

FEDERAL RESERVE BANK OF SAN FRANCISCO

WORKING PAPER SERIES

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April 2012

Working Paper 2011-12

<http://www.frbsf.org/publications/economics/papers/2011/wp11-12bk.pdf>

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Correcting Estimation Bias in Dynamic Term Structure Models*

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First version: April 4, 2011

This draft: April 2, 2012

Abstract

The affine dynamic term structure model (DTSM) is the canonical empirical finance representation of the yield curve. However, the possibility that DTSM estimates may be distorted by small-sample bias has been largely ignored. We show that conventional estimates of DTSM coefficients are indeed severely biased, and this bias results in misleading estimates of expected future short-term interest rates and of long-maturity term premia. We provide a variety of bias-corrected estimates of affine DTSMs, both for maximally-flexible and over-identified specifications. Our estimates imply short rate expectations and term premia that are more plausible from a macro-finance perspective.

Keywords: small-sample bias correction, vector autoregression, dynamic term structure models, term premium

JEL Classifications: C53, E43, E47

*We thank Jim Hamilton, Chris Hansen, Oscar Jorda, Lutz Kilian, and Jonathan Wright for their helpful comments, as well as participants of research seminars at the Federal Reserve Bank of San Francisco and UC San Diego, and of the Econometric Society 2011 Winter Meetings, the European Economic Association 2011 Conference, the Society for Computational Economics 2011 Conference, and the Society of Financial Econometrics 2011 Conference. The views in this paper do not necessarily reflect those of others in the Federal Reserve System.

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1 Introduction

The affine Gaussian dynamic term structure model (DTSM) is the canonical empirical finance representation of the yield curve, used to study a variety of questions about the interactions of asset prices, risk premia, and economic variables. One question of fundamental importance to both researchers and policymakers is to what extent movements in long-term interest rates reflect changes in expected future policy rates or changes in term premia. The answer to this question depends on the estimated dynamic system for the risk factors underlying yields, which in affine DTSMs is specified as a vector autoregression (VAR). Because of the high persistence of interest rates, maximum likelihood (ML) estimates of such models likely suffer from serious small-sample bias. Namely, interest rates will be spuriously estimated to be less persistent than they really are. While this problem has been recognized in the literature, no study to date has attempted to obtain bias-corrected estimates of a DTSM, quantify the extent of estimation bias, or assess the implications of that bias for economic inference. In this paper we provide a readily applicable methodology for bias-corrected estimation of both maximally-flexible (exactly identified) and restricted (over-identified) affine DTSMs. Our estimates uncover significant bias in standard DTSM coefficient estimates and show that accounting for this bias substantially alters economic conclusions.

The bias in ML estimates of the VAR parameters in an affine DTSM parallels the well-known bias in ordinary least squares (OLS) estimates of autoregressive systems. Such estimates will generally be biased toward a dynamic system that displays less persistence than the true process. This bias is particularly severe when the estimation sample is short and the dynamic process is very persistent. Empirical DTSMs are invariably estimated under just such conditions, with data samples that contain only a limited number of interest rate cycles. Hence, the degree of interest rate persistence is likely to be seriously underestimated. Consequently, expected future short rates will appear to revert too quickly to their unconditional mean, resulting in spuriously stable estimates of risk-neutral rates. Furthermore, the estimation bias that contaminates readings on expected future short rates also distorts estimates of long-maturity term premia.

While the qualitative implications of the small-sample DTSM estimation bias are quite intuitive, the magnitude of the bias and its impact on inference about expected short-rate paths and risk premia have been unclear. The ML methods typically used to estimate DTSMs were intensive, “hands-on” procedures because these models exhibited relatively flat likelihood surfaces with many local optima.¹ The computational burden of estimation effectively

¹Studies that describe these problems include Hamilton and Wu (2010) and Christensen et al. (2011).

precluded the application of simulation-based bias correction methods. However, recent work by Joslin et al. (2011) (henceforth JSZ) and Hamilton and Wu (2010) (henceforth HW) has shown that OLS can be used to solve part of the estimation problem. We exploit these new procedures to facilitate bias-corrected estimation of DTSMs through repeated simulation and estimation. Specifically, we adapt the two-step estimation approaches of JSZ and HW by replacing the OLS estimates of the autoregressive system in the first step by simulation-based bias-corrected estimates. We then proceed with the second step of the estimation, which recovers the parameters determining the cross-sectional fit of the model, in the usual way. This new estimation approach is a key methodological innovation of the paper.

There are several different existing approaches to correct for small-sample bias in estimates of a VAR, including analytical bias approximations and bootstrap bias correction. While each of these could be applied to our present context, we favor our own novel bias correction procedure for VAR estimation: Our “inverse bootstrap” bias correction finds the data-generating process (DGP) parameters that lead to a mean or median of the OLS estimator equal to the original OLS estimates. While this approach is not conceptually novel—it is closely related to indirect inference (Gourieroux et al., 2000) and to the median-unbiased estimators of Andrews (1993) and Rudebusch (1992)—we provide a new algorithm, based on results from the stochastic approximation literature, that allows us to quickly and reliably calculate bias-corrected estimators.

We first apply our methodology for bias-corrected DTSM estimation to the maximally-flexible DTSM that was estimated in JSZ. In this setting, the ML estimates of the VAR parameters are exactly recovered by OLS. Using the authors’ same model specifications and data samples, we quantify the bias in the reported parameter estimates and describe the differences in the empirical results when the parameters governing the factor dynamics are replaced with bias-corrected estimates. We find a very large estimation bias in JSZ. That is, the conventional estimates of JSZ imply a severe overestimation of the speed of interest rate mean reversion. As a result, the decomposition of long-term interest rates into expectations and risk premium components differs in statistically and economically significant ways between conventional ML and bias-corrected estimates. Risk-neutral forward rates, i.e., short-rate expectations, are substantially more volatile after correction for estimation bias, and they show a pronounced decrease over the last twenty years, consistent with lower longer-run inflation and interest rate expectations documented in the literature (Kozicki and Tinsley, 2001; Kim and Orphanides, 2005; Wright, 2011). Furthermore, bias correction leads to term premia that are elevated around recessions and subdued during expansions, consistent with much theoretical and empirical research that supports countercyclical risk compensation.

In our second empirical application, we estimate a DTSM with overidentifying restrictions. HW show that any affine DTSM—maximally-flexible or overidentified—can be estimated by first obtaining reduced-form parameters using OLS and then calculating all structural parameters via minimum-chi-squared estimation. Many estimated DTSMs impose parameter restrictions to avoid overfitting and to facilitate numerical optimization of the likelihood function (examples include Ang and Piazzesi, 2003; Kim and Wright, 2005; Joslin et al., 2010). Restrictions on risk pricing (Cochrane and Piazzesi, 2008; Bauer, 2011b; Joslin et al., 2010) have an additional benefit: They exploit the no-arbitrage condition, which ties the cross-sectional behavior of interest rates to their dynamic evolution, to help pin down the estimates of the parameters of the dynamic system. In this way, such restrictions could potentially reduce the bias in the estimates of these parameters. However, we find that the bias in ML estimates of a DTSM with risk price restrictions is large, indeed, similar in magnitude to our results for the maximally-flexible model. While this result may not generalize to all restricted models, it shows that simply zeroing out some risk price parameters will not necessarily eliminate estimation bias.

There are a number of papers in the literature that are related to ours. Several studies attempt to indirectly reduce the bias in DTSM estimates—using risk price restrictions (see above), survey data (Kim and Orphanides, 2005; Kim and Wright, 2005), or near-cointegrated VAR specifications (Jardet et al., 2011)—but do not quantify the bias nor provide evidence as to how much it is reduced. Another group of papers has performed simulation studies to show the magnitude of the bias in DTSM estimates relative to some stipulated DGP (Ball and Torous, 1996; Duffee and Stanton, 2004; Kim and Orphanides, 2005). These studies demonstrate that small-sample bias can be an issue using simulation studies, but do not quantify its magnitude or assess its implications for models estimated on real data. The most closely related paper Phillips and Yu (2009), which also performs bias-corrected estimation of asset pricing models. That analysis parallels ours in that the authors also use simulation-based bias correction and show the economic implications of correcting for small-sample bias. However, their focus differs from ours in that they aim at reducing the bias in prices of contingent claims, whereas we address a different economic question, namely the implications of small-sample bias on estimated policy expectations and nominal term premia.

Our paper is structured as follows: Section 2 describes the model, the econometric problems with conventional estimation, and the intuition of our methodology for bias-corrected estimation. In Section 3, we discuss OLS estimates of interest rate VARs and the improvements from bias-corrected estimates. In Section 4, we describe how to estimate maximally-flexible models with bias correction, apply this methodology to the model of JSZ, and discuss the

statistical and economic implications. We also perform a simulation study to systematically assess the value of bias correction in such a context. In Section 5, we show how to perform bias-corrected estimation for restricted models, adapting the methodology of HW, and apply this approach to a model with restrictions on the risk pricing. Section 6 concludes.

2 Estimation of affine models

In this section, we set up a standard affine Gaussian DTSM, and describe the econometric issues, including small-sample bias, that arise due to the persistence of interest rates. Then we discuss recent methodological advances and how they make bias correction feasible.

2.1 Model specification

The discrete-time affine Gaussian DTSM, the workhorse model in the term structure literature since Ang and Piazzesi (2003), has three key elements. First, a vector of N risk factors, X_t , follows a first-order Gaussian VAR under the objective probability measure \mathbb{P} :

$$X_{t+1} = \mu + \Phi X_t + \Sigma \varepsilon_{t+1}, \quad (1)$$

where $\varepsilon_t \stackrel{iid}{\sim} N(0, I_N)$ and Σ is lower triangular. Time t is measured in months throughout the paper. Second, the short rate, r_t , is an affine function of the pricing factors:

$$r_t = \delta_0 + \delta_1' X_t. \quad (2)$$

Third, the stochastic discount factor (SDF) that prices all assets under the absence of arbitrage is of the essentially affine form (Duffee, 2002):

$$-\log(M_{t+1}) = r_t + \frac{1}{2} \lambda_t' \lambda_t + \lambda_t' \varepsilon_{t+1},$$

where the N -dimensional vector of risk prices is affine in the pricing factors,

$$\lambda_t = \lambda_0 + \lambda_1 X_t,$$

for N -vector λ_0 and $N \times N$ matrix λ_1 . As a consequence of these assumptions, a risk-neutral probability measure \mathbb{Q} exists such that the price of an m -period default-free zero coupon bond

is $P_t^m = E_t^{\mathbb{Q}}(e^{-\sum_{h=0}^{m-1} r_{t+h}})$, and under \mathbb{Q} the risk factors also follow a Gaussian VAR,

$$X_{t+1} = \mu^{\mathbb{Q}} + \Phi^{\mathbb{Q}} X_t + \Sigma \varepsilon_{t+1}^{\mathbb{Q}}. \quad (3)$$

The prices of risk determine how the change of measure affects the VAR parameters:

$$\mu^{\mathbb{Q}} = \mu - \Sigma \lambda_0 \quad \Phi^{\mathbb{Q}} = \Phi - \Sigma \lambda_1. \quad (4)$$

Bond prices are exponentially affine functions of the pricing factors:

$$P_t^m = e^{\mathcal{A}_m + \mathcal{B}_m' X_t},$$

with loadings $\mathcal{A}_m = \mathcal{A}_m(\mu^{\mathbb{Q}}, \Phi^{\mathbb{Q}}, \delta_0, \delta_1, \Sigma)$ and $\mathcal{B}_m = \mathcal{B}_m(\Phi^{\mathbb{Q}}, \delta_1)$ that follow the recursions

$$\begin{aligned} \mathcal{A}_{m+1} &= \mathcal{A}_m + (\mu^{\mathbb{Q}})' \mathcal{B}_m + \frac{1}{2} \mathcal{B}_m' \Sigma \Sigma' \mathcal{B}_m - \delta_0 \\ \mathcal{B}_{m+1} &= (\Phi^{\mathbb{Q}})' \mathcal{B}_m - \delta_1 \end{aligned}$$

with starting values $\mathcal{A}_0 = 0$ and $\mathcal{B}_0 = 0$. Model-implied yields are $y_t^m = -m^{-1} \log P_t^m = A_m + B_m' X_t$, with $A_m = -m^{-1} \mathcal{A}_m$ and $B_m = -m^{-1} \mathcal{B}_m$. Risk-neutral yields, the yields that would prevail if investors were risk-neutral, can be calculated using

$$\tilde{y}_t^m = \tilde{A}_m + \tilde{B}_m' X_t, \quad \tilde{A}_m = -m^{-1} \mathcal{A}_m(\mu, \Phi, \delta_0, \delta_1, \Sigma), \quad \tilde{B}_m = -m^{-1} \mathcal{B}_m(\Phi, \delta_1).$$

Risk-neutral yields reflect policy expectations over the lifetime of the bond, $m^{-1} \sum_{h=0}^{m-1} E_t r_{t+h}$, plus a time-constant convexity term. The *yield term premium* is defined as the difference between actual and risk-neutral yields, $ytp_t^m = y_t^m - \tilde{y}_t^m$. Model-implied forward rates for loans starting at $t+n$ and maturing at $t+m$ are given by $f_t^{n,m} = (m-n)^{-1} (\log P_t^n - \log P_t^m) = (m-n)^{-1} (m y_t^m - n y_t^n)$. Risk-neutral forward rates $\tilde{f}_t^{n,m}$ are calculated in analogous fashion from risk-neutral yields. The *forward term premium* is defined as $ftp_t^{n,m} = f_t^{n,m} - \tilde{f}_t^{n,m}$.

