THE UNIVERSITY OF SYDNEY

Economics Working Paper Series

2019 - 08

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April 2019

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Abstract

The period of unconventional monetary policy in the low-interest rate environment since the Great Recession has suggested that unconventional policy has a different transmission mechanism to the term structure of interest rates from that of conventional policy. We study how conventional and unconventional monetary policies affect forecasting performance of individual yield curve models and their mixtures. The individual models considered here are the dynamic Nelson-Siegel model, the arbitrage-free Nelson-Siegel model, and the random-walk model. Out-of-sample forecasts for U.S. bond yields show that the arbitrage-free Nelson-Siegel model and its mixtures with other models perform well in the period of conventional monetary policy, whereas the random-walk model outperforms all the other models in the period of unconventional monetary policy. We show that the tightly constrained cross-equation restrictions of the no-arbitrage condition are associated with high correlations of bond yields across different maturities. The diminishing role of the no-arbitrage restriction in forecasting the yield curve since 2009 can be attributed to unconventional monetary policy, which involved direct purchases of long-term bonds while the short-term interest rates were stuck near zero. This policy resulted in low correlations between short- and long-term bond yields and little variation in the short-term bond yields. The random-walk model performs well when the yields are less correlated and exhibit little variation over time. During the period of the maturity extension program ("Operation Twist") in 2011–2012, which moved short- and long-term bond yields in opposite directions, the superiority of the random-walk forecasts is more pronounced; these results reinforce our finding that the monetary policy framework affects yield curve forecasts.

*We thank Gianni Amisano, Sung Je Byun, Cem Cakmakh, Marcelle Chauvet, Graham Elliott, Domenico Giannone, Massimo Guidolin, Tae-hwy Lee, Michael McCracken, James Morley, Barbara Rossi, Rodrigo Sekkel, Tara Sinclair, Daniel Waggoner and seminar and conference participants at Texas A&M University, the Federal Reserve Bank of Dallas, the Reserve Bank of New Zealand, University of California Riverside, Hitotsubashi University, the Bank of Korea, the Narodowy Bank Polski Workshop on Forecasting, the International Association for Applied Econometrics conference, the Society for Nonlinear Dynamics and Econometrics Conference, Recent Developments in Financial Econometrics and Applications, EFaB@Bayes 250 Workshop, International Conference on Computational and Financial Econometrics, and Econometric Society Australasian Meeting for useful feedback. Andrew Gaffney provided invaluable research assistance. All remaining errors are our own.

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JEL Classification: C11; E43; E47; E52; G12;

Keywords: Quantitative Easing; Operation Twist; Dynamic Nelson-Siegel model; Arbitrage-free term structure model; Random-walk model; Markov-switching mixture;

1 Introduction

Yield curve forecasts are important for pricing financial assets, optimizing bond portfolios, managing financial risk, and analyzing business cycles. This paper aims to understand how conventional and unconventional monetary policies affect forecasting the yield curve.

In the United States, the Fed conducts conventional monetary policy in "normal" times by adjusting a short-term policy interest rate, i.e., the federal funds rate, to achieve its objectives of full employment and stable prices. Changes in the federal funds rate affect the entire path of expected future short-term interest rates, resulting in changes to long-term interest rates through this channel. Since the global financial crisis (GFC) and the subsequent Great Recession, however, the federal funds rate had been persistently near the zero lower bound and the Fed's ability to use its conventional monetary policy tool in response to economic and financial conditions has been limited. As a result, while the short-term interest rate was constrained by the zero lower bound, the Fed adopted additional policy tools such as forward guidance – communication about future policy rates – and quantitative easing – direct purchases of long-term bonds – to achieve its legislated goals.

In addition, many studies in the literature find that the natural rate of interest, known as r-star, is very likely to remain low for quite some time.[1] This low real interest rate environment – coupled with the fact that the Fed has reduced the federal funds rates by about 5 percentage points on average to combat recessions in the postwar period – potentially increases the likelihood of hitting the zero lower bound more frequently in the future. For example, Kiley and Roberts (2017) employ the FRB/US model and a dynamic stochastic general equilibrium model and find that the zero lower bound is binding about 30 or 40 percent of the time if the real interest rate remains low.

The differing channels and effects of conventional and unconventional monetary policies on the term structure of interest rates and the heightened likelihood of requiring unconventional monetary policy in the near future motivate us to investigate how the alternative frameworks for monetary policy affect the forecasting performance of different yield curve models.

[1] For example, see Laubach and Williams (2016), Hamilton et al. (2016), Pescatori and Turunen (2016), and Christensen and Rudebusch (2017) among others.

We find that the forecasting performance of various yield curve models (including mixtures thereof) is dependent on the monetary policy framework. During a period of conventional monetary policy, imposing the no-arbitrage restrictions significantly improves forecasts of the yield curve, though naive forecasts from a random-walk model are superior during the period of unconventional monetary policy. We discuss our findings in detail below.

We consider three widely used models in this study: (i) the dynamic Nelson–Siegel model, (ii) the Arbitrage–free Nelson–Siegel model, and (iii) the random-walk model. Diebold and Li (2006) develop a dynamic Nelson-Siegel (DNS) model, which is a dynamic version of the Nelson and Siegel (1987) model.[2] The DNS model is purely statistical and parsimonious, but still flexible when fitting the yield curve. Therefore, its forecasting performance is better than that of the theoretical approach, overall. The affine arbitrage-free model is a theoretical bond pricing approach that imposes cross-equation restrictions and eliminates the no-arbitrage opportunities across different maturities and over time.[3] This approach provides many economically interpretable outcomes, such as the term premium and term structure of real interest rates. We, in particular, consider the arbitrage-free version of Nelson–Siegel (AFNS) model, because it can be useful to understand the role of the additional cross-equation restrictions of no-arbitrage in forecasting yield curves when compared to the DNS. The random-walk (RW) is often used as a benchmark in terms of forecasting ability in the literature. Outperforming the RW is a challenging task as shown in Duffee (2002).[4] However, it is well known that none of the three individual models uniformly outperform the other models for all maturities and forecast horizons. The mixed results for out-of-sample predictions in the literature strongly suggest that these prediction models may be misspecified. To avoid the case that our results are driven by any potential misspecifications, we also consider three different mixture approaches of the models: (i) equal weights; (ii) constant weights; and (iii) Markov-switching weights. The mixtures consist of either two different models or all three models. These forecast combination schemes are in line with the

[2] For its applications, see de Pooter (2007) and Zantedeschi, Damien and Polson (2011) among many others.

[3] For example, see Moench (2008), Christensen, Diebold and Rudebusch (2011), Chib and Kang (2013), Almeida and Vicente (2008), and Carriero and Giacomini (2011) for a class of arbitrage-free models.

