARMA is a univariate model, thus the near-term forecast can depend substantially on the recent realized inflation. (When the previous period’s realized inflation is high, current period’s inflation expectation tends to be high.) The RMSEs of the one-quarter-ahead forecast are 1.19% and 1.40% (annual percentage unit) in the 1988-2006 period for the survey forecast and the ARMA(1,1) model, respectively; thus the survey indeed performed better. Nonetheless, much of the realized inflation is missed by the survey forecast. Granting the caveat that surveys might not necessarily be the best possible forecast, this still suggests that a substantial part of short-run inflation is genuinely unforecastable *ex ante*, lending support to a formulation like the two-component model (32) in which the inflation process is separated into a trend inflation component and an unforecastable component.

Let us now examine the inflation forecast that most studies focus on, namely the one-year inflation forecast. Figure 5b shows the one-year forecasts based on the BCFF survey and the ARMA(1,1) model, along with the realized one-year inflation ($\pi_{t,t-1Y}$ plotted at $t - 1Y$). For reasons that will become clear soon, both the ARMA(1,1) forecasts from an expanding sample and from a rolling sample are shown. The ARMA forecasts produce substantially larger RMSEs than the survey forecast (1.04% for the 20-year rolling sample ARMA, 1.15% for the expanding sample ARMA, 0.76% for the

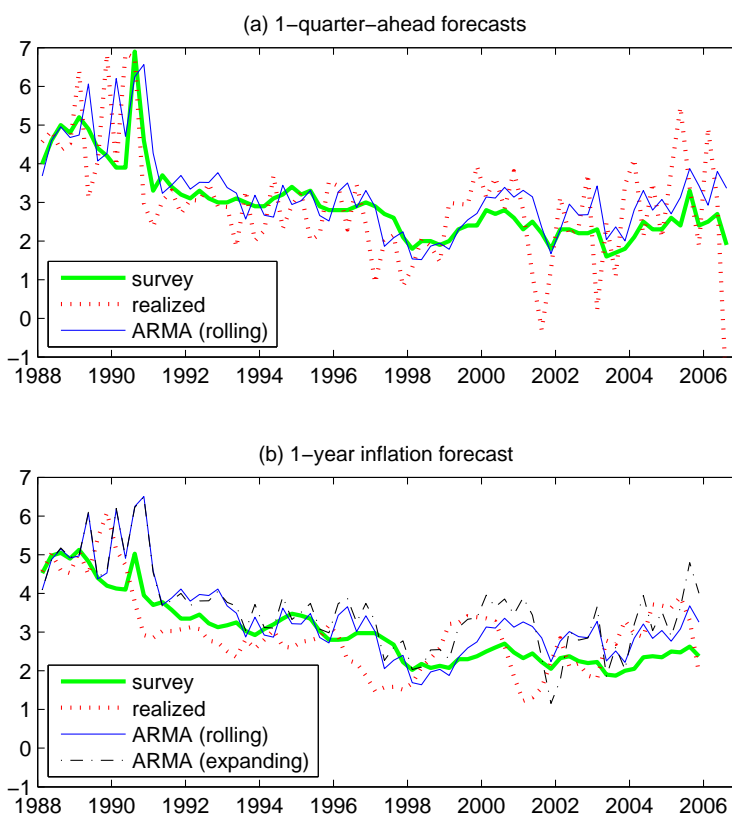


Figure 5: Comparison of the realized CPI inflation, BCFF survey forecast, and the ARMA(1,1) model forecasts.

survey). Since one fourth of the one-year forecast is the one-quarter-ahead forecast (i.e., $E_t(\pi_{t+1Y,t}) = \frac{1}{4}E_t(\pi_{t+1}) + \frac{1}{4}E_t(\pi_{t+2} + \pi_{t+3} + \pi_{t+4})$), the superior one-quarter-ahead survey forecast explains part of this. But a still more basic reason for the superior forecast of the survey is that the ARMA model-based forecasts substantially overpredicted inflation in the 1990s. It can be seen that the ARMA forecasts lie notably above the realized inflation (and survey forecast). This overprediction is due in large measure to the fact that the ARMA model in real time tended to generate “too high” values of the long-run mean level (μ in eq. (28)) to which the forecasts are converging.