The appeal of a DTSM is that all yields, forward rates, and risk premia are functions of a small number of risk factors. Let M be the number of yields in the data used for estimation. The M -vector of model-implied yields is $Y_t = A + B X_t$, with $A = (A_{m_1}, \dots, A_{m_M})'$ and $B = (B_{m_1}, \dots, B_{m_M})'$. A low-dimensional model will not have perfect empirical fit for all yields, so we specify observed yields to include a measurement error, $\hat{Y}_t = Y_t + e_t$. While measurement error can potentially have serial correlation (Adrian et al., 2012; Hamilton and Wu, 2011), we follow much of the literature and take e_t to be an i.i.d. process.

As in JSZ and HW we assume that N linear combinations of yields are priced without error.

Specifically, we take the first three principal components of yields as risk factors. Denote by W the $3 \times M$ matrix that contains the eigenvectors corresponding to the three largest eigenvalues of the covariance matrix of \hat{Y}_t . By assumption, $X_t = WY_t = W\hat{Y}_t$.² Generally, risk factors can be unobserved factors (which are filtered from observed variables), observables such as yields or macroeconomic variables, or any combination of unobserved and observable factors. Our estimation method is applicable to cases with observable and/or unobservable yield curve factors, as well as to macro-finance DTSMs (Ang and Piazzesi, 2003; Rudebusch and Wu, 2008; Joslin et al., 2010). The only assumption that is necessary for our method to be applicable is that N linear combinations of risk factors are priced without error.

One possible parameterization of the model is in terms of $\gamma = (\mu, \Phi, \mu^Q, \Phi^Q, \delta_0, \delta_1, \Sigma)$, leaving aside the parameters determining the measurement error distribution. Given γ , the risk sensitivity parameters λ_0 and λ_1 follow from equation (4). Model identification requires normalizing restrictions (Dai and Singleton, 2000). For example, γ has 34 free elements in a three-factor model, but only 22 parameters are identified, so at least 12 normalizing restrictions are necessary. If the model is exactly identified, one speaks of a “maximally-flexible” model, as opposed to an over-identified model, in which additional restrictions are imposed.

2.2 Maximum likelihood estimation and small-sample bias

While it is conceptually straightforward to calculate the ML estimator (MLE) of γ , this has been found to be very difficult in practice.³ The first issue is to numerically find the MLE, which is problematic since the likelihood function is high-dimensional, badly behaved, and typically exhibits local optima (with different economic implications). The second issue is the considerable statistical uncertainty around the point estimates of DTSM parameters (Kim and Orphanides, 2005; Rudebusch, 2007; Bauer, 2011b). The third issue, which is the focus of this paper, is that the MLE suffers from small-sample bias (Ball and Torous, 1996; Duffee and Stanton, 2004; Kim and Orphanides, 2005). All three of these problems are related to the high persistence of interest rates, which complicates the inference about the VAR parameters. Intuitively, because interest rates revert to their unconditional mean very slowly, a data sample will typically contain only very few interest rate cycles, which makes it difficult to infer μ and Φ . The likelihood surface is rather flat in certain dimensions around its maximum, thus numerical optimization is difficult and statistical uncertainty is high. Furthermore, the severity of the

²Note that our principal components are not demeaned, and hence μ is not assumed to be zero.

³The list of studies that have documented such problems is long and includes Ang and Piazzesi (2003); Duffee and Stanton (2004); Kim and Orphanides (2005); Duffee (2011a) and Hamilton and Wu (2010). Also see Christensen et al. (2009) and Christensen et al. (2011), who introduce an arbitrage-free Nelson-Siegel DTSM that can be readily estimated.

small-sample bias depends positively on the persistence of process.

The economic implications of small-sample bias are likely to be important, because the VAR parameters determine the risk-neutral rates and term premia. Since the bias causes the speed of mean reversion to be overestimated, model-implied short-rate forecasts will tend to be too close to their unconditional mean, especially at long horizons. Therefore, risk-neutral rates will be too stable, and too large a portion of the movements in nominal interest rates will be attributed to movements in term premia.

2.3 Bias correction for DTSMs

Simulation-based bias correction methods require repeated sampling of new data sets and calculation of the estimator. For this to be computationally feasible, the estimator needs to be calculated quickly and reliably for each simulated data set. In the DTSM context, MLE has typically involved high computational cost, with low reliability in terms of finding a global optimum, which effectively precluded simulation-based bias correction.

However, two important recent advances in the DTSM literature substantially simplify estimation of affine Gaussian DTSMs. First, JSZ prove that in a maximally-flexible model the MLE of μ and Φ can be obtained using OLS. Second, HW show that any affine Gaussian model can be estimated by first estimating a reduced form of the model by OLS and then finding the structural parameters by minimizing a chi-squared statistic. Given these methodological innovations, there is no need to maximize a high-dimensional, badly behaved likelihood function. Estimation can be performed by a consistent and efficient two-stage estimation procedure, where the first stage consists of OLS, and the second stage involves finding the remaining (JSZ) or structural (HW) parameters, without minimal computational difficulties.

These methodological innovations make correction for small-sample bias feasible, because of their use of linear regressions to solve part of the estimation problem. In both approaches, a VAR system is estimated in the first stage, which is the place where bias correction is needed. We propose to apply bias correction techniques to the estimation of the VAR parameters, and to carry out the rest of the estimation procedure in the normal fashion. This, in a nutshell, is the methodology that we will use in this paper.

Before detailing our approach in Sections 4 (for maximally-flexible models) and 5 (for over-identified models), we first discuss how to obtain bias-corrected estimates of VAR parameters, as well as the particular features of the VARs in term structure models.

3 Bias correction for interest rate VARs

This section describes interest rate VARs, i.e., VARs that include interest rates or factors derived from interest rates, and discusses small-sample OLS bias and bias correction in this context.

3.1 Characteristic features of interest rate VARs

The factors in a DTSM include either individual interest rates, linear combinations of these, or latent factors that are filtered from the yield curve, and hence will typically have similar statistical properties as individual interest rates. The amount of persistence displayed by both nominal and real interest rates is extraordinarily high (see, for example, Rose, 1988; Goodfriend, 1991; Rapach and Weber, 2004). That is, first order autocorrelation coefficients are typically close to one, and unit root tests often do not reject the null of a stochastic trend. However, economic arguments strongly suggest that interest rates are stationary: A unit root is implausible, since nominal interest rates generally do not turn negative and remain within some limited range, and an explosive root (exceeding one) is unreasonable since forecasts would diverge. For these reasons, empirical DTSMs almost invariably assume stationarity by implicitly or explicitly imposing the constraint that all roots of the factor VAR are less than one in absolute value.⁴ We assume that interest rates are stationary but potentially with a very slow speed of mean reversion.

The data samples used in estimation of interest rate VARs are typically rather short. Researchers often start their samples in the 80s or later because of data availability or potential structural breaks (e.g., Joslin et al., 2010, 2011; Wright, 2011). Even if one goes back to the 60s (e.g., Cochrane and Piazzesi, 2005; Duffee, 2011b), the sample can be considered rather short in light of the high persistence of interest rates—there are only few interest rate cycles, and uncertainty around the VAR parameters remains high. Notably, it does not matter whether one samples at quarterly, monthly, weekly or daily frequency: sampling at a higher frequency increases the sample length but also the persistence (Pierse and Snell, 1995).

Researchers attempting to estimate DTSMs are thus invariably faced with highly persistent risk factors and short available data samples to infer the dynamic properties of the model.

⁴The stationarity prior is made explicit in the Bayesian frameworks of Ang et al. (2009) and Bauer (2011b).

3.2 Small-sample bias of OLS

Consider the VAR system in equation (1). We focus our exposition on a first-order VAR since the extension to higher order models is straightforward. We assume that the VAR is stationary, i.e., all the eigenvalues of Φ are less than one in modulus. The parameters of interest are $\theta = \text{vec}(\Phi)$. Denote the true values by θ_0 . The MLE of θ can be obtained by applying OLS to each equation of the system (Hamilton, 1994, chap. 11.1). Let $\hat{\theta}_T$ denote the OLS estimator, and $\hat{\theta}$ the estimates from a particular sample.

Because of the presence of lagged endogenous variables, the assumption of strict exogeneity is violated, and the OLS estimator is biased in finite samples, i.e., $E(\hat{\theta}_T) \neq \theta_0$. The *bias function* $b_T(\theta) = E(\hat{\theta}_T) - \theta$ relates the bias of the OLS estimator to the value of the data-generating θ .⁵ The bias in $\hat{\theta}_T$ is more severe the shorter the available sample and the more persistent the process is (see, for example, Nicholls and Pope, 1988). Hence, for interest rate VARs the bias is potentially sizeable. The consequence is that OLS *underestimates the persistence* of the system, as measured for example by the largest eigenvalue of Φ or by the half-life of shocks. Therefore, forecasts revert to the unconditional mean too quickly.

An alternative for defining bias is to consider the median as the relevant central tendency of an estimator. Some authors, including Andrews (1993) and Rudebusch (1992), have argued that median-unbiased estimators have useful impartiality properties, given that the distribution of the OLS estimator can be highly skewed in autoregressive models for persistent processes. For a vector-valued random variable, the median is not uniquely defined, because orderings of multivariate observations are not unique. Hence median bias is defined relative to the definition of the median that is used. We use the element-by-element median as in Rudebusch (1992) and Meerschaert and Scheffler (2001, p. 53), which is intuitive and has a straightforward sample analog that is easy to calculate. The *median bias function* is defined as $B_T(\theta) = \text{Med}(\hat{\theta}_T) - \theta$, where $\text{Med}(Y)$ is the element-by-element median of random vector Y . The bias will generally be non-zero for OLS estimates of VAR parameters.

3.3 Methods for bias correction

The aim of all bias correction methods is to estimate the value of the bias function, i.e., $b_T(\theta_0)$ or $B_T(\theta_0)$. We now discuss alternative analytical and simulation-based approaches for this purpose.

⁵Because $\hat{\theta}_T$ is distributionally invariant with respect to μ and Σ , the bias function depends only on θ and not on μ or Σ . The proof of distributional invariance for the univariate case in Andrews (1993) naturally extends to VAR models.