[4] Guidolin and Thornton (2018) recently test the null hypothesis of equal predictive accuracy of each model considered in their paper relative to the RW for predictions of short-term yields and find that they are unable to reject the null hypothesis for many individual forecasting models.

new approaches developed in the econometrics literature, such as linear combinations of the predictive densities with constant model weights proposed in Geweke and Amisano (2012) and Markov-switching mixtures of alternative prediction models developed in Waggoner and Zha (2012). In the case of constant weights, the weights are estimated as constant parameters. This approach can be interpreted as a special case of the dynamic mixture models.

We forecast monthly U.S. bond yields with eight different maturities at one-, four-, and 12-month forecasting horizons. We evaluate the out-of-sample forecasts for two subsamples of conventional monetary policy and unconventional monetary policy. We first choose the best model for each maturity at each forecasting horizon based on the mean squared forecast errors (MSFE). For the first out-of-sample period of conventional monetary policy, the AFNS or its mixtures with other models consistently outperform other forecasting models in most cases. On the other hand, during the second out-of-sample period corresponding to the period of unconventional monetary policy, the RW significantly outperforms all possible mixtures and other individual models in most cases. Thus, we can conclude that the no-arbitrage restrictions play an important role in improving forecasting ability during the period of conventional monetary policy, while they do not during the period of unconventional monetary policy.

Although model selection gives an indication of which model forecasts best, it is possible that some competing models exhibit statistically indistinguishable forecasting accuracy. For this reason, we construct a model confidence set (MCS) based on MSFEs for each maturity at each forecasting horizon, as proposed by Hansen, Lunde and Nason (2011). We find that for the conventional monetary policy period, the Markov-mixture of all three models are included in the MCSs most often (in 19 out of 24 cases), followed by the equal weights of all three models and the constant weights of the DNS and the AFNS (in 16 out of 24 cases), whereas the RW is included in 10 cases only.[5] However, during the unconventional monetary policy period, the RW is included in the MCSs for all the maturities at all the forecasting horizons. In short, during the conventional monetary policy period, the Markov-

[5] Note that for our forecasting evaluations, we consider 24 cases given by 8 different maturities $\times$ 3 different forecasting horizons.

mixture of all three models and other mixture models outperform the RW and the mixtures always include the AFNS, whereas the RW dominates the other individual models and the mixture models during the unconventional monetary policy period. The improved forecasting accuracy of the forecasting model combinations still holds for the yield curve models in the period of conventional monetary policy as reported in Geweke and Amisano (2012), Amisano and Geweke (2017), and Waggoner and Zha (2012), but does not hold in our application to yield curve models during the unconventional monetary policy period.

A natural question arising from our findings is why the no-arbitrage restriction is relevant during the conventional monetary policy period, but not during the unconventional monetary policy period. We argue that these mixed results are attributable to unconventional monetary policy, which results in changes to the correlation structure as well as the size of variations in short-term bond yields. The AFNS has a small number of factors and their loadings are tightly constrained by the no-arbitrage restriction so that the model is expected to fit to the bond yields and forecast effectively when the yields are highly correlated, as in the period of conventional monetary policy. In contrast, the RW is expected to perform well when the yields are less correlated and exhibit little variation over time. This is because the forecasts of the RW are equal to the current values of the yields, which means the predicted changes are essentially zero.

To verify these implications, we first calculate the correlations across maturities and the standard deviations of the changes in yields for the two subsamples. We find that the yields are highly correlated across different maturities during the conventional monetary policy period, but that the correlations are, in general, much lower in the period of unconventional monetary policy. In particular, the correlation between the short- and long-term bond yields decreases significantly from 0.74 in the first subsample to 0.40 in the second subsample. In addition, the variation in bond yields with 36 months or less to maturity has decreased markedly since 2009. Next, we generate a model-implied yield curve distribution from the parameter estimates of each of the DNS and AFNS. We find that the simulated bond yields from the AFNS reveal higher correlations across maturities compared to the DNS. The correlations from the AFNS range from 0.89 to 0.99, which are sensible for the period of conventional monetary policy as suggested above.

We also calculate cumulative squared forecasting errors over time to examine the relative importance of the competing forecasting models at each point in time. We first compare the AFNS with the RW to verify the role of the no-arbitrage restrictions against the RW and find that the AFNS forecasts better during the conventional monetary policy period, whereas the RW started forecasting significantly better around late 2008 when unconventional monetary policy began. In addition, we conduct the same procedure to compare the Markov-switching mixture of all three models with the RW, since the Markov-switching mixture has the highest frequency of being included in the MCSs across different maturities at different forecasting horizons. We find very similar patterns as in the previous case that the RW performs very well during the unconventional monetary policy period.

We believe that our results are driven by changes in the monetary policy framework. In the period of conventional monetary policy the Fed adjusts the short-term policy rate to stabilize the economy by affecting the entire path of expected future short-term interest rates as well as the long-term interest rates through this channel. As a result, the short- and long-term bond yields are highly correlated. In contrast, during the unconventional monetary policy period, the Fed made a series of large-scale asset purchases, so-called "Quantitative Easing", between December 2008 and October 2014. The Fed purchased long-term Treasuries and other long-term bonds and this alternative policy framework put downward pressure on the yields of a wide range of longer-term securities, while short-term yields were constrained by the zero lower bound. In addition, in September 2011 the Fed announced a Maturity Extension Program, the so called "Operation Twist", involving the purchase of longer-term Treasury securities and the liquidation of an equivalent amount of shorter-term securities. Therefore, Operation Twist would make the short- and long-term bond yields move in opposite directions and these movements of the bond yields are consistent with our finding that the superiority of RW forecasts is more pronounced during this period.

In short, unconventional monetary policy involves directly lowering long-term bond yields while short-term yields are constrained by the zero lower bound, resulting in low correlations between short- and long-term bond yields and little variation in short-term bond yields. The effects of unconventional monetary policy on the entire yield curve are therefore quite different from those of conventional monetary policy. The changes to yield curve dynamics in periods of conventional and unconventional monetary policy are also closely related to the forecasting performance of competing yield curve models.

We show that the monetary policy framework affects the forecasting accuracy of the competing yield curve models due to the differing transmission mechanisms of conventional and unconventional monetary policy. These findings are closely related to the recent literature on unconventional monetary policy, forecasting the yield curves, and model combinations of forecasting models.