This is illustrated in Figure 6, where the long-run mean parameter μ from the expanding sample estimation is seen to lie significantly above the long-horizon survey forecast. Because the expanding sample includes periods of high inflation (70s and early 80s), the estimated mean does not fall quickly with declining inflation in the 80s and 90s. The use of the 20-year rolling sample produces lower μ (than the expanding sample) as

the estimation sample moves away from those periods, but still the adjustment in the long-run mean is not fast enough, compared with the surveys.⁵³

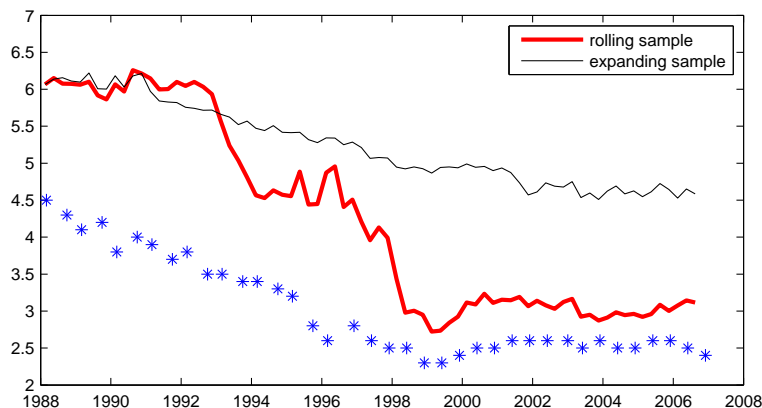


Figure 6: Long-run means from the ARMA(1,1) model estimations of US quarterly inflation data. The long-horizon BCFF survey inflation forecast is also shown (* symbol).

The key point that emerges from this discussion is that surveys produce a more successful forecast of inflation in large part because they capture the *trend component* of inflation better than time-series models like the ARMA(1,1) model. In stationary time series models (e.g., models in Figure 5), forecasts tend to converge to a value close to the sample mean, while nonstationary models put too much weight on recent past; thus there is scope for judgmental information to play a role, especially if trend inflation varies significantly over time. These considerations shed light on the attention that policy makers pay to long-term inflation expectations (better indicator of the trend inflation than realized inflation) and also on the use of judgmental forecasts at central banks like the Federal Reserve.

The importance of modeling the variation of long-term expectations deepens the challenge for macro-finance models: besides the specification challenge, the nearly nonstationary nature of the inflation process indicated by the substantial variability of long-term survey forecasts poses considerable empirical difficulties (discussed in Section 5). These challenges notwithstanding, the discussions in this paper can be viewed as encouraging for attempts to use term structure models to extract inflation expectations: it

⁵³ABW (2007a) also note that survey forecasts' ability to quickly adapt to major changes in the economic environment contributes to the superior performance of the surveys. While the majority of ABW's estimations were done with expanding samples, they also examine the forecast RMSEs based on rolling-sample estimation for a subset of their models. Because their rolling sample (10 years) is shorter than the 20-year rolling sample used here, ABW's rolling-sample results are even closer to the surveys. For example, the ratio of the AR model RMSE and the survey RMSE in the post-1995 window is 0.879/0.861, very close to 1.

makes intuitive sense that the yield curve contains, at least, information about trend inflation, and the indication that the near-term informational advantage of surveys seems to wear out quickly (beyond a few quarters) gives some hope that models could capture much of the variation in inflation expectations and compete with surveys.⁵⁴

7. CONCLUDING REMARKS

I conclude this paper with a recapitulation of some of the key points and some remarks on how they are related to each other and to other points also made. In particular, consider the following points: (1) Not all of the variation in key macro variables is related to yield curve movements. (2) The yield curve contains useful information about the *trend* component of inflation. (3) The no-arbitrage principle might not be sufficient to guarantee sensible outputs from macro-finance models in practice.