3.3.1 Analytical bias approximation

The statistical literature has developed analytical approximations for the mean bias in univariate autoregressions (Kendall, 1954; Marriott and Pope, 1954; Stine and Shaman, 1989) and in VARs (Nicholls and Pope, 1988; Pope, 1990), based on approximations of the small-sample distribution of the OLS estimator. These closed form solutions are fast and easy to calculate, and are accurate up to first order. They have been used for obtaining more reliable VAR impulse responses by Kilian (1998a) and Kilian (2011), and in finance applications by Amihud et al. (2009) and Engsted and Pedersen (2012), among others.

3.3.2 Bootstrap bias correction

Simulation-based bias correction methods rely on the bootstrap to estimate the bias. Data is simulated using a (distribution-free) residual bootstrap, taking the OLS estimates as the data-generating parameters, and the OLS estimator is calculated for each simulated data sample. Comparing the mean of these estimates to $\hat{\theta}$ provides an estimate of $b_T(\hat{\theta})$, which approximates the bias at the true data-generating parameters, $b_T(\theta_0)$. Hence bootstrap bias correction removes first-order bias as does analytical bias correction, and both methods are asymptotically equivalent. In contrast to analytical approximation, the bootstrap can also be used to correct for median bias. Applications in time series econometrics include Kilian (1998b) and Kilian (1999). Prominent examples of the numerous applications in finance are Phillips and Yu (2009) and Tang and Chen (2009). For a detailed description of bootstrap bias correction see Appendix A.

3.3.3 Inverse bootstrap bias correction

Analytical and bootstrap bias correction estimate the bias function at $\hat{\theta}$, whereas the true bias is equal to the value of the bias function at θ_0 . The fact that these generally differ motivates a more refined bias correction procedure. For removing higher-order bias and improving accuracy further, one possibility is to iterate on the bootstrap bias correction, as suggested by Hall (1992). However, the computational burden of this “iterated bootstrap” quickly becomes prohibitively costly. Here we propose to instead choose the value of θ by inverting the mapping from data-generating parameters to the mean or median of the OLS estimator. More precisely we choose that θ which, if taken as the data-generating parameter vector, leads to a mean or median of the OLS estimator equal to $\hat{\theta}$. We call this procedure “inverse bootstrap bias correction.” The idea is not new: For mean bias correction, our estimator is a special case of

the indirect inference estimator of [Gourieroux et al. \(1993\)](#).⁶ [MacKinnon and Smith \(1998\)](#) call it a “nonlinear-bias-correcting” estimator. It removes first- and higher-order bias, but is not exactly unbiased because the bias function is generally nonlinear. For the case of median bias, our estimator is a generalization of the median-unbiased estimators of [Andrews \(1993\)](#) and [Rudebusch \(1992\)](#), who applied the same idea to estimation of AR(1) and AR(p) models. We generalize to the VAR context, using, as mentioned above, the element-by-element median among the different possible definitions for the median of a vector-valued random variable. While this estimator has the potential to be exactly unbiased, our motivation to include it here is a concern about the high skewness of the sampling distribution $\hat{\theta}_T$.⁷

Calculation of this estimator requires the inversion of the unknown mapping from DGP parameters to the central tendency of the OLS estimator. The residual bootstrap provides a measurement of this mapping for a given value of θ . Since the use of the bootstrap introduces a stochastic element, one cannot use conventional numerical root-finding methods. However, the stochastic approximation literature has developed algorithms to find the root of functions that are measured with error. We adapt an existing algorithm to our present context, which allows us to efficiently and reliably calculate our bias-corrected estimators. The idea behind the algorithm is the following: For each iteration, simulate a small set of bootstrap samples using some “trial” DGP parameters, calculate the central tendency of the OLS estimator, and the distance to the target (the OLS estimates in the original data). In the following iteration, adjust the DGP parameters based on this distance. After a fixed number of iterations, take the average of the DGP parameters over all iterations, discarding some initial values. This average has desirable convergence properties and will be close to the true solution. For the formal definition of our mean- and median-bias-corrected estimators and for a detailed description of the algorithm and underlying assumptions, refer to [Appendix B](#).

In addition to our main methodological contribution, namely bias-corrected estimation of DTSMs, we also make a contribution to the bias correction literature. Our estimator for bias-corrected VAR estimation is closely related to existing ones, but our algorithmic implementation is novel. Notably, our algorithm could be used in other contexts, for example for calculating other indirect inference estimators. In [Appendix C](#) we compare alternative bias correction methods to OLS and to each other, and show that our approach performs well.

⁶The application of the indirect inference estimator to the context of bias correction is described in [Gourieroux et al. \(2000\)](#).

⁷The median goes through monotone, non-linear functions. If the object of interest is θ itself, and the function $B_T(\theta)$ is monotone in the relevant neighborhood of θ_0 , our bias-corrected estimator will be exactly median-unbiased.

3.4 Eigenvalue restrictions

We assume stationarity of the VAR, hence we need to ensure that estimates of Φ have eigenvalues that are less than one in modulus, i.e., that the VAR has only stationary roots. In the context of bias correction, this restriction is particularly important, because bias-corrected VAR estimates exhibit explosive roots much more frequently than OLS estimates (as is evident in our simulation studies). In a DTSM, one might impose the tighter restriction that the largest eigenvalue of Φ does not exceed the largest eigenvalue of Φ^Q , in order to ensure that short rate forecasts are no more volatile than forward rates. Either way, it will generally be necessary to impose restrictions on the set of possible eigenvalues.

In this paper, we impose the restriction that bias-corrected estimates are stationary using the stationarity adjustment suggested in Kilian (1998b). If the bias-corrected estimates have explosive roots, the bias estimate is shrunk toward zero until the restriction is satisfied. This procedure is simple, fast, and effective. It is also flexible: We can impose any restriction on the largest eigenvalue of Φ , as long as the OLS estimates satisfy this restriction. Naturally this ex post adjustment of the bias-corrected estimator introduces additional bias—the price to pay for imposing the restriction—but the bias is still smaller than for OLS. A related issue is that all bias estimates rely on the VAR being stationary, so this ad hoc stationarity adjustment is in a way problematic. A more systematic alternative would be to minimize the bias while satisfying the stationarity restriction. For the purpose at hand, however, the approach here is a pragmatic, reasonable solution.

4 Estimation of maximally-flexible models

In this section, we describe our methodology to obtain bias-corrected estimates of maximally-flexible models. We apply this approach to the empirical setting of JSZ, quantify the small-sample bias in their model estimates, and assess the economic implications of bias correction. Although the approach we develop in Section 5 is more general and could be applied here, adapting the estimation framework of JSZ has two advantages. First, we start from a well-understood benchmark, namely the ML estimates of the affine model parameters. Second, our numerical results are directly comparable to those of JSZ.

4.1 Estimation methodology

We assume that there are no overidentifying restrictions and, as mentioned above, that N linear combinations of yields are exactly priced by the model. Under these assumptions,

any affine Gaussian DTSM is equivalent to one where the pricing factors X_t are taken to be those linear combinations of yields. The MLE can be obtained by first estimating the VAR parameters μ and Φ using OLS, and then maximizing the likelihood function for given values of μ and Φ (as shown by JSZ). This suggests a natural way to obtain bias-corrected estimates of the DTSM parameters: First obtain bias-corrected estimates of the VAR parameters, and then proceed with estimation of the remaining parameters as usual. This, in a nutshell, is the approach we propose here.

The normalization suggested by JSZ parameterizes the model in terms of $(\mu, \Phi, \Sigma, r_\infty^Q, \lambda^Q)$, where r_∞^Q is the risk-neutral unconditional mean of the short rate and the N -vector λ^Q contains the eigenvalues of Φ^Q . What characterizes this normalization is that (i) the model is parameterized in terms of physical dynamics and risk-neutral dynamics, and (ii) all the normalizing restrictions are imposed on the risk-neutral dynamics. It is particularly useful because of the separation result that follows: the joint likelihood function of observed yields can be written as the product of (i) the “P-likelihood,” the conditional likelihood of X_t , which depends only on (μ, Φ, Σ) , and (ii) the “Q-likelihood,” the conditional likelihood of the yields, which depends only on $(r_\infty^Q, \lambda^Q, \Sigma)$ and the parameters for the measurement errors.⁸ Because of this separation the values of (μ, Φ) that maximize the joint likelihood function are the same as the ones that maximize the P-likelihood, namely the OLS estimates. This gives rise to the simple two-step estimation procedure suggested by JSZ.

The OLS estimates of the VAR parameters, denoted by $(\hat{\mu}, \hat{\Phi})$, suffer from the small-sample bias that plagues all least squares estimates of autoregressive systems. To deal with this problem, we obtain bias-corrected estimates, denoted by $(\tilde{\mu}, \tilde{\Phi})$. We focus on inverse bootstrap bias correction⁹ and present results for analytical and bootstrap bias correction in Appendix D. Because of the JSZ separation result, our first-step estimates are independent of the parameter values that in the second step maximize the joint likelihood function. Differently put, we do not have to worry in the first step about cross-sectional fit. We estimate the remaining parameters by maximizing the joint likelihood function over $(r_\infty^Q, \lambda^Q, \Sigma)$, fixing the values of μ and Φ at $\tilde{\mu}$ and $\tilde{\Phi}$. This procedure will take care of the small-sample estimation bias, while achieving similar cross-sectional fit as MLE.

To calculate standard errors for $\tilde{\mu}$ and $\tilde{\Phi}$ we use the conventional asymptotic approximation, and simply plug the bias-corrected point estimates into the usual formula for OLS standard errors. Alternative approaches using bootstrap simulation are possible, but for the

⁸There are $M - N$ independent measurement errors, which JSZ assume to have equal variance. This error variance is not estimated but concentrated out of the likelihood function.

⁹For the inverse bootstrap, we run 6000 iterations, discarding the first 1000, with 50 bootstrap samples in each iteration. We use an adjustment parameter of $\alpha_i = 0.5$.

present context we deem this pragmatic solution sufficient. For the estimates of $(r_\infty^Q, \lambda^Q, \Sigma)$ we calculate quasi-MLE standard errors, approximating the gradient and Hessian of the likelihood function numerically.

4.2 Data and parameter estimates

We first replicate the estimates of JSZ and then assess the implications of bias correction. We focus on their “RPC” specification, in which the pricing factors X_t are the first three principal components of yields and Φ^Q has distinct real eigenvalues. There are no overidentifying restrictions, thus there are 22 free parameters, not counting measurement error variances. The free parameters are μ (3), Φ (9), r_∞^Q (1), λ^Q (3), and Σ (6). The monthly data set of zero-coupon Treasury yields from January 1990 to December 2007, with yield maturities of 6 months and 1, 2, 3, 5, 7 and 10 years, is available on Ken Singleton’s website.

To obtain the MLE we follow the estimation procedure of JSZ, and we denote this set of estimates by “OLS.” We apply both mean and median bias correction, denoting the resulting estimates by “Mean-BC” and “Median-BC.” Table 1 shows point estimates and standard errors for the DTSM parameters. The OLS estimates in the left panel exactly correspond to the ones reported in JSZ.¹⁰ The bias-corrected estimates are reported in the middle and right panel. Because of the JSZ separation result, the estimated risk-neutral dynamics and the estimated Σ are very similar across all three sets of estimates.¹¹ The cross-sectional fit also is basically identical, with a root-mean-squared fitting error of about six basis points. The estimated VAR dynamics are however substantially different with and without bias correction.

4.3 Economic implications of bias correction

To assess the economic implications of bias-corrected DTSM estimates, we first consider measures of persistence of the estimated VAR, shown in the top panel of Table 2. The first row reports the maximum absolute eigenvalue of the estimated Φ , which increases significantly when bias correction is applied. The statistics in the second and third row are based on the impulse response function (IRF) of the level factor (the first principal component) to a level shock. The second row shows the half-life, i.e., the horizon at which the IRF falls below 0.5,

¹⁰Compare the top left panel of our Table 1 with the top row of JSZ’s Table 3, noting that $(I - \Phi)^{-1} \mu = \theta^P/12$ and $(\Phi - I) = K_1^P/12$. Compare the middle left panel of our Table 1 with the top row of JSZ’s Table 2, noting that our risk-neutral eigenvalues are one plus JSZ’s risk-neutral eigenvalues.