First, the decrease in the correlations between the short- and long-term bond yields during the unconventional monetary policy period is relevant to findings in the literature on changes in the transmission channels of monetary policy to the yield curve during the periods of conventional and unconventional monetary policy. For example, Swanson and Williams (2014) estimate the time-varying sensitivity of yields to macroeconomic news using high-frequency data. They find that yields with six months or less to maturity were severely constrained since early 2009, whereas medium- and longer-term yields were essentially unconstrained by the zero bound. In addition, Inoue and Rossi (2018) compare how monetary policy shocks affect the yield curve during the conventional and unconventional monetary policy periods. They construct the monetary policy shocks following the traditional approach in Romer and Romer (2004) and calculate the shocks' correlations with yields across different maturities during the two subsamples. They document that the correlation is highest for short-term maturities during the conventional monetary policy period, while the correlation is highest for the longest-term maturities during the unconventional monetary policy period. These empirical studies indicate that the Fed affects the yield curve in different ways during periods of conventional and unconventional monetary policy, resulting in different values of the correlations between the short- and long-term bond yields.[6] While our work is closely related to their findings on the different sensitivities of short- and long-term bond yields in response to monetary policy shocks, our paper differs from those in the literature in that we use yield curve models to show the diminishing role of the no-arbitrage restrictions in forecasting the yield curve during the unconventional policy period.

[6] For the effect of conventional and unconventional monetary policy on interest rates, see Kuttner (2001), Gürkaynak, Sack and Swanson (2005), and Wright (2012) among others.

Second, our finding that no-arbitrage restrictions improve forecasting performance is consistent with the findings in the literature. For example, Ang and Piazzesi (2003) find that the forecasting performance of a VAR improves when no-arbitrage restrictions are imposed and Moench (2008) finds that no-arbitrage restrictions are useful in improving the forecasting ability of factor-augmented VAR models. In addition, Carriero and Giacomini (2011) consider an affine term structure model and find positive prediction gains against the RW. Christensen, Diebold and Rudebusch (2011) derive the class of affine arbitrage-free dynamic term structure models that approximate the DNS and find that imposing no-arbitrage restrictions can improve predictive performance relative to standard DNS models. However, these results on the importance of no-arbitrage restrictions in forecasting the yield curve are mainly based on out-of-sample forecasts for the sample period of conventional monetary policy. We find that in the period of unconventional monetary policy no-arbitrage restrictions were no longer useful.

Third, our approach is based on the forecasting literature on model combinations. To avoid the case that our findings are driven by any potential model misspecifications, we use various mixtures of prediction models. The central idea of this approach is to construct the one-step-ahead predictive density as a linear combination of the predictive densities obtained from each of the alternative prediction models. Geweke and Amisano (2012) and Amisano and Geweke (2017) show that the linear combination of various macroeconomic models can improve on any individual model for the postwar U.S. economy.[7] Extending this idea, Waggoner and Zha (2012) propose the use of a Markov-switching mixture of a DSGE model and a VAR model and find that the mixture model dominates both individual models.[8] These results highlight the importance of integrating model uncertainty and parameter uncertainty to address potential model misspecifications. As such, we employ mixtures of two or three of these models in addition to individual models.[9]

[7] The models are a dynamic factor model, a dynamic stochastic general equilibrium (DSGE) model, and a vector autoregressive (VAR) model.

[8] Time-varying combination methods are widely studied in the literature using different schemes. For example, see Granger and Newbold (1973), Diebold and Pauly (1987), Deutsch, Granger and Teräsvirta (1994), Elliott and Timmermann (2005), Aiolfi and Timmermann (2006), and Guidolin and Timmermann (2009) among others.

[9] As an alternative way to account for instability in yield curve models, several recent papers consider Markov-switching models which allow for changes in model *parameters* in a given model (e.g., Ang and Bekaert (2002), Guidolin and Timmermann (2007), Hevia et al. (2015), Levant and Ma (2017), and Guidolin

The remainder of the paper is organized as follows. Section 2 briefly describes our forecasting models and Section 3 presents our model combination approaches and estimation method. Section 4 provides the empirical results for the conventional and unconventional monetary policy periods and Section 5 discusses the implications of the monetary policy framework for forecasting the yield curve. Finally, Section 6 concludes the paper.

2 Yield Curve Models

In this section, we discuss the three widely used individual yield curve models considered in this study.

2.1 Dynamic Nelson-Siegle Model

We begin by describing the three-factor DNS model proposed by Diebold and Li (2006)). In this model, the bond yields are specified as a linear function of the vector of three exogenous latent factors, $\mathbf{x}_t$:

$$\mathbf{y}_t|\mathbf{x}_t, \mathbf{\Sigma}_{NS} \sim \mathcal{N}\left(\mathbf{\Lambda}\mathbf{x}_t, \mathbf{\Sigma}_{NS}\right), \tag{1}$$

with the factor loadings

$$\mathbf{\Lambda}=\begin{pmatrix} 1 & \frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} & \frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} - e^{-\tau_1\lambda} \\ 1 & \frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} & \frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} - e^{-\tau_2\lambda} \\ \vdots & \vdots & \vdots \\ 1 & \frac{1-e^{-\tau_N\lambda}}{\tau_N\lambda} & \frac{1-e^{-\tau_N\lambda}}{\tau_N\lambda} - e^{-\tau_N\lambda} \end{pmatrix} \tag{2}$$

and the factors

$$\mathbf{x}_t = \begin{pmatrix} \mathbf{x}_t^L & \mathbf{x}_t^S & \mathbf{x}_t^C \end{pmatrix}', \tag{3}$$

where $\mathcal{N}(.,.)$ denotes the multivariate normal distribution, the measurement error variance matrix $\mathbf{\Sigma}_{NS}$ is diagonal, and the coefficient λ is the decay parameter. The vector of the

and Pedio (2019)). The key aspect that differentiates our work from theirs is that allowing for changes in model *weights* across different models can be useful in understanding the relative importance of different cross-equation restrictions; for example, no-arbitrage restrictions against simple factor loadings of level, slope, and curvature, as shown in our paper.

dynamic factors $\mathbf{x}_t$ is assumed to follow a first-order stationary VAR process,

$$\mathbf{x}_t|\mathbf{x}_{t-1}, \kappa, \phi, \Omega_{NS} \sim \mathcal{N}\left(\kappa + \phi\mathbf{x}_{t-1}, \Omega_{NS}\right). \tag{4}$$

For stationarity, the absolute values of any eigenvalues of ϕ, which is a 3×3 diagonal matrix, are constrained to be less than one, and the initial value, $\mathbf{x}_0$, is generated from the unconditional distribution of $\mathbf{x}_t$. Because of the functional form of the factor loadings ($\mathbf{\Lambda}$ in (2)), the latent dynamic factors, $\mathbf{x}_t^L$, $\mathbf{x}_t^S$, and $\mathbf{x}_t^C$, are identified and interpreted as the level, slope, and curvature effects, respectively. The decay parameter determines the exponential decay rate of the factor loadings and is fixed at 0.0607, as in Diebold and Li (2006). Furthermore, the factor-shock variance matrix can be decomposed into $\Omega_{NS} = V_{NS}\Gamma_{NS}V_{NS}$, where V_{NS}, a 3×3 diagonal matrix, and Γ_{NS}, a 3×3 off-diagonal matrix, are the factor-shock volatility and correlation matrices, respectively. Then, the parameters for the DNS model are collected in

$$\Theta_{NS} = \{\kappa, \phi, V_{NS}, \Gamma_{NS}, \mathbf{\Sigma}_{NS}\}.$$

Finally, because equations (1) and (4) are a standard state-space representation, the resulting conditional density of $\mathbf{y}_t$ at each point in time

$$p(\mathbf{y}_t|Y_{t-1}, \Theta_{NS}, \mathcal{M}_{NS}) \tag{5}$$

can be obtained easily using the usual Kalman filtering procedure.