As I have stressed in Section 2, the spanning argument is the basis of the no-arbitrage framework; hence the presence of a short-run inflation component that is not related to yield curve movements may undermine the validity of the models that use inflation as a state variable. Such a component may also cause difficulties in the estimation stage as well, since taking too seriously the one-period conditional moments that involve it may not be justified (Section 5.3). Furthermore, they may cause special difficulties when one tries to go beyond the affine-Gaussian setup to model time-varying uncertainties about macro variables explicitly. For example, as discussed in Section 4.2, monthly CPI inflation in recent years has been more volatile than in the 1990s, but there isn't strong evidence that this is reflected in the yield curve (e.g., as an increased term premium); an attempt to link them may thus lead to greater specification errors.

I have also argued in this paper that much of the “spanned” component of inflation (the part of inflation that *is* related to the yield curve) is about the *trend component* (whose importance was stressed in the discussion in Section 6 of why surveys perform better). This can help resolve the puzzle that the “conventional wisdom” that the change in nominal yields often reflects changes in inflation expectations dies hard, despite the poor performance of inflation forecasting models involving term structure variables. In some sense, the latent-factor models can be viewed as a way to represent market's implicit processing (filtering) of information.

No-arbitrage models of the term structure have been viewed as a promising way to go beyond the restrictive assumptions implicit in the expectations hypothesis (about

⁵⁴Although ABW (2007a) find that survey forecasts cannot be improved by combination with models that they consider, few policy makers would regard survey forecasts as the ultimate measure of inflation expectations. Consider, for example, the fact that between 1999 and 2006 the 10-year CPI inflation expectation from the SPF survey has been almost stuck at 2.5%. While there is a broad consensus that long-term inflation expectations were “better anchored” in the 2000s than in the earlier decades, it may be a stretch to regard that long-term inflation expectation has become so well anchored as to be practically immovable. This may be one example in which the yield curve contains useful information that is unavailable in the SPF survey.

how risk is incorporated in the yield curve). However, reduced-form affine-Gaussian no-arbitrage models with flexible specification of market price of risk can quickly become “too unrestrictive”, with a profusion in the number of parameters of the market price of risk. In other words, the no-arbitrage principle by itself may be too weak to provide enough discipline in the model. Note also that the two technical problems with estimation discussed in Section 5 (overfitting and small sample problems) can be viewed as an extension of the specification discussion, as the main source of the problems can be viewed as there being not enough information in the data or not enough structure in the model. Coming up with an effective and non-*ad hoc* structure on the market price of risk and other parameters of macro-finance models thus remains an important challenge for these models.

APPENDIX A. DERIVATION OF THE MAXIMALLY IDENTIFIED MODELS

This Appendix shows that any n -dimensional “yield-only” internal basis affine-Gaussian model (1) whose feedback matrix has all-real eigenvalues can be transformed to the normalized form

$$(55) \quad \tilde{\mathcal{K}} = \begin{bmatrix} \kappa_1 & 0 & 0 \\ 0 & \kappa_2 & 0 \\ 0 & 0 & \kappa_3 \end{bmatrix}, \quad \tilde{\Sigma} = \begin{bmatrix} 1 & 0 & 0 \\ \Sigma_{21} & 1 & 0 \\ \Sigma_{31} & \Sigma_{32} & 1 \end{bmatrix}, \quad \tilde{\mu} = 0_{3 \times 1}, \quad \tilde{\rho}_o, \quad \tilde{\rho}, \quad \tilde{\lambda}_a, \quad \tilde{\Lambda}_b,$$

written out for the case $n = 3$. Note that we have specified $\mathcal{K} \equiv I - \Phi$, instead of Φ , and matrices and vectors that are not fully written out are unrestricted.

First, diagonalize the \mathcal{K} matrix, i.e., write

$$(56) \quad \mathcal{K} = PDP^{-1},$$

where D is the diagonal matrix consisting of the eigenvalues of \mathcal{K} . Now, make an invariant transformation $x \rightarrow z = P^{-1}(x - \mu)$. Then

$$(57) \quad \Delta z_{t+1} = -Dz_t + P^{-1}\Sigma\epsilon_t.$$

Define an new normal random vector e_t ,

$$(58) \quad e_t = \mathcal{O}\epsilon_t,$$

with an orthogonal matrix \mathcal{O} (i.e., $\mathcal{O}\mathcal{O}' = I$) such that $P^{-1}\Sigma\epsilon_t = We_t$, where W is a lower triangular matrix. This can be easily constructed by making use of the Cholesky decomposition, i.e.,

$$(59) \quad W = chol(\Omega), \quad \Omega = P^{-1}\Sigma\Sigma'P^{-1'} = WW'.$$