¹¹The differences in the Q-parameters between the left and the right panel stem from the fact that Σ enters both the P-likelihood and the Q-likelihood. Therefore, different values of μ and Φ will lead to different optimal values of $(r_\infty^Q, \lambda^Q, \Sigma)$ in the second stage.

calculated as in Kilian and Zha (2002). The half-life is two years for OLS, about 22 years for Mean-BC, and eleven years for Median-BC. The third row reports the value of the IRF at the five-year horizon, which is increased through bias correction by a factor of about five to six. The results here show that OLS greatly understates the persistence of the dynamic system. Bias correction substantially increases the estimated persistence, with Mean-BC estimates leading to the most persistent dynamics, due to the highly skewed distribution of the OLS estimator.

We now turn to risk-neutral rates and nominal term premia, focusing on a decomposition of the one-month forward rate for a loan maturing in four years, i.e., $f_t^{47,48}$. The last three rows of Table 2 show standard deviations of the model-implied forward rate and of its risk-neutral and term premium components. The volatility of the forward rate itself is the same across estimates, since the model fit is similar. The volatility of the risk-neutral forward rate is higher for the bias-corrected estimates than for OLS by a factor of about three to four. The slower mean reversion leads to much more volatile short rate forecasts and risk-neutral rates. The mean-BC estimates lead to a particularly high volatility of risk-neutral rates. The volatility of the forward term premium is similar across estimates, with slightly more variability after bias correction. Figure 1 shows the alternative estimates of the risk-neutral forward rate in the top panel, and the estimated forward term premia in the bottom panel. The differences are rather striking. The risk-neutral forward rate resulting from OLS estimates displays little variation, and the associated term premium closely mirrors the movements of the forward rate. The secular decline in the forward rate is attributed to the term premium, which does not show any discernible cyclical pattern. In contrast, the risk-neutral forward rates implied by bias-corrected estimates vary much more over time and account for a considerable portion of the secular decline in the forward rate. There is a pronounced cyclical pattern both for the risk-neutral rate and the term premium. The mean-BC and median-BC estimates of risk-neutral rates and forward term premium are very similar, with the former displaying slightly higher volatility.

From a macro-finance perspective, the decomposition implied by bias-corrected estimates seems more plausible. The secular decline in risk-neutral rates is consistent with results from survey-based interest rate forecasts (Kim and Orphanides, 2005) and far-ahead inflation expectations (Kozicki and Tinsley, 2001; Wright, 2011), which have drifted downward over the last twenty years. The bias-corrected term premium estimates display a pronounced countercyclical pattern, rising notably during recessions. Most macroeconomists believe that risk premia vary significantly at the business cycle frequency and behave in such a countercyclical fashion, given theoretical work such as Campbell and Cochrane (1999) and Wachter (2006)

as well as empirical evidence from Harvey (1989) to Lustig et al. (2010). In contrast, the OLS estimated term premium is very stable and, if anything, appears to decline a bit during economic recessions.

This empirical application shows that the small-sample bias in a typical maximally-flexible estimated DTSM as the one in JSZ is sizable and economically significant. Taking account of this bias leads to risk-neutral rates and term premia that are significantly different from the ones implied by MLE. Specifically, bias-corrected policy expectations show higher and more plausible variation and contribute to some extent to the secular decline in long-term interest rates. Bias-corrected term premium estimates show a very pronounced countercyclical pattern, whereas conventional term premium estimates just parallel movements in long-term interest rates.

4.4 Monte Carlo study

Bias correction is designed to provide more accurate estimates of the model parameters, but the main objects of interest, risk-neutral rates and term premia, are highly nonlinear functions of these parameters. We use a Monte Carlo study to investigate whether bias-corrected estimation of a maximally-flexible DTSM improves inference about the persistence of interest rates and about expected short rates and term premia.

The DGP corresponds to the same model specification as used above. Using as model parameters the Median-BC estimates in Table 1, we simulate 1000 yield data sets. First, we simulate time series for X_t with $T=216$ observations from the VAR, drawing the starting values from their stationary distribution. Then, model-implied yields are calculated using the yield-loadings for given DGP parameters $(r_\infty^Q, \lambda^Q, \Sigma)$, and taking W as corresponding to the principal components in the original data. We add independent Gaussian measurement errors with a standard deviation of 6 basis points.

For each simulated data set we perform the same estimation procedures as we used above, obtaining OLS, Mean-BC, and Median-BC estimates.¹² For bias-corrected estimates that have explosive roots, we apply the stationarity adjustment. In those cases where even the OLS estimates are explosive, we shrink the estimated Φ matrix toward zero until it is stationary, and only then proceed to obtain bias-corrected estimates. Because of the very high persistence of the DGP process, bias-corrected estimates often imply explosive VAR dynamics—the frequency of explosive eigenvalues before the stationarity adjustment is 62.9% for Mean-BC and 52.9% for Median-BC. The OLS estimates have an explosive root in 4.9% of the replications.

¹²Here we run our inverse bootstrap bias correction algorithm for 1500 iterations, discarding the first 500, using 5 bootstrap replications in each iteration and an adjustment parameter of $\alpha_i = .1$.

Turning to the results, the model parameters governing the VAR system are estimated with substantial bias when using OLS, while bias-corrected estimates display much smaller bias, as expected. The remaining parameters of the DTSM are estimated with similar accuracy in either case, confirming the intuition that Q-measure parameters are pinned down with high precision by the data, while inference about P-measure parameters is troublesome. The estimates of the model parameters are presented and discussed further in Appendix E.

Table 3 summarizes how accurate alternative estimates recover the main objects of interest. The first three rows show measures of persistence for the true parameters (DGP) and means and medians of these measures for the estimated parameters. As before, we calculate the largest absolute eigenvalue of Φ , the half-life, and the value of the impulse response function (IRF) at the five-year horizon for the response of the level factor to own shocks. As expected, the persistence of the VAR is significantly underestimated by OLS, with central tendencies of the estimated persistence measures significantly below their true value. Bias-corrected estimation leads to much better results: It does not perfectly recover the true persistence, but the estimated persistence is higher than for OLS and closer to the true model.¹³

How accurately do the estimates capture policy expectations and term premia? We decompose the four-year forward rate into expectations and risk premium components, for the true DGP parameters and for each set of estimated parameters. Rows four to six of Table 3 show means and medians across replications of sample standard deviations of forward rates and the components, in annualized percentage points. Volatilities of forward rates are similar for the DGP and for the estimated series because the models generally fit the cross section of interest rates well. For risk-neutral rates and term premia there are substantial differences. Due to the downward bias in estimated persistence, OLS implies risk-neutral rates that are too stable, with volatilities that are significantly below those of the true risk-neutral rates. On the other hand, bias-corrected estimation leads to estimated risk-neutral rates that are about equally as volatile as for the true model. The volatility of policy expectations is captured better by bias-corrected than conventional estimates. For term premia, the picture is less clear, with OLS premia being slightly too stable and bias-corrected premia too volatile.

To measure the accuracy of estimated rates and premia in relation to the series implied by the true model, we calculate root-mean-squared errors (RMSEs), in percentage points, for each replication. The last three rows of Table 3 show the means and medians of these RMSEs. Forward rates are naturally fit very accurately, with an average error of about one basis point. Risk-neutral forward rates and forward premia are estimated much more imprecisely, because

¹³For the half-life, means/medians are calculated only across those replications for which the estimates imply a half-life of less than 40 years, the cutoff for our half-life calculation (Kilian and Zha, 2002).

they depend on the imprecisely measured VAR parameters. Their RMSEs are between 1.2 and 1.4 percentage points. Importantly, the bias-corrected estimates imply lower RMSEs than OLS, indicating that the decomposition of long-rates based on these estimates more closely corresponds to the true decomposition. This clearly demonstrates the higher accuracy of bias-corrected DTSM estimation for inference about short rate expectations and risk premia.

5 Estimation of over-identified models

We now turn to models that include overidentifying restrictions. After first discussing the type of restrictions that are typically imposed on DTSMs, we propose a bias-corrected estimation procedure for such models. Then, we examine the consequences of bias-corrected estimation for a model with restrictions on risk prices that are common in the DTSM literature.

5.1 Restrictions in DTSMs

Most studies in the DTSM literature impose over-identifying parameter restrictions—either on the dynamic system (Ang and Piazzesi, 2003; Kim and Orphanides, 2005; Duffee, 2011a), on the \mathbb{Q} -measure parameters (Christensen et al., 2011), or on the risk sensitivity parameters λ_0 and λ_1 (Ang and Piazzesi, 2003; Kim and Orphanides, 2005; Cochrane and Piazzesi, 2008; Joslin et al., 2010; Bauer, 2011b)—with the purpose of avoiding overfit, increasing precision, or facilitating computation. Particularly appealing are restrictions on the risk pricing, i.e., on (λ_0, λ_1) . Intuitively, under such restrictions, the cross-sectional information helps to pin down the estimates of the VAR parameters. In this way, the no-arbitrage assumption helps overcome problems of small-sample bias and statistical uncertainty. This point was made forcefully by Cochrane and Piazzesi (2008) and has since been used effectively in other studies (Bauer, 2011b; Joslin et al., 2010).

In the following, we will present a methodology for bias-corrected estimation of restricted DTSMs. This makes it possible to assess the impact of risk price restrictions on small-sample bias. Since a complete analysis of the interaction between bias and various possible risk price restrictions is beyond the scope of this paper, we focus on one restricted model with the type of restrictions that are representative in the literature.

5.2 Estimation methodology

For models with over-identifying restrictions, the estimation methods discussed in Section 4 are not applicable. Here we introduce an alternative approach based on the framework of HW.

They show that for *any* affine Gaussian DTSM that exactly prices N linear combinations of yields, all the information in the data can be summarized by the parameters of a reduced-form system—a VAR for the exactly priced linear combinations of yields Y_t^1 and a contemporaneous regression equation for the linear combinations of yields Y_t^2 that are priced with error,

$$Y_t^1 = \mu_1 + \Phi_1 Y_{t-1}^1 + u_t^1, \quad (5)$$

$$Y_t^2 = \mu_2 + \Phi_2 Y_t^1 + u_t^2. \quad (6)$$

We denote $Var(u_t^1) = \Omega_1$ and $Var(u_t^2) = \Omega_2$ (taken to be diagonal). Since we take $Y_t^1 = WY_t$ as the risk factors, we have $Y_t^1 = X_t$, $\mu_1 = \mu$, $\Phi_1 = \Phi$, $u_t^1 = \Sigma \varepsilon_t$, and $\Omega_1 = \Sigma \Sigma'$. We also have $Y_t^2 = \hat{Y}_t$.

HW suggest an efficient two-step procedure for DTSM estimation. In the first step, one obtains estimates of the reduced-form parameters by OLS. In the second step, the structural model parameters are found via minimum-chi-squared estimation: a chi-squared statistic measures the (weighted) distance between the estimates of the reduced-form parameters and the values implied by the structural parameters, and it is minimized via numerical optimization.

For bias-corrected estimation, we replace the OLS estimates of the VAR in equation (5) with bias-corrected parameter estimates. For the contemporaneous regression in equation (6), OLS is unbiased, so bias correction is not necessary. Having obtained bias-corrected estimates of the reduced-form parameters, we perform the second stage of the estimation as before, minimizing the chi-squared distance statistic. To calculate standard errors for the bias-corrected estimates, we use HW's asymptotic approximation and simply plug in bias-corrected point estimates in the relevant formula.