2.2 Arbitrage-Free Nelson-Siegel Model

The AFNS model is a theoretical bond pricing approach based on a partial equilibrium. In contrast, the DNS model is a purely statistical approach. Satisfying the arbitrage-free condition, the bond prices are determined endogenously by economic agents who know the model parameters. We, in particular, consider the arbitrage-free version of Nelson–Siegel (AFNS) model because it can be useful to understand the role of the additional cross-equation restrictions of no-arbitrage in forecasting yield curves compared to the DNS.

Bond Prices and No-Arbitrage Restrictions Let $P_t(\tau)$ denote the price of the bond at time t that matures in period $(t+\tau)$. Following Duffie and Kan (1996), we assume that $P_t(\tau)$ is an exponential affine function of a vector of three-dimensional factors $\mathbf{f}_t$ taking the form

$$P_t(\tau) = \exp(-\tau y_t(\tau)), \tag{6}$$

where $y_t(\tau)$ is the continuously compounded yield given by

$$y_t(\tau) = -\frac{\log P_t(\tau)}{\tau} = a(\tau) + b(\tau)'\mathbf{f}_t,$$

$a(\tau)$ is a scalar, and $b(\tau)$ is a 3×1 vector. The latter two both depend on τ. These coefficients are determined endogenously by the no-arbitrage condition, given certain assumptions about the dynamic evolution of the factors and the stochastic discount factor (SDF).

To impose the no-arbitrage condition

$$P_t(\tau) = \mathbb{E}[M_{t,t+1}P_{t+1}(\tau-1)|\mathbf{f}_t]$$

given the SDF, $M_{t,t+1}$, we solve the risk-neutral pricing equation for these coefficients. To do this, we specify the factor process and the SDF. The distribution of $\mathbf{f}_t$, conditioned on $\mathbf{f}_{t-1}$, is determined by the Gaussian mean-reverting first-order autoregression

$$\mathbf{f}_t = G\mathbf{f}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \Omega_{AF}), \tag{7}$$

where $G : 3\times 3$ is a diagonal VAR coefficient matrix. In the following, we express $\boldsymbol{\eta}_t$ in terms of a vector of i.i.d. standard normal variables $\boldsymbol{\omega}_t$ as $\boldsymbol{\eta}_t = \mathbf{L}\boldsymbol{\omega}_t$, where $\mathbf{L}$ is the lower-triangular Cholesky decomposition of Ω_{AF}.

We complete our model by assuming that the SDF $M_{t,t+1}$ that converts the payoff at time $(t+1)$ to a payoff at time t is given by

$$M_{t,t+1} = \exp\left(-r_t - \frac{1}{2}\boldsymbol{\gamma}_t'\boldsymbol{\gamma}_t - \boldsymbol{\gamma}_t'\boldsymbol{\omega}_{t+1}\right), \tag{8}$$

where r_t is the short rate, $\boldsymbol{\gamma}_t$ is a vector of time-varying market prices of factor risks, and

$\boldsymbol{\omega}_{t+1}$ is an i.i.d. vector of factor shocks at time $t+1$. We suppose that the short rate and the market price of the factor risk are both affine in the factors

$$r_t = \delta + \boldsymbol{\beta}'\mathbf{f}_t, \tag{9}$$

$$\boldsymbol{\gamma}_t = \bar{\boldsymbol{\gamma}} + \boldsymbol{\Phi}\mathbf{f}_t. \tag{10}$$

Given the above assumptions, we find the solutions for $a(\tau)$ and $b(\tau)$ in terms of the structural parameters by using the method of undetermined coefficients. Incorporating the assumptions for the factor and the SDF process into the risk-neutral pricing formula yields the following recursive system for the unknown functions:

$$a(\tau) = \delta/\tau + a(\tau-1) - b(\tau-1)'\mathbf{L}\bar{\boldsymbol{\gamma}} - \frac{\tau}{2}b(\tau-1)'\Omega_{AF}b(\tau-1) \tag{11}$$

$$b(\tau) = \boldsymbol{\beta}/\tau + (G - \mathbf{L\Phi})'b(\tau-1), \tag{12}$$

where $G^Q = G - \mathbf{L\Phi}$ and τ runs over the positive integers. These recursions are initialized by setting $a(0) = 0$ and $b(0) = 0_{3\times 1}$.

State-Space Form Now, we express the AFNS model as an econometric model for the estimation. First, we let $\mathbf{a}$ and $\mathbf{b}$ be the intercept and factor loadings, respectively, for $\mathbf{y}_t$ obtained from the recursive equations (11) and (12), respectively:

$$\mathbf{a} = \begin{pmatrix} a(\tau_1) & a(\tau_2) & \cdots & a(\tau_N) \end{pmatrix}' : N \times 1$$
$$\mathbf{b} = \begin{pmatrix} b(\tau_1) & b(\tau_2) & \cdots & b(\tau_N) \end{pmatrix}' : N \times 3. \tag{13}$$

For computational convenience, we follow Bansal and Zhou (2002) and Chib and Kang (2013) and assume that three basis bonds (three-month, three-year, and 10-year) are observed without errors. These three maturities are the first, fifth, and eighth maturities, respectively, in our data set. This implies a one-to-one mapping between the three latent factors and the basis yields, such that

$$\begin{aligned}\mathbf{y}_t^B &= \mathbf{a}_B + \mathbf{b}_B \mathbf{f}_t \\ \text{or } \mathbf{f}_t &= (\mathbf{b}_B)^{-1} \times \left(\mathbf{y}_t^B - \mathbf{a}_B\right),\end{aligned}$$

where

$$\begin{aligned}\mathbf{y}_t^B &= \begin{pmatrix} y(\tau_1) & y(\tau_5) & y(\tau_8) \end{pmatrix}', \\ \mathbf{a}_B &= \begin{pmatrix} a(\tau_1) & a(\tau_5) & a(\tau_8) \end{pmatrix}' : 3 \times 1, \\ \text{and } \mathbf{b}_B &= \begin{pmatrix} b(\tau_1) & b(\tau_5) & b(\tau_8) \end{pmatrix}' : 3 \times 3.\end{aligned}$$

Let $\mathbf{a}_{NB}$ and $\mathbf{b}_{NB}$ denote the intercept term and the factor loadings, respectively, corresponding to the nonbasis yields. The nonbasis yields, denoted by $\mathbf{y}_t^{NB}$, are observed with errors

$$\mathbf{y}_t^{NB} | \mathbf{a}_{NB}, \mathbf{b}_{NB}, \mathbf{f}_t \sim \mathcal{N}(\mathbf{a}_{NB} + \mathbf{b}_{NB}\mathbf{f}_t, \mathbf{\Sigma}_{AF}),$$

where $\mathbf{\Sigma}_{AF} : 5 \times 5$ is a diagonal matrix.