Thus we have

$$(60) \quad \mathcal{O} = W^{-1}P^{-1}\Sigma.$$

Now, define $\tilde{x} = Sz$, where S is a diagonal matrix whose diagonal elements are the inverse of the diagonal elements of W , i.e.,

$$(61) \quad S = (diag(W))^{-1}.$$

We have

$$(62) \quad \Delta \tilde{x}_{t+1} = -D\tilde{x}_t + Te_t,$$

where

$$(63) \quad T = SW$$

is by construction a lower triangular whose diagonal elements are 1's. We can now express the pricing kernel in terms of \tilde{x}_t and e_t , for example, $\lambda'_t \epsilon_{t+1} = \tilde{\lambda}'_t e_t$ implying $\tilde{\lambda}_t \equiv \tilde{\lambda}_a + \tilde{\Lambda}_b \tilde{x}_t = \mathcal{O}\lambda_t$.

The model parameters (denoted with tildes) in the new normalization are given by the old model parameters as follows:

$$(64) \quad \begin{aligned} \tilde{\mathcal{K}} &= D, \quad \tilde{\Sigma} = T, \quad \tilde{\rho}_o = \rho_o + \rho' \mu, \quad \tilde{\rho} = S^{-1} P' \rho, \\ \tilde{\lambda}_a &= \mathcal{O}(\lambda_a + \Lambda_b \mu), \quad \tilde{\Lambda}_b = \mathcal{O} \Lambda_b P S^{-1}, \end{aligned}$$

where D, P, S, \mathcal{O}, T were defined in eqs. (56), (60), (61), and (63).

Therefore, a normalization like the following,

$$(65) \quad \mathcal{K} = \begin{bmatrix} \kappa_{11} & 0 & 0 \\ \kappa_{21} & \kappa_{22} & 0 \\ \kappa_{31} & \kappa_{32} & \kappa_{33} \end{bmatrix}, \quad \Sigma = I_{3 \times 3}, \quad \mu = 0_{3 \times 1}, \quad \rho_o, \quad \rho, \quad \lambda_a, \quad \Lambda_b,$$

is equivalent to the normalization in eq. (55), i.e., it can be written in the form of eq. (55) through an invariant transformation (64).

APPENDIX B. BIAS IN THE MISHKIN REGRESSION

This appendix presents a heuristic demonstration of a bias in the Mishkin regression. Suppose that nominal yields are entirely inflation expectations (no real yield component). Thus,

$$(66) \quad y_{\tau,t} = E(\pi_{t+\tau,t})$$

for general τ . Now suppose that the inflation process is given by the bivariate model, eq. (32), in which case $y_{\tau,t}$ takes the form

$$(67) \quad y_{\tau,t} = \alpha_\tau(\phi) \chi_t,$$

where

$$(68) \quad \alpha_\tau(\phi) \equiv (1 - \phi^\tau) / (\tau(1 - \phi)).$$

It is well known that ϕ tends to be downward biased in the conventional estimation. Thus, we can write heuristically

$$(69) \quad \pi_{t+\tau,t} = \alpha_\tau(\phi^*) \chi_t + e,$$

where $\phi^* < \phi$. Thus,

$$(70) \quad \pi_{t+\tau,t} - \pi_{t+u,t} = (\alpha_\tau(\phi^*) - \alpha_u(\phi^*)) \chi_t + e.$$

Using eq. (67), this can be written

$$(71) \quad \pi_{t+\tau,t} - \pi_{t+u,t} = \beta(y_{\tau,t} - y_{u,t}) + e,$$

where

$$(72) \quad \beta = \frac{\alpha_\tau(\phi^*) - \alpha_u(\phi^*)}{\alpha_\tau(\phi) - \alpha_u(\phi)}.$$

It can be shown that for $\phi^* < \phi$, we have $\beta > 1$.

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