5.3 Data and parameter estimates

For estimation, we use the zero-coupon yield data described in Gürkaynak et al. (2007). The data are available on the Federal Reserve Board's website. We use end-of-month observations from January 1985 to December 2011 on yields with maturities of 1, 2, 3, 5, 7, and 10 years.

For the identifying restrictions, we again use the JSZ normalization. Since we want to impose restrictions on risk prices, the model is parameterized in terms of $(\Sigma \lambda_0, \Sigma \lambda_1, \Sigma, r_\infty^Q, \lambda^Q)$, plus the measurement error variance Ω_2 , which as usual is assumed to be diagonal. We focus on $(\Sigma \lambda_0, \Sigma \lambda_1)$ instead of on (λ_0, λ_1) , since we do not want our inference to depend on the arbitrary factorization of the covariance matrix of the VAR innovations (Joslin et al., 2010).

In order to decide which restrictions to impose, we first estimate a maximally-flexible model without bias correction. Parameter estimates and standard errors are obtained exactly

as in HW. This set of estimates will be called “OLS-UR” (for unrestricted). Then, we set to zero the five elements of $\Sigma\lambda_1$ with t -statistics less than one. While this is an ad hoc choice of restrictions that ignores issues of the joint significance of parameters and model uncertainty, it is a common practice in the DTSM literature.¹⁴ This restricted specification is then estimated in the conventional way (“OLS-R”) as well as using bias correction (“BC-R”), where we use the inverse bootstrap to correct for mean bias.

In Table 4, we report parameter estimates and standard errors for $(\Sigma\lambda_0, \Sigma\lambda_1, r_\infty^Q, \lambda^Q, \Sigma)$. The Q-parameters are very similar across all three sets of estimates, since these are pinned down by the cross section of yields and are largely unaffected by the restrictions. However, the risk price parameters generally change between OLS-R to BC-R. Evidently, even for this tightly restricted model, bias correction has a noticeable impact on the magnitudes of the estimated risk sensitivities.

5.4 Economic implications of bias correction

We decompose five-to-ten year forward rates into risk-neutral rate and term premium components. The top panel of Figure 2 displays alternative estimates of the risk-neutral forward rate, the bottom panel shows estimates of the forward term premium. Both panels also include the actual forward rate. Table 5 presents summary statistics related to persistence of the estimated process, as well as sample standard deviations for the forward rate and its components.

Imposing the restrictions has small effects on the persistence of the estimated process and on the decomposition of long rates. The two series corresponding to OLS-UR and OLS-R in each panel are very close to each other. A look at the summary statistics reveals that the restrictions make the risk-neutral forward rate slightly less volatile and the forward term premium slightly more volatile. The persistence measures indicate a slightly faster speed of mean reversion under the risk price restrictions. Overall, the impact of imposing the five zero restrictions on $\Sigma\lambda_1$ does not change the implications of the model in economically significant ways.

Bias-correcting the DTSM estimates has important economic consequences. The persistence increases significantly, which leads to more variable risk-neutral forward rates. The estimated forward term premium becomes slightly more volatile for BC-R than for OLS-R. Overall, the observations here parallel the ones in the previous section for the JSZ data and model specification: The downward trend in forward rates is attributed to term premia alone

¹⁴Bauer (2011b) provides a framework to systematically deal with model selection and model uncertainty in this context.

for conventional DTSM estimates, whereas the bias-corrected estimates imply that policy expectations also played an important role for the secular decline. The counter-cyclical pattern of the term premium becomes more pronounced when we correct for bias. With regard to the most recent recession in 2007-2009, the bias-corrected estimates imply a term premium that increases significantly more before and during the economic downturn.

One potential issue with a more persistent VAR process relates to the zero-lower-bound on nominal interest rates. If the short rate is close to zero, then forecasts based on a highly persistent VAR can potentially drop below zero and stay negative for an extended period of time. In our setting, at some times during 2010 and 2011, the predicted short rate becomes negative for horizons up to two years. One way to deal with this problem is to truncate predicted short rates at zero. Since we focus on distant forward rates, this would not change our results, but it would change the decomposition of other forward rates and yields.

It should be noted that our results are specific to the data, model, and restrictions we have imposed. They cannot be taken as representative for the impact of risk price restrictions in general. In some cases, restrictions on risk pricing in a DTSM might well be able to largely eliminate small-sample bias (Ball and Torous, 1996; Joslin et al., 2010). However, we clearly demonstrate that in a very standard model setting, zeroing out even a majority of the risk price parameters—we set five of the nine parameters in $\Sigma\lambda_1$ to zero—does not reduce the estimation bias. For both unrestricted and restricted models, small-sample bias is a potentially serious problem. The only way to assess its importance in a particular model and dataset is to obtain bias-corrected estimates, and to evaluate the economic consequences of bias correction. We provide a framework that researchers can use to make an assessment of small-sample bias and its interaction with the parameter restrictions of their choice.

6 Conclusion

Correcting for finite-sample bias in estimates of affine DTSMs has important implications for the estimated persistence of interest rates and for inference about short rate expectations and term premia. Risk-neutral rates, which reflect expectations of future monetary policy, show significantly more variation for bias-corrected estimates of the underlying VAR dynamics than for conventional OLS/ML estimates. Our paper shows how one can overcome the problem of implausibly stable far-ahead short rate expectations that several previous studies have criticized. Furthermore, the time series of nominal term premia implied by bias-corrected DTSM estimates show more reasonable variation at business cycle frequencies from a macro-finance perspective than those implied by conventional term premium estimates. Since our results

show that correcting for small-sample bias in estimates of DTSMs has important economic implications, researchers and policy makers who analyze movements in interest rates are well advised to use bias-corrected estimators.

Our paper is the first to quantify the bias in estimates of DTSMs and opens up several promising directions for future research. In particular, the question of how other methods that aim at improving the specification and/or estimation of the dynamic system fare in terms of bias reduction can be answered using our framework. Among the approaches that have been proposed in the literature are inclusion of survey information (Kim and Orphanides, 2005), near-cointegrated specification of the VAR dynamics (Jardet et al., 2011) and fractional integration (Schotman et al., 2008). Furthermore, a thorough investigation of the interactions between risk price restrictions and small-sample bias is warranted.

One issue that this paper is not dealing with is whether bias-corrected confidence intervals are more accurate in repeated sampling. A related question is to what extent the reduction of bias increases the variance of the estimator. These are important questions that are beyond the scope of our analysis.

In terms of extensions of our approach, generalizing it to the context of non-affine and non-Gaussian term structure models is a desirable next step. One important class of models are affine models that allow for stochastic volatility, which may be spanned or unspanned. Another direction is to develop bias-corrected estimation for models that explicitly impose the zero lower bound on nominal interest rates.

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Appendices

A Bootstrap bias correction

The bootstrap has become a common method for correcting small-sample mean bias.¹⁵ Denote the demeaned observations by $\tilde{X}_t = X_t - T^{-1} \sum_{i=1}^T X_i$, and let B denote the number of bootstrap samples. The algorithm for mean bias correction using the bootstrap is as follows:

1. Estimate the model by OLS and save the OLS estimates $\hat{\theta} = \text{vec}(\hat{\Phi})$ and the residuals. Set $b = 1$.
2. Generate bootstrap sample b using the residual bootstrap: Resample the OLS residuals, denoting the bootstrap residuals by u_t^* . Randomly choose a starting value among the T observations. For $t > 1$, construct the bootstrap sample using $\tilde{X}_t^* = \hat{\Phi} \tilde{X}_{t-1}^* + u_t^*$.
3. Calculate the OLS estimates on bootstrap sample b and denote it by $\hat{\theta}_b^*$.
4. If $b < B$ then increase b by one and return to step two.
5. Calculate the average over all samples as $\bar{\theta}^* = B^{-1} \sum_{b=1}^B \hat{\theta}_b^*$.
6. Calculate the bootstrap bias-corrected estimate as

$$\tilde{\theta}^B = \hat{\theta} - [\bar{\theta}^* - \hat{\theta}] = 2\hat{\theta} - \bar{\theta}^*.$$

For large B , the estimated bias $\bar{\theta}^* - \hat{\theta}$ will be close to $b_T(\hat{\theta})$. The motivation for this approach comes from the fact that $E(b_T(\hat{\theta}_T)) = b_T(\theta_0) + O(T^{-2})$, thus we can reduce the bias to order T^{-2} by using this bias correction (Horowitz, 2001).

The bootstrap can also be applied to correct for median bias in a straightforward fashion (although it appears not to have been employed for this purpose before). Denote by m^* the vector stacking the element-wise sample medians of $\{\hat{\theta}_b^*\}_{b=1}^B$. The estimate of the median bias $m^* - \hat{\theta}$ will be close to $B_T(\hat{\theta})$ for sufficiently large B .

If the bias were constant in a neighborhood around θ_0 that contains $\hat{\theta}$, this procedure would eliminate the bias (up to simulation error), which prompted MacKinnon and Smith (1998) to call this a “constant-bias-correcting” (CBC) estimator. In general, however, the bias function is not constant, thus the bootstrap will systematically get the bias estimate wrong. The reason of course is that this method estimates the true bias with an approximation error. This is illustrated by the median of the bootstrap-bias-corrected estimator, which (for large B and under the assumption that $B_T(\cdot)$ is monotone) is $\theta_0 + B_T(\theta_0) - B_T(\theta_0 + B_T(\theta_0)) \neq \theta_0$. To obtain higher accuracy and remove high-order bias, one can use the iterated bootstrap (Hall, 1992), but the computational burden quickly becomes prohibitively costly.

¹⁵For a detailed exposition see Hall (1992) or Efron and Tibshirani (1993, Chapter 10); for a review of the bootstrap including its application to bias correction, refer to Horowitz (2001).

B Inverse bootstrap bias correction

The method we propose here to obtain bias-corrected estimates of θ_0 is to choose that parameter value which yields a distribution of the OLS estimator with a central tendency equal to the OLS estimate in the actual data, using the residual bootstrap to estimate this central tendency. We call our method “inverse bootstrap” bias correction because it is based on what one might call an inversion principle, instead of the plug-in principle of conventional bootstrap bias correction. While the idea is not new, we extend it to the context of VAR estimation and suggest a fast and reliable algorithm to implement it with low computational cost even if $\dim(\theta)$ is large. We first discuss separately the case of mean bias and median bias correction and then present our algorithm.

B.1 Mean bias correction

Define $g_T(\theta) = E_\theta(\hat{\theta}_T)$, the mean of the OLS estimator if the data are generated under θ . The mean-bias-corrected estimator of θ_0 is the value of θ that solves

$$g_T(\theta) = \hat{\theta}_T. \quad (7)$$

We denote this bias-corrected estimator by $\tilde{\theta}_T$.

For identifiability, we need $g_T(\cdot)$ to be uniformly continuous and one-to-one (injective) in a neighborhood around θ_0 that includes $\hat{\theta}_T$. Notably, this implies that the function is monotone. In that case there is always exactly one solution to equation (7). Since the function $g_T(\theta)$ is not known analytically, a proof that these conditions are fulfilled is not possible. However, intuition and simulation exercises (not shown) suggest that these conditions are satisfied in the context of a stationary VAR.

The residual bootstrap can be used to obtain estimates of $g_T(\theta)$ for any value of θ , with the precision depending on the number of bootstrap samples. We can write $\tilde{\theta}_T = g_T^{-1}(\hat{\theta}_T)$, which makes it clear why we speak of an inversion principle. Since the motivation for this method is valid for general bias functions, $\tilde{\theta}_T$ is termed a “nonlinear-bias-correcting” (NBC) estimator by MacKinnon and Smith (1998).

This method of correcting for mean bias is closely related to the indirect inference estimator of Gourieroux et al. (1993).¹⁶ In fact, if the true model and the instrumental model are the same, so that we have a consistent estimator for the true model, the indirect inference estimator for an infinite number of simulations is exactly $\tilde{\theta}_T$ (Gourieroux et al., 2000).