Identifying Restrictions For the factor identification, we impose two restrictions. First, the matrix $\boldsymbol{G}^Q$ has the form

$$\boldsymbol{G}^Q = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \exp(-g^Q) & g^Q \exp(-g^Q) \\ 0 & 0 & \exp(-g^Q) \end{bmatrix}. \tag{14}$$

Second, following Dai, Singleton and Yang (2007), we set δ in (11) to the sample mean of the short rate, because the short rate is highly persistent, δ tends to be estimated inefficiently, and the vector $\boldsymbol{\beta}$ in (12) is constrained to be

$$\boldsymbol{\beta} = (1, 1, 0,)'.$$

As shown in Niu and Zeng (2012), as a result of these restrictions, $\mathbf{b}$ in equation (13) reduces exactly to the form of the DNS factor loading structure $\mathbf{\Lambda}$. Therefore, the factors $\mathbf{f}_t$ are also identified as the level, slope, and curvature effects, respectively, as in the DNS model.[10]

The factor-shock matrix in the AFNS model can be decomposed in the same manner as in the DNS model. Thus, the decomposition is given by $\Omega_{AF} = V_{AF}\Gamma_{AF}V_{AF}$, where $V_{AF} : 3 \times 3$ is the factor-shock volatility and $\Gamma_{AF} : 3 \times 3$ is the factor-shock correlation matrix.

Finally, the parameters in the AFNS model to be estimated are as follows:

$$\Theta_{AF} = \{G, g^Q, \Omega_{AF} = V_{AF}\Gamma_{AF}V_{AF}, \mathbf{\Sigma}_{AF}\}.$$

Note that the structural parameters in the AFNS model, which determine the intercept term, factor loadings, factor persistence, and factor volatilities, are estimated jointly, whereas the intercept term and the factor loadings in the DNS model are fixed.

Based on the model specification described above, the resulting conditional density of $\mathbf{y}_t$ is obtained by

$$\begin{aligned} p(\mathbf{y}_t|Y_{t-1}, \Theta_{AF}, \mathcal{M}_{AF}) &= p(\mathbf{y}_t^{NB}|\mathbf{y}_t^{B}, \Theta_{AF}, \mathcal{M}_{AF}) \times p(\mathbf{y}_t^{B}|\mathbf{y}_{t-1}^{B}, \Theta_{AF}, \mathcal{M}_{AF}) \\ &= \mathcal{N}(\mathbf{y}_t^{NB}|\mathbf{a}_{NB} + \mathbf{b}_{NB}\mathbf{f}_t, \mathbf{\Sigma}_{AF}) \times \mathcal{N}(\mathbf{f}_t|G\mathbf{f}_{t-1}, \Omega_{AF}) \times |\mathbf{b}_B^{-1}|, \end{aligned} \tag{15}$$

where $\mathbf{f}_t = (\mathbf{b}_B)^{-1} \times \left(\mathbf{y}_t^B - \mathbf{a}_B\right)$ and $\mathcal{N}(x|m, V)$ denotes the multivariate normal density of x with mean m and variance-covariance V.

2.3 Random-Walk Model

The third individual prediction model we examine here is the RW model, given by:

$$\mathbf{y}_t|\mathbf{y}_{t-1}, \mathbf{\Sigma}_{RW} \sim \mathcal{N}(\mathbf{y}_{t-1}, \mathbf{\Sigma}_{RW}), \tag{16}$$

[10] In addition to our specification, we also examined the standard affine model in which $\boldsymbol{G}^Q$ is constrained to be a lower triangular matrix. However, we found that the latter model's out-of-sample prediction performance is poorer than that of the our AFNS model.

where $\Theta_{RW} = \mathbf{\Sigma}_{RW}$ is an $N \times N$ diagonal matrix. The conditional density of $\mathbf{y}_t$ is given by

$$p(\mathbf{y}_t|Y_{t-1}, \Theta_{RW}, \mathcal{M}_{RW}) = \mathcal{N}(\mathbf{y}_t|\mathbf{y}_{t-1}, \mathbf{\Sigma}_{RW}). \tag{17}$$

Duffee (2002) show that outperforming the RW model for out-of-sample yield curve forecasts is difficult.[11] As a result, it is often used as a benchmark in prediction ability comparisons.

3 Forecasting the Yield Curve

3.1 Model Combinations

Diebold and Li (2006) show that, overall, the DNS model produces better forecast accuracy in out-of-sample predictions than does Duffee's (2002) best, essentially affine model, although the RW model works better with short forecast horizons. Although these prediction models are all widely used to forecast the term structure of interest rates, none consistently outperform the others at all maturities and forecast horizons. One potential reason for this is that the alternative models are somewhat misspecified, which would indicate significant model uncertainty.

In addition, as discussed in Geweke and Amisano (2012), Bayesian model averaging as a model selection method sets the weight close to one for an individual model as the sample size increases, even though the chosen model is not the true data-generating process. In contrast, the mixture model that combines multiple forecasts sets the weight of an individual model to one only when the model is the true data-generating process. For example, Geweke and Amisano (2012) consider three macroeconomic forecasting models for seven U.S. macroeconomic variables, showing that the combined model substantially outperforms each of the three individual models and the Bayesian model averaging for one-period-ahead predictions.

Therefore, unless one of the existing yield curve models is the true data-generating process, all the alternative models for the yield curve are potentially misspecified. Thus, combin-

[11] See also Diebold and Li (2006), Altavilla, Giacomini and Ragusa (2014), and Guidolin and Thornton (2018) among others for similar findings.

ing predictions from the different yield curve models can substantially improve the predictive performance of the best model from a model selection procedure. This implication motivates us to consider the combination of predictions obtained from the different yield curve models.

We now briefly illustrate the method used to combine the models using an example of two prediction models, $\mathcal{M}_1$ and $\mathcal{M}_2$. It is straightforward to extend the framework to combining more than two models in the same way. Let Θ_1 and Θ_2 be the set of parameters in $\mathcal{M}_1$ and $\mathcal{M}_2$, respectively. The set of maturities is $\{\tau_i\}_{i=1}^N$, the τ-period bond yield at time t is denoted by $y_t(\tau)$, and the vector of yields with N different maturities at time t is

$$\mathbf{y}_t = (y_t(\tau_1), y_t(\tau_2), .., y_t(\tau_N))'.$$

We let $Y_t = \{y_i\}_{i=1}^t$ denote the observed yield curve data up to time t. Then, Geweke and Amisano (2011, 2012) study predictive densities of the form

$$w_1 \times p(\mathbf{y}_t | Y_{t-1}, \Theta_1, \mathcal{M}_1) + (1 - w_1) \times p(\mathbf{y}_t | Y_{t-1}, \Theta_2, \mathcal{M}_2), \tag{18}$$

where $w_1 \in [0, 1]$ is the model weight on $\mathcal{M}_1$.

Waggoner and Zha (2012) extend Geweke and Amisano's (2011) approach to allow the model weights to vary over time. They replace w_1 in equation (18) with $w_{1,s_t} \in [0, 1]$, where s_t takes values of either one or two, following a first-order, two-state Markov process with constant transition probabilities

$$q_{ij} = \Pr\left[s_t = j | s_{t-1} = i\right], \; i, j = 1, 2.$$

By doing so, they consider the case that the relative importance of each of the prediction models can change over time. The resulting predictive density, conditioned on the regime s_t, is given by

$$w_{1,s_t} \times p(\mathbf{y}_t | Y_{t-1}, \Theta_1, \mathcal{M}_1) + (1 - w_{1,s_t}) \times p(\mathbf{y}_t | Y_{t-1}, \Theta_2, \mathcal{M}_2).$$

Table 1 presents 15 competing combination models using various combination approaches,

Table 1: The mixture models

	DNS	AFNS	RW
Single model			
N	◯	×	×
A	×	◯	×
R	×	×	◯
Equal weight			
NA_E	◯	◯	×
NR_E	◯	×	◯
AR_E	×	◯	◯
NAR_E	◯	◯	◯
Constant weight			
NA_C	◯	◯	×
NR_C	◯	×	◯
AR_C	×	◯	◯
NAR_C	◯	◯	◯
Markov-switching weight			
NA_{MS}	◯	◯	×
NR_{MS}	◯	×	◯
AR_{MS}	×	◯	◯
NAR_{MS}	◯	◯	◯

Note: The circle ◯ indicates that an individual model is included in a mixture model. The mixture model is specified as follows: The model index "N" denotes the DNS model, "A" denotes the AFNS model, and "R" denotes the RW model. The subscript "E" denotes equal weights, "C" denotes constant weights, and "MS" denotes Markov-switching weights. For example, "NR_E" indicates a mixture of the DNS and the RW models with equal weights.

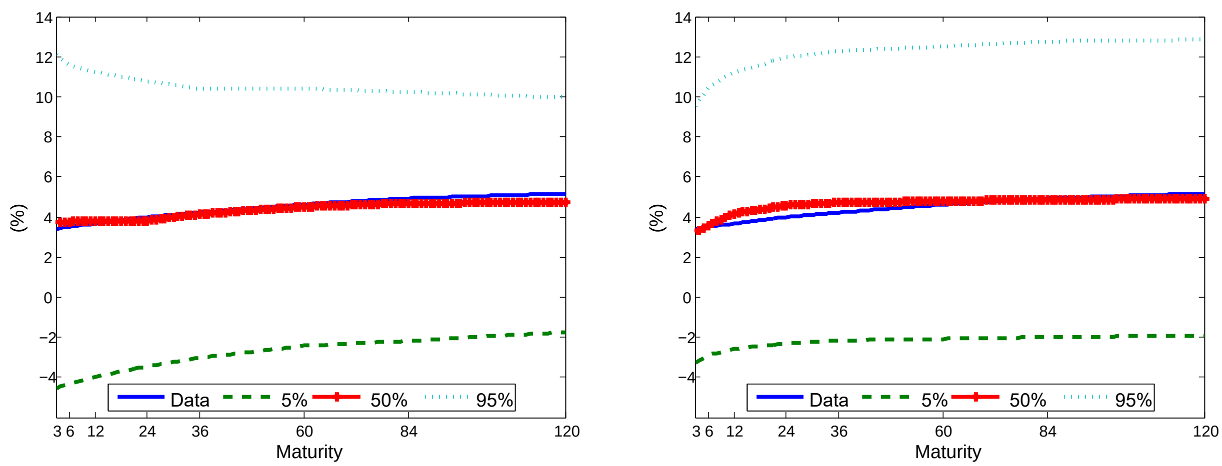
including the individual models.[12] We first consider the three individual models described in Section 2, as well as linear combinations of two or three of the alternatives. We employ three methods for determining the model weights: the equal weight method, constant weight method, and time-varying weight method. The time-varying weights follow a first-order Markov process. For ease of reference, we use the following shorter model specification indices: "N" denotes the DNS model, "A" denotes the AFNS model, and "R" denotes the RW model. The subscript "E" denotes equal weights, "C" denotes constant weights, and "M" denotes Markov-switching weights. For instance, NAR_C is a mixture of the DNS, AFNS, and RW models with constant weights. This implies that the weights are allowed to

[12] An individual model can be regarded as a special case of a combination with a weight of one on the individual model and weights of zero on the others.

vary across the models, but are constant over time. Then, NAR_{MS} is a mixture model with Markov regime-switching weights, in which the model weights vary over time according to the Markov process. In NAR_E, each of the model weights is fixed at one-third.

3.2 Bayesian Estimation

Figure 1: Prior-implied Unconditional Distribution of the Yield Curve



(a) DNS (b) AFNS

Note: We plot the 5%. 50%, and 95% quantiles for the distribution of the prior-implied yield curve for each model against the historical mean of the yield curve (blue solid line) for the data from February 1994 to December 2013.

We denote the model-specific parameters, transition probabilities, and regime-dependent model weight by $\Theta = \{\Theta_1,\, \Theta_2\}$, $Q = \{q_{11},\, q_{22}\}$, and $w = \{w_{1,1},\, w_{1,2}\}$, respectively. Then, the likelihood can be constructed using the predictive density as

$$\log p(Y_T|\Theta, Q, w) = \sum_{t=1}^{T} \log p(\mathbf{y}_t|Y_{t-1}, \Theta, Q, w), \tag{19}$$

where the regime s_t is integrated out. For more details on constructing the likelihood in (19), refer to Appendix A.