Correcting for mean bias does not lead to an unbiased estimator. We have

$$E_{\theta_0}(\tilde{\theta}_T) = E_{\theta_0}(g_T^{-1}(\hat{\theta}_T)) \neq g_T^{-1}(E_{\theta_0}(\hat{\theta}_T)) = g_T^{-1}(g_T(\theta_0)) = \theta_0,$$

except for the unlikely special case that the bias function is linear, since the expectation operator does not go through nonlinear functions.

¹⁶For a review of indirect inference, see Gourieroux and Monfort (1996, Chapter 4).

B.2 Median bias correction

Let $G_T(\theta) = \text{Med}_\theta(\hat{\theta}_T)$ denote the element-wise median of the OLS estimator if the DGP is governed by θ . The median bias-corrected estimator of θ_0 is the value of θ that solves

$$G_T(\theta) = \hat{\theta}_T.$$

For the median-bias-corrected estimator we write $\check{\theta}_T$.

Similar conditions are necessary for $G_T(\cdot)$ as for $g_T(\cdot)$ to ensure identifiability. Under these conditions the inverse function exists and we can write $\check{\theta}_T = G_T^{-1}(\hat{\theta}_T)$.

For the case of an AR(1) model, this estimator exactly corresponds to the one proposed by Andrews (1993). Rudebusch (1992) used this estimator to obtain parameter estimates in an AR(p) model. We extend it to VAR models.

As opposed to the case of mean bias correction, this estimator has the potential to be exactly median-unbiased for θ , namely is $G_T(\cdot)$ is monotone:

$$\text{Med}_{\theta_0}(\check{\theta}_T) = \text{Med}_{\theta_0}(G_T^{-1}(\hat{\theta}_T)) = G_T^{-1}(\text{Med}_{\theta_0}(\hat{\theta}_T)) = G_T^{-1}(G_T(\theta_0)) = \theta_0.$$

The crucial difference is that the median operator, as opposed to the mean operator, does go through monotone functions.

B.3 Algorithmic implementation

We now present an algorithm that can be used to reliably and rather quickly find the bias-corrected estimates for a given sample and $\hat{\theta}$, focusing for this exposition on the mean-bias-corrected estimates, denoted by $\check{\theta}$. Define $R(\theta) = \hat{\theta} - g_T(\theta)$. The bias-corrected estimates are given by the root of this function, i.e., by $R(\check{\theta}) = 0$.¹⁷ Unfortunately, the function $R(\cdot)$ is not known analytically and we only have measurements that are contaminated with error—since the bootstrap gives us noisy measurements of $g_T(\theta)$ —which makes this problem fundamentally different from classical root-finding.

Finding the root of a function that is measured with error is a problem in the area of “stochastic approximation” (SA), pioneered by Robbins and Monro (1951). Their crucial insight was that for each attempted value of θ we do not need a very precise measurement of $R(\theta)$, because it is only used to lead us in the right direction. For our application that means that a small number of bootstrap replications is sufficient in each iteration, which greatly lowers our computational cost. The basic stochastic approximation algorithm is to construct a sequence according to

$$\theta^{(j+1)} = \theta^{(j)} + \alpha^{(j)} Y^{(j)}, \tag{8}$$

where $\alpha^{(j)}$ is a deterministic scalar sequence and $Y^{(j)}$ is a noisy measurement of $R(\theta^{(j)})$. Under some specific conditions about $\alpha^{(j)}$, the sequence will converge to $\check{\theta}$. However, the sequence of averages, $\bar{\theta}^{(j)} = j^{-1} \sum_{i=1}^j \theta^{(i)}$, converges even if $\alpha^{(j)}$ is taken to be a constant (between zero and one) and it does so at an optimal rate (Polyak and Juditsky, 1992). Under some rather weak conditions on $R(\cdot)$, $\alpha^{(j)}$ and the measurement error, we have $\bar{\theta}^{(j)} \rightarrow \check{\theta}$ almost

¹⁷The conditions mentioned above for $g_T(\cdot)$ imply that $R(\theta) = 0$ has a unique solution.

surely, \sqrt{j} -asymptotic normality, as well as optimality in the sense of a maximum rate of convergence.¹⁸

Motivated by these results, we use the following algorithm:

1. Choose as a starting value $\theta^{(1)} = \hat{\theta}$. Set $j = 1$.
2. Using $\theta^{(j)}$, obtain a measurement $Y^{(j)}$: estimate $g_T(\theta^{(j)})$ using a residual bootstrap with B replications (for details, see below) and set $Y^{(j)}$ equal to the difference between $\hat{\theta}$ and this estimate.
3. Calculate $\theta^{(j+1)}$ using equation (8).
4. If $j < N_0 + N_1$ increase j by one and return to step 2.
5. Calculate the bias-corrected estimate as

$$\hat{\theta} = N_1^{-1} \sum_{i=N_0+1}^{N_0+N_1} \theta^{(i)}.$$

In step two the approximate mean of the OLS estimator for a given $\theta^{(j)}$, i.e., an estimate of $g_T(\theta^{(j)})$, is obtained using a residual bootstrap with B replications. We randomly choose the starting values among the T observations. For $t > 1$ the bootstrapped series is obtained using $\tilde{X}_t^* = \Phi^{(j)} \tilde{X}_{t-1}^* + u_t^*$, where u_t^* are the bootstrap residuals, and $\Phi^{(j)}$ denotes the $N \times N$ matrix containing the elements of $\theta^{(j)}$. Importantly, the bootstrap residuals have to be obtained for a given $\theta^{(j)}$: One cannot resample the original VAR residuals since these do not, together with $\theta^{(j)}$, generate the original data. Instead one has to first obtain a series of residuals $\hat{u}_t = \tilde{X}_t - \Phi^{(j)} \tilde{X}_{t-1}$, for $t > 1$, which then can be resampled in the usual way to create the bootstrap residuals u_t^* .¹⁹ In other words, the bootstrap residuals are draws not from the empirical distribution of the original VAR residuals, but from the empirical distribution of the VAR residuals that are obtained given $\Phi^{(j)}$.

We choose $\alpha^{(j)} = 0.5$ and $B = 50$, unless otherwise specified. Instead of devising a specific exit condition which might be computationally costly to check, we simply run the algorithm for a fixed number of iterations. We do not calculate $\hat{\theta}^{(j)}$ using all iterations but instead discard the first part of the sample, corresponding to the idea of a burn-in sample in the Markov chain Monte Carlo literature. Unless otherwise specified, we use $N_0 = 1000$ iterations as a burn-in sample and then take as our estimate the average of the next $N_1 = 5000$ iterations.

To verify the convergence of the algorithm, we then check how close $\hat{\theta}$ is to $\tilde{\theta}$. This is feasible despite $\tilde{\theta}$ being unknown, since we can obtain a measurement of $R(\hat{\theta})$ with arbitrarily

¹⁸The only assumption that needs mentioning here is that the Jacobian at the solution point needs to be a Hurwitz matrix, i.e., the real parts of the eigenvalues of $R'(\tilde{\theta})$ need to be strictly negative. Only if $R(\cdot)$ is decreasing in this sense does it make sense to increase the value of $\theta^{(j)}$ when we have positive measurements (equation 8). We check this condition by estimating the Jacobian at $\hat{\theta}$, verifying that it is Hurwitz, and relying on the assumption that this does not change between $\hat{\theta}$ and $\tilde{\theta}$. Details on how we estimate the Jacobian in this particular setting are available upon request.

¹⁹This notation suppresses the dependence on the bootstrap replication b and on the iteration j .

small noise by using a large B , and check how close it is to zero. As the distance measure, we take root mean-square distance, that is $d(a, b) = (l^{-1}(a - b)'(a - b))^{1/2}$ for two vectors a, b of equal length l . We use this distance metric because it is invariant to the dimensionality of θ . We calculate $d(R(\hat{\theta}), 0)$, using a precision for the measurement of $B = 100,000$, and verify that this distance is small, e.g., on the order of less than 10^{-3} . In short, this additional step tells us whether we have really found a value of θ that is very close to $\tilde{\theta}$, and yields a mean for the OLS estimator close to $\hat{\theta}$. Should we have been worried about some of the required conditions for equation (7) to have a solution and for our SA algorithm to work reliably in finding it, this step after all enables us to be confident in having found a solution.

While the structure of our algorithm has solid theoretical foundations, our specific configuration ($\alpha^{(j)}$, B , number of burn-in/actual iterations) is admittedly arbitrary. We chose it based on our own experience with the algorithm. The specifics of the problem likely would allow us to reduce the computational cost further by choosing the configuration in some optimal way. We leave this for future research. With our configuration, the computational costs are very manageable: For a VAR(1) with 3 variables and about 300 observations, using a Dell Laptop with Intel Core i5 CPU (2.53 GHz, 3.42 GB RAM), it takes about five minutes to run the algorithm.

C AR/VAR Monte Carlo study

To assess the performance of our bias correction method, we present the results of a simulation study, which considers a bivariate VAR model. To create a setting that is comparable to the reality faced by researchers analyzing interest rates, we first estimate such a model on actual interest rates. We use the same monthly data set as in JSZ and Section 4. We extract the first two principal components from the cross section of yields and estimate the VAR. We take the OLS estimates, rounded to two decimals, as our DGP parameters:

$$X_{t+1} = \begin{pmatrix} .98 & .01 \\ 0 & .97 \end{pmatrix} X_t + \varepsilon_{t+1}, \quad \varepsilon_t \stackrel{iid}{\sim} N(0, I_2).$$

We generate $M = 2000$ samples and calculate for each replication six alternative estimates: OLS, analytical bias correction as in Pope (1990), bootstrap and inverse bootstrap mean bias correction, as well as bootstrap and inverse bootstrap median bias correction. For the conventional bootstrap bias correction, we use 1,000 replications. For the inverse bootstrap, we use 1500 iterations, discarding the first 500, with 5 bootstrap samples in each iteration. Estimates that imply explosive VAR dynamics are stationarity-adjusted in the same way as described in Section 4.4.

Table C.1 shows the results of our simulations. The first four rows show for each parameter the true value, the mean bias of OLS and the three mean-bias-correcting estimators, and the median bias of OLS and the two median-bias-correcting estimators. The fifth and sixth row show the “root-mean-squared bias” (RMSB), which is the square root of the mean-squared bias across the four parameters, and the “total absolute bias” (TAB), which is the sum of the absolute values of the bias in each parameter. The results show that bias correction

Table C.1: VAR Monte Carlo simulation results

	true value	Mean bias				Median bias		
		OLS	analytical	bootstrap	inv. boot.	OLS	bootstrap	inv. boot.
Φ_{11}	0.98	-0.0281	-0.0087	-0.0068	-0.0049	-0.0227	-0.0040	-0.0009
Φ_{12}	0.01	0.0015	-0.0007	-0.0004	-0.0007	0.0013	-0.0008	-0.0014
Φ_{21}	0.00	-0.0028	-0.0010	-0.0011	-0.0014	-0.0034	-0.0009	-0.0015
Φ_{22}	0.97	-0.0305	-0.0102	-0.0086	-0.0056	-0.0260	-0.0066	-0.0029
RMSB		0.0208	0.0067	0.0055	0.0038	0.0174	0.0039	0.0018
TAB		0.0629	0.0206	0.0168	0.0126	0.0534	0.0123	0.0066
max. eig.	0.98	-0.0154	0.0058	0.0081	0.0090	-0.0129	0.0091	0.0117
half-life	34	-14.1930	13.7945	14.3122	23.0127	-18.0000	-10.0000	-7.0000
IRF at $h = 60$	0.2976	-0.1726	0.0978	0.1433	0.1644	-0.2207	-0.0064	0.0503
freq. expl.		0.25%	23.90%	35.00%	30.80%	0.25%	23.75%	21.50%

Notes: True values, mean bias, and median bias for parameters and persistence measures, and summary statistics capturing total bias for the VAR Monte Carlo study. For details refer to the text.

significantly reduces the small-sample parameter bias. This holds for all three bias correction methods, and for both mean and median bias. The total absolute bias is reduced by about 75% using the bootstrap. The inverse bootstrap is able to further reduce bias. It estimates most elements of Φ with less bias, and reduces the measures of total bias. For the case of median bias it roughly cuts the total parameter bias in half, compared to conventional bootstrap bias correction.