The priors of the parameters for the DNS model and the AFNS model $(\Theta_{NS}, \Theta_{AF})$ are set to reflect the a priori belief that the yield curve slopes gently upward and is concave, on average. In particular, the prior of Θ_{AF} should be chosen carefully, because the bond yields are highly nonlinear to the parameters and the likelihood surface of the AFNS model tends to be irregular. The irregularity of the posterior surface can be more serious or mitigated depending on the choice of the prior. Here, we adopt the prior used in Chib and Kang (2016). Following Chib and Ergashev (2009), Chib and Kang (2016) arrive at the prior using a simulation technique. They sample the parameters from the assumed prior and then sample the artificial data given the parameters, repeating this process many times until the mean of the resulting prior-implied unconditional distribution of the yield curve is mildly upward sloping and concave as depicted in Figure 1. This simulation-based prior smooths out the many local modes of the likelihood surface.

In combination of the prior with the likelihood, the target distribution to be sampled is the joint posterior distribution of the parameters, factors, and predictive yield curves. For further details on the MCMC sampling, see Appendix B.

4 The Effects of Monetary Policy on Forecasting the Yield Curve

We now examines how monetary policy affects the yield curve using the out-of-sample forecasting performance of the competing models. In particular, we concentrate on identifying best models during conventional and unconventional monetary policy periods.

4.1 Data and Forecasting Evaluation

Our data comprise monthly yields on U.S. government bonds. The sample period is February 1994 to December 2013. The set of maturities (in months) is $\{3, 6, 12, 24, 36, 60, 84, 120\}$. Our last forecast sample period is December 2013 in which the Fed officially announced that it began to taper its bond purchases from January 2014. The announcement would substantially alter the effects of unconventional monetary policy on the yield curve, especially for the long-term bonds as investors expected the Fed to reduce its demand for the bonds.

For the model comparison, we calculate the MSFE values using a rolling window esti-

Table 2: Rolling windows and out-of-sample forecasting periods

		Rolling window sample for estimation	Out-of-sample forecasts h=1	h=4	h=12
	1	1994:M2 – 2004:M1	2004:M2	2004:M5	2005:M1
Conventional	2	1994:M3 – 2004:M2	2004:M3	2004:M6	2005:M2
Policy		⋮		⋮	
	54	1997:M8 – 2008:M7	2008:M8	2008:M11	2009:M7
	55	1997:M9 – 2008:M8	2008:M9	2008:M12	2009:M8
Unconventional		⋮		⋮	
Policy	107	2002:M12 – 2012:M11	2012:M12	2013:M3	2013:M11
	108	2003:M1 – 2012:M12	2013:M1	2013:M4	2013:M12

Note: Given a rolling window sample, we produce yield curve forecasts for each maturity and forecast horizon pair.

mation with a fixed number of observations. The window size is 120 months ($m = 120$), and the forecasts are made for eight maturities at horizons of $h = 1, 4$, and 12 months ahead. The first estimation sample covers the period February 1994 to January 2004, and the corresponding out-of-sample forecasts are the yields for February 2004, May 2004, and January 2005 ($h = 1, 4, 12$). We then move the estimation window sample period and the out-of-sample forecasts forward by one month. Thus, the next estimation sample period is March 1994 to February 2004, and the corresponding out-of-sample forecasts are the yields for March 2004, June 2004, and February 2005, and so on. This procedure is repeated 108 times ($n = 108$), where the last estimation sample period is January 2012 to December 2012, and the corresponding out-of-sample forecasts are the yields for January 2013, April 2013, and December 2013. We conduct forecasting evaluations to understand the effects of monetary policy on forecasting the yield curves using two subsamples for the conventional monetary policy period and the unconventional monetary policy period. QE1 was announced on November 25, 2008 and we set November 2008 to the last out-of-sample forecast at the forecasting horizon of $h = 4$ for the first subsample associated with conventional monetary policy. Thus, both subsamples have the same forecasting evaluation sample size of 54. Our rolling window and the out-of-sample pairs are shown in Table 2.

We forecast the yield curves for each pair of a maturity and a forecast horizon and evaluate the predictive accuracy using two methods: (i) best model selection and (ii) MCS proposed by Hansen, Lunde and Nason (2011) based on the mean squared forecast error (MSFE).[13] The MCS is constructed such that it contains the best models with a given level of confidence.[14] The MCS procedure does not assume that a particular model is the true model. As such, it is useful when considering that the models contained in the model prediction set are potentially misspecified, as in our study.

4.2 Mean Squared Forecast Error Results

We produce the forecasts using a rolling window estimation scheme. Let T be the total sample size and m be the estimation window. We formulate the h-step-ahead forecasts for the τ-month bond yield at time t using the data $\mathbf{Y}_{t-m+1:t} = (Y_{t-m+1}, ..., Y_{t-1}, Y_t)$. Then, we compare these forecasts $y_{t+h}(\tau)$ to the realization $y^o_{t+h}(\tau)$. Iterating this procedure for $t = (T-h-n+1), ..., (T-h)$ produces n out-of-sample forecasts and relative forecast errors. Let $\overline{y_{i,t+h}(\tau)}$ denote the posterior mean of $y_{i,t+h}(\tau)$, conditional on a combination model i and data $\mathbf{Y}_{t-m+1:t}$. Given each combination model i and the data, the MSFE of the h-month-ahead bond yield with τ months to maturity, denoted by $MSFE_i(\tau, h)$, is given by

$$MSFE_i(\tau, h) = \frac{1}{n} \sum_{t=T-h-n+1}^{T-h} L_{i,t}(\tau, h),$$

where the loss function is given by $L_{i,t}(\tau, h) = \left[y^o_{t+h}(\tau) - \overline{y_{i,t+h}(\tau)}\right]^2$. By definition, smaller values of MSFE are preferred.

We choose the best prediction models that produce the smallest MSFE value for each pair of a maturity τ and a forecast horizon h, $MSFE(\tau, h)$. To examine the effect of monetary policy on forecasting the yield curve, we split the 108 out-of-sample periods into two subsamples. The first and second 54 out-of-sample periods range from January 2004 to June 2008 (conventional monetary policy period) and from July 2008 to December 2013 (unconventional monetary policy period), respectively, as presented in Table 2.

Table 3 reports the best models that achieve the smallest MSFE values for the two out-

[13]Throughout this paper, we evaluate the predictive accuracy of multiple individual bond yields rather than that of the yield curve to determine the maturity-specific prediction performance of the models and to compare the results with those in the literature.

[14]The MCS can be interpreted as being analogous to a confidence interval for a parameter.