The seventh to ninth rows show true values and the bias for three measures of persistence—the largest eigenvalue of Φ as well as the half-life and value of the IRF at a horizon of 60 periods for the response of the first variable to own shocks. To calculate the half-life we use the same approach as in Kilian and Zha (2002), with a cutoff of 500 periods—mean and median of the half-life are calculated across those replications for which it is available, which consequently excludes values for which the half-life would be larger than 500.

The downward bias in estimated persistence for the OLS estimator is sizable. The half-life and long-horizon IRF are on average half as large as for the true DGP. Bias correction increases the estimated persistence significantly, and the dramatic downward bias in the largest eigenvalue disappears. Notably, for mean bias, the bias corrected estimates tend to be even more persistent than the DGP, whereas for median bias, they get the persistence about right. Conventional bootstrap and inverse bootstrap bias correction display similar performance in terms of the implied persistence of the estimates.

The last row shows the frequency with which explosive eigenvalues occur. Evidently, although the DGP is stationary and the estimated model is correctly specified, there is a sizable probability that the realized value of the OLS estimator is such that bias correction leads to explosive estimates. Consequently, in practice one will often have to perform some type of stationarity adjustment to ensure that estimated dynamics are not explosive. The method used in this paper, following Kilian (1998b), is admittedly ad hoc, and there is room

Table D.1: Maximally-flexible DTSM – summary statistics

	OLS	mean-BC			median-BC	
		analytical	bootstrap	inv. boot.	bootstrap	inv.boot.
$\max(\text{eig}(\Phi))$	0.9678	0.9961	0.9999	0.9991	0.9953	0.9946
half-life	24	147	n.a.	265	128	132
IRF at 5y	0.16	0.75	0.95	0.93	0.72	0.75
$\sigma(f_t^{47,48})$	1.392	1.392	1.392	1.392	1.392	1.392
$\sigma(\tilde{f}_t^{47,48})$	0.388	1.206	1.431	1.635	1.178	1.333
$\sigma(ftp_t^{47,48})$	1.301	1.216	1.322	1.656	1.254	1.430

Notes: Summary statistics for OLS and bias-corrected estimates of the DTSM in Joslin et al. (2011). First row: maximum eigenvalue of the estimated Φ . Second and third row: half-life and value of the impulse response function at the five-year horizon for the response of the level factor to a level shock. Rows six to eight show sample standard deviations of the fitted 47-to-48-month forward rates and of the corresponding risk-neutral forward rates and forward term premia.

for future methodological improvement for reducing bias under the restriction of stationarity.

We draw two conclusions from this simulation study: First, both the bootstrap and inverse bootstrap are useful and reliable methods to reduce the bias in OLS estimates of VAR parameters. Second, the inverse bootstrap is a superior bias correction method compared to analytical or bootstrap correction in a setting like ours, because it reduces higher-order bias and hence further improves the accuracy of the parameter estimates.

D Maximally-flexible DTSM: alternative bias correction methods

In the main text we present bias-corrected DTSM estimates that are obtained by applying inverse bootstrap bias correction. Here we compare the results for the maximally-flexible model of Section 4 to those obtained using alternative bias correction methods.

Table D.1 shows the summary statistics for six alternative sets of estimates: OLS, analytical mean bias correction, bootstrap mean bias correction, inverse bootstrap mean bias correction, bootstrap median bias correction, and inverse bootstrap median bias correction. Correcting for mean bias using the bootstrap leads to explosive VAR dynamics, so we apply Kilian’s stationarity adjustment in this case—for the resulting Φ matrix the IRF does not fall below 0.5 within 40 years, our cutoff for half-life calculation as in Kilian and Zha (2002).

There are some differences in results across bias correction methods. Analytical bias correction leads to a less persistent VAR system than inverse bootstrap bias correction. But the key result is robust to using these alternative approaches: The persistence is substantially increased by bias correction, so that short rate forecasts and risk-neutral rates are much more volatile than for OLS. In practice, a researcher will likely use that method for bias correction that (s)he is most comfortable with on practical or theoretical grounds. For us, this is the inverse bootstrap method.

Table E.1: DTSM Monte Carlo study – parameter bias

	DGP	Mean bias						Median bias					
		OLS			Mean-BC			OLS			Median-BC		
1200 μ Φ	-0.343 -0.219 0.077	-0.363 0.142 -0.013	-0.167 0.062 -0.011	-0.275 0.102 -0.012	-0.091 0.030 -0.010								
	0.996 0.001 0.440	-0.024 0.025 -0.010	-0.010 0.012 0.010	-0.020 0.024 -0.001	-0.005 0.009 0.015								
	-0.001 0.990 0.352	0.006 -0.022 0.002	0.003 -0.009 -0.002	0.005 -0.018 0.002	0.001 -0.005 0.001								
	0 0.001 0.873	-0.003 -0.003 -0.023	-0.001 -0.001 -0.004	-0.002 -0.002 -0.017	-0.001 -0.001 0.000								
1200 r_∞^Q λ^Q	8.647	-0.852	-0.822	-0.675	-0.683								
	0.998 0.952 0.929	-0.001 0.000 -0.004	-0.001 -0.001 -0.004	-0.001 0.004 -0.007	-0.001 0.003 -0.007								
1200 Σ	0.643 0 0	-0.020 0 0	-0.015 0 0	-0.022 0 0	-0.016 0 0								
	-0.146 0.210 0	0.005 0.013 0	0.004 0.014 0	0.006 0.012 0	0.005 0.014 0								
	0.063 -0.011 0.087	-0.002 0.004 0.027	-0.001 0.004 0.028	-0.002 0.004 0.027	-0.001 0.004 0.028								

Notes: DGP parameter values, mean bias of OLS and Mean-BC estimates, and median bias of OLS and Median-BC estimates. For details refer to main text.

E Parameter bias in DTSM Monte Carlo study

In Table E.1 we show the DGP parameters that are used to simulate interest rate data from the DTSM, as well as mean and median parameter bias of the alternative estimates. The mean bias is shown for the OLS and Mean-BC estimates, whereas the median bias is shown for the OLS and Median-BC estimates.

The bias in the estimates of VAR parameters μ and Φ is sizable for the OLS estimates. As expected, the bias-corrected estimates generally display reduced bias.

With regard to the \mathbb{Q} -measure parameters, the values of λ^Q are estimated very accurately for all three estimators. This confirms the intuition that in DTSM estimation, cross-sectional information helps to pin down the parameters determining cross-sectional loadings very precisely. The risk-neutral long-run mean r_∞^Q is estimated with a slight downward bias by all estimators because the largest root under \mathbb{Q} is very close to one, which naturally makes inference about the long-run mean under \mathbb{Q} difficult. This has motivated some researchers to restrict the largest root under \mathbb{Q} to one and r_∞^Q to zero, in which case the long end of the yield curve is determined by a level factor (Bauer, 2011a; Christensen et al., 2011).

In sum, bias-corrected estimation methods reduce bias in estimates of the VAR parameters in comparison to MLE, whereas the remaining parameters are estimated with similar accuracy.

Table 1: Maximally-flexible DTSM – parameter estimates

	OLS			Mean-BC			Median-BC		
1200μ	-0.5440	-0.1263	0.0700	-0.3290	-0.2321	0.0738	-0.3427	-0.2190	0.0768
	(0.2330)	(0.0925)	(0.0398)	(0.2358)	(0.0931)	(0.0401)	(0.2354)	(0.0929)	(0.0400)
Φ	0.9788	0.0133	0.4362	0.9987	0.0006	0.4721	0.9961	0.0007	0.4400
	(0.0111)	(0.0392)	(0.2127)	(0.0112)	(0.0397)	(0.2152)	(0.0112)	(0.0396)	(0.2148)
	0.0027	0.9737	0.3532	-0.0020	0.9926	0.3462	-0.0012	0.9900	0.3520
	(0.0044)	(0.0156)	(0.0844)	(0.0044)	(0.0019)	(0.0366)	(0.0044)	(0.0157)	(0.0848)
	-0.0025	-0.0023	0.8537	0.0001	0.0021	0.8813	-0.0002	0.0013	0.8733
	(0.0019)	(0.0067)	(0.0364)	(0.0019)	(0.0068)	(0.0366)	(0.0019)	(0.0067)	(0.0365)
$ eig(\Phi) $	0.9678	0.9678	0.8706	0.9991	0.9991	0.8744	0.9946	0.9946	0.8700
$1200r_\infty^Q$	8.6055			8.6568			8.6475		
	(0.6590)			(0.6537)			(0.6524)		
λ^Q	0.9976	0.9519	0.9287	0.9976	0.9518	0.0287	0.9976	0.9519	0.9287
	(0.0004)	(0.0082)	(0.0145)	(0.0004)	(0.0082)	(0.0145)	(0.0004)	(0.0082)	(0.0145)
1200Σ	0.6365	0	0	0.6442	0	0	0.6430	0	0
	(0.0324)			(0.0317)			(0.0317)		
	-0.1453	0.2097	0	-0.1468	0.2107	0	-0.1464	0.2105	0
	(0.0216)	(0.0143)		(0.0216)	(0.0146)		(0.0217)	(0.0146)	
	0.0630	-0.0117	0.0867	0.0635	-0.0113	0.0873	0.0633	-0.0115	0.0872
	(0.0075)	(0.0072)	(0.0048)	(0.0076)	(0.0076)	(0.0045)	(0.0075)	(0.0068)	(0.0045)

Notes: Parameter estimates for the DTSM in Joslin et al. (2011). Left panel shows OLS/MLE estimates, middle panel shows mean-bias-corrected estimates, right panel shows median-bias-corrected estimates.

Table 2: Maximally-flexible DTSM – summary statistics

	OLS	Mean-BC	Median-BC
$max(eig(\Phi))$	0.9678	0.9991	0.9946
half-life	24	265	132
IRF at 5y	0.16	0.93	0.75
$\sigma(f_t^{47,48})$	1.392	1.392	1.392
$\sigma(\tilde{f}_t^{47,48})$	0.388	1.635	1.333
$\sigma(ftp_t^{47,48})$	1.301	1.656	1.430

Notes: Summary statistics for OLS and bias-corrected estimates of the DTSM in Joslin et al. (2011). First row: maximum eigenvalue of the estimated Φ . Second and third row: half-life and value of the impulse response function at the five-year horizon for the response of the level factor to a level shock. Rows six to eight show sample standard deviations of the fitted 47-to-48-month forward rates and of the corresponding risk-neutral forward rates and forward term premia.

Table 3: DTSM Monte Carlo study – summary statistics

	Mean				Median			
	DGP	OLS	Mean-BC	Median-BC	DGP	OLS	Mean-BC	Median-BC
$max(eig(\Phi))$	0.9946	0.9805	0.9965	0.9956	0.9946	0.9831	0.9993	0.9993
half-life	133	40.54	105.65	98.89	133	22.00	40.00	38.00
IRF at 5y	0.75	0.20	0.52	0.51	0.75	0.14	0.55	0.52
$\sigma(f_t^{47,48})$	1.57	1.58	1.58	1.58	1.45	1.45	1.45	1.46
$\sigma(\tilde{f}_t^{47,48})$	1.74	1.17	1.95	1.89	1.63	0.97	1.81	1.77
$\sigma(ftp_t^{47,48})$	1.84	1.73	2.09	2.04	1.72	1.49	1.91	1.87
RMSE($f_t^{47,48}$)		0.01	0.01	0.01		0.01	0.01	0.01
RMSE($\tilde{f}_t^{47,48}$)		1.37	1.20	1.18		1.31	1.13	1.11
RMSE($ftp_t^{47,48}$)		1.37	1.20	1.18		1.31	1.13	1.11

Notes: Summary statistics for persistence, variability, and accuracy of estimated rates and premia in DTSM Monte Carlo study. First three rows show true values (DGP) and means/medians of estimated values for the largest root of Φ , the half-life in months (across estimates that have a half-life of less than 40 years), and the value of the impulse response function (IRF) at the five-year horizon for response of the first risk factor to own shocks. Rows four to six show means/medians of sample standard deviations of forward rates, risk-neutral forward rates, and forward premia. Last three rows show means/medians of root-mean-squared errors (RMSE) for estimated rates and premia. Volatilities and RMSE's are in annualized percentage points. For details refer to main text.

Table 4: Restricted DTSM – parameter estimates

	OLS-UR			OLS-R			BC-R		
$1200\Sigma\lambda_0$	0.3146 (0.2293)	0.1159 (0.0708)	0.0790 (0.0260)	0.3329 (0.1240)	0.1015 (0.0512)	0.0652 (0.0186)	0.3274 (0.1250)	0.1006 (0.0513)	0.0537 (0.0187)
$\Sigma\lambda_1$	-0.0116 (0.0074)	-0.1303 (0.0439)	-0.0340 (0.2773)	-0.0161 (0.0060)	-0.1229 (0.0358)	0 (0.0789)	-0.0092 (0.0060)	-0.1271 (0.0361)	0 (0.0792)
	0.0012 (0.0023)	-0.0113 (0.0136)	-0.1577 (0.0856)	0	0	-0.1552 (0.0789)	0	0	-0.1420 (0.0792)
	-0.0008 (0.0008)	-0.0021 (0.0050)	-0.1043 (0.0315)	0	0	-0.1065 (0.0287)	0	0	-0.0886 (0.0288)
$1200r^Q$	15.0635 (0.5418)			15.0609 (0.5420)			15.1111 (0.5456)		
λ^Q	0.9976 (0.0001)	0.9488 (0.0072)	0.9563 (0.0058)	0.9976 (0.0001)	0.9490 (0.0076)	0.9561 (0.0062)	0.9976 (0.0001)	0.9491 (0.0077)	0.9561 (0.0063)
1200Σ	0.7264 (0.0284)	0	0	0.7261 (0.0284)	0	0	0.7327 (0.0287)	0	0
	0.0982 (0.0117)	0.2125 (0.0078)	0	0.0981 (0.0117)	0.2125 (0.0078)	0	0.0990 (0.0117)	0.2132 (0.0079)	0
	-0.0291 (0.0044)	0.0211 (0.0040)	0.0728 (0.0029)	-0.0291 (0.0044)	0.0211 (0.0040)	0.0728 (0.0029)	-0.0292 (0.0044)	0.0212 (0.0040)	0.0729 (0.0029)

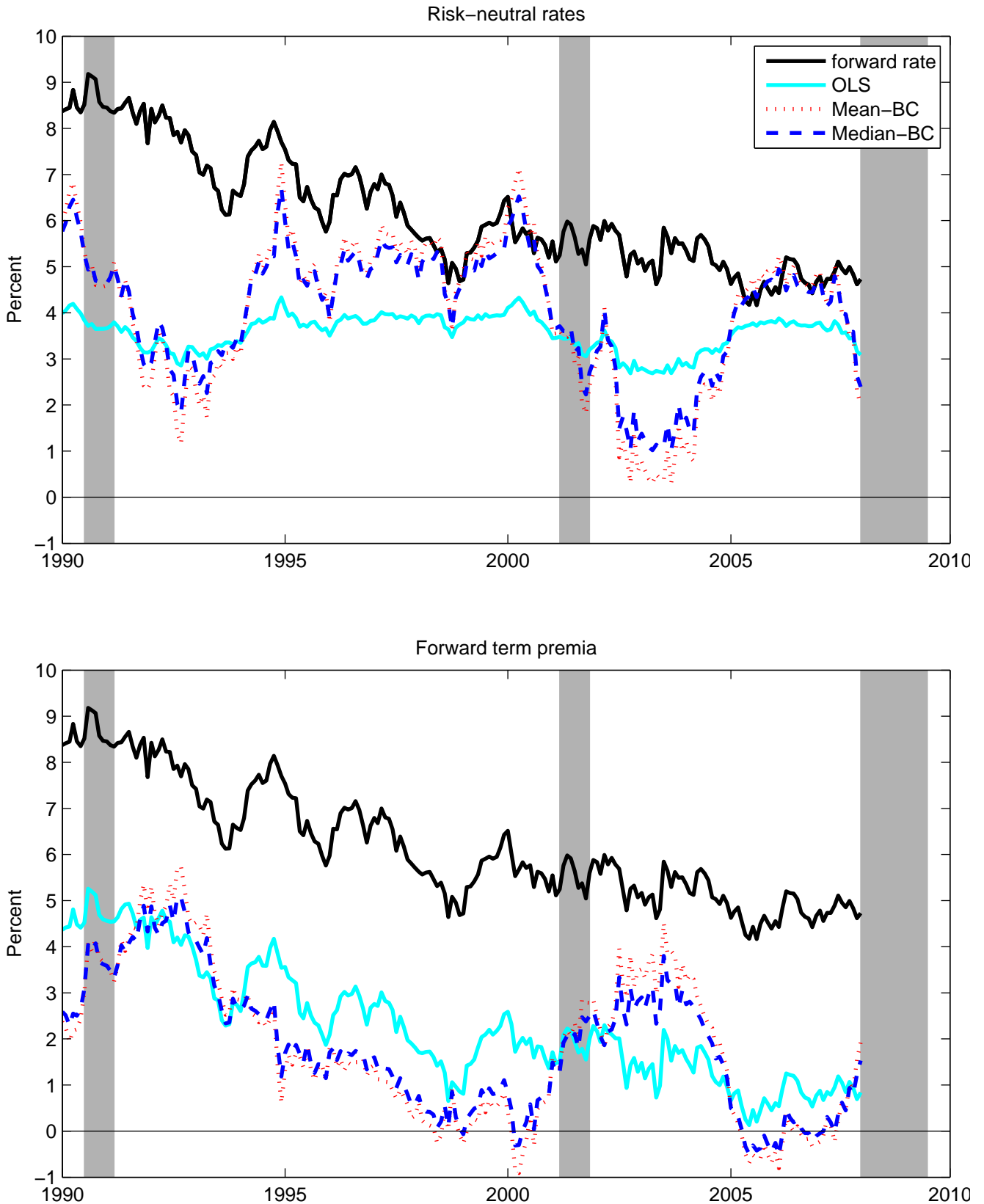
Notes: Conventional parameter estimates for maximally-flexible model specification (OLS-UR), as well as conventional (OLS-R) and bias-corrected (BC-R) estimates of the model with zero restrictions on risk price parameters.

Table 5: Restricted DTSM – summary statistics

	OLS-UR	OLS-R	BC-R
$\max(\text{eig}(\Phi))$	0.9909	0.9904	0.9953
half-life	64	44	92
IRF at 5y	0.52	0.41	0.60
$\sigma(f_t^{61,120})$	1.755	1.755	1.755
$\sigma(\tilde{f}_t^{61,120})$	1.148	1.058	1.705
$\sigma(ftp_t^{61,120})$	1.230	1.369	1.425

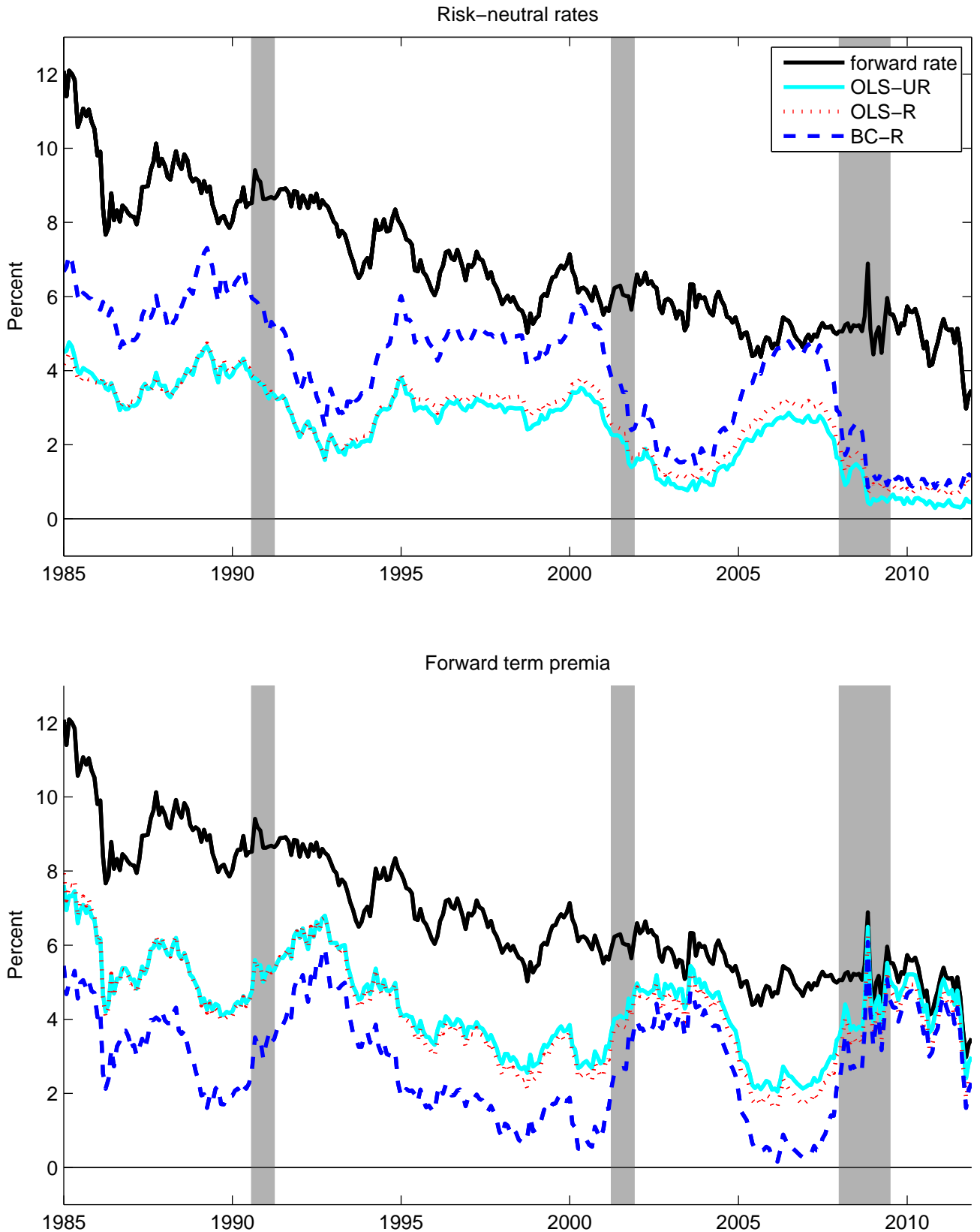
Notes: Summary statistics for OLS estimates of unrestricted model (OLS-UR), as well as OLS and bias corrected estimates of restricted model. Persistence measures and standard deviations of the fitted five-to-ten-year forward rates and of the corresponding risk-neutral forward rates and forward term premia.

Figure 1: Maximally-flexible DTSM – decomposition of forward rates



One-month forward rates with four years maturity, decomposed into risk-neutral forward rates and forward term premia using the affine Gaussian DTSM of Joslin et al. (2011). Sample: Monthly observations from January 1990 to December 2007. Gray shaded areas correspond to NBER recessions.

Figure 2: Risk price restrictions – decomposition of forward rates



Decomposition of five-to-ten year forward rates into risk-neutral and term premium components using alternative DTSM estimates Sample: Monthly observations from January 1985 to December 2011. Gray shaded areas correspond to NBER recessions.