Table 3: Best models

	3 m	6 m	12 m	24 m	36 m	60 m	84 m	120 m
1-month-ahead	NAR_M	NAR_E	NAR_E	NA_C	NAR_{MS}	NAR_{MS}	R	NA_C
4-month-ahead	NAR_E	NAR_E	NAR_E	NAR_E	NAR_{MS}	NAR_{MS}	NAR_C	NA_C
12-month-ahead	A	A	A	A	A	A	R	R

(a) Conventional monetary policy

	3 m	6 m	12 m	24 m	36 m	60 m	84 m	120 m
1-month-ahead	R	N	NR_M	R	R	R	R	NR_E
4-month-ahead	R	R	R	R	R	R	R	R
12-month-ahead	R	R	R	R	R	R	R	R

(b) Unconventional monetary policy

	3 m	6 m	12 m	24 m	36 m	60 m	84 m	120 m
1-month-ahead	R	NR_E	NR_{MS}	R	R	R	R	NR_{MS}
4-month-ahead	R	N	N	R	R	R	R	NA_C
12-month-ahead	R	NR_{MS}	R	R	R	R	R	R

(c) Both conventional and unconventional monetary policy

Note: The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively. The forecasts for conventional monetary policy are made in January 2004 to July 2008 while those for unconventional monetary policy are made in August 2008 to December 2012. Finally, the forecasts for conventional and unconventional monetary policy are made in both periods, ranging from January 2004 to December 2012. For more details on the periods of conventional and unconventional policy, see Table 2.

of-sample periods in addition to best models over both conventional and unconventional monetary policy periods.[15] The forecasting performance evaluation results show that the best models are markedly different during the periods of conventional and unconventional monetary policy.

For the conventional monetary policy period, best models include the AFNS in 21 cases as forms of NAR_{MS}, NAR_E, NA_C, NAR_C, and A. Also, various mixtures models are selected in 15 cases out of 24. It implies that the restriction of no arbitrage appears to be useful in improving the forecasting accuracy during the normal period. The mixtures of competing models also improve forecasting performance. These findings are all consistent with those reported in the literature.

[15] Tables C.1– C.9 report the MSFEs across all the maturities at all the forecasting horizons considered here.

However, during the unconventional monetary policy period the RW model seems to be most important as a single model. The RW model outperforms the other combination models in 21 of 24 cases. In particular, the RW model produces the most accurate point forecasts for 3-, 24-, 36-, 60-, and 84-month bond yields at all forecast horizons. The bigger role of the RW model during this period can be attributed to the advantage it has considering the possibility of structural changes in the U.S. yield curve dynamics. In addition, the results for the out-of-sample forecasts during the unconventional monetary policy period appear to be consistent with those over both the conventional and unconventional monetary policy periods. Because the results for the second half of the out-of-sample periods dominate those for the first half of the out-of-sample periods, the RW model appears to be the best model in most cases for samples that include both periods.

4.3 Model Confidence Set Results

Although the model choice in the previous section is simple and straightforward, choosing one model combination may disregard other models that show statistically similar forecasting performance to the best model. For this reason, we consider an MCS for an out-of-sample forecasting evaluation as a complementary model selection criterion.

Let $\mathcal{M}^0$ be a collection of combination models, including the individual models, and let the number of combinations of models be finite. The relative performance variables for combination models i and j are defined by

$$d_{ij,t}(\tau,h) = L_{i,t}(\tau,h) - L_{j,t}(\tau,h), \text{for all } i,j \in \mathcal{M}^0, \tag{20}$$

and the expected loss is given by $\mu_{ij}(\tau,h) = E\left[d_{ij,t}(\tau,h)\right]$. We rank the alternative combination models in terms of the expected loss, such that for a pair (τ,h), the combination model i is preferred to alternative j if $\mu_{ij}(\tau,h) < 0$.

The MCS at level α is defined as follows: for each pair of τ and h,

$$\mathcal{M}^*_{1-\alpha}(\tau,h) = \left\{i \in \mathcal{M}^0 : \mu_{ij}(\tau,h) \leq 0 \text{ for all } j \in \mathcal{M}^0\right\}, \tag{21}$$

where the MCS procedure conducts a sequence of significance tests at level α. The combination models that are found to be significantly inferior to other combination models of $\mathcal{M}^0$ are eliminated. Therefore, the hypotheses for the tests take the form

$$H_{0,\mathcal{M}} : \mu_{ij} = 0 \text{ for all } i, j \in \mathcal{M}, \tag{22}$$

where $\mathcal{M} \subset \mathcal{M}^0$.[16] Thus, the MCS at level α, $\mathcal{M}^*_{1-\alpha}(\tau, h)$, for a pair (τ, h) consists of the combination models that survive all tests at level α. We compute the MCS p-values for the tests using $B = 10,000$ bootstraps with a block size of $k = 12$.[17]

Table 4 reports the frequency of inclusion in 90% model confidence sets for each model combination across different maturities at each forecasting horizon. The models with p-values greater than or equal to 0.10 are included in the MCSs.[18] We focus on the competing models that are included in the MCSs for more than five of the eight different maturities at each forecasting horizon.

At the one-month-ahead forecasting horizon during the conventional monetary policy period, NAR_{MS} is included for all maturities, and NA_C and NA_{MS} are included for seven of the maturities. Furthermore, R is included for all maturities during the unconventional monetary policy period, but the other mixture models are only included for three different maturities or less. At the four-month-ahead horizon, NAR_E is included for six different maturities during the conventional monetary policy period, whereas R is included for all maturities during the unconventional monetary policy period. Finally, at the 12-month-ahead horizon during the conventional monetary policy period, A is included for seven different maturities and AR_E, NAR_E, AR_{MS}, and NAR_{MS} are included for six different maturities. Here, R is included for all maturities during the unconventional monetary policy period.

For the overall forecasting evaluation period at one-, four-, and 12-month-ahead fore-

[16] Hansen, Lunde and Nason (2014) find that the range statistic $(T_{R,M}, e_{R,M})$ has better power properties and produces smaller model confidence sets with proper coverage probabilities than the maximum t-statistic $(T_{max,M}, e_{max,M})$ does. Thus, they recommend the range-based procedure over that based on the maximum t-statistic. Therefore, we follow their suggestion and use the range-based procedure. For further details on the MCS procedure and its test statistics, see Hansen, Lunde and Nason (2011, 2014).

[17] We use an R package MCS developed by Bernardi and Catania (2018). We thank them for sharing their code.

[18] Tables C.1– C.9 in Appendix C report the MCS p-values across all the maturities at all the forecasting horizons considered here.

Table 4: MCS Results during the Periods of Conventional and Unconventional Monetary Policy

	Frequency of inclusion in the 90% MCSs								
	1-month-ahead			4-month-ahead			12-month-ahead		
	Con.	Uncon.	All	Con.	Uncon.	All	Con.	Uncon.	All
Single model									
N	1	3	3	1	2	3	1	0	3
A	4	0	1	1	0	1	7	0	1
R	4	8	8	1	8	8	5	8	8
Equal weight									
NA_E	3	0	0	2	1	0	4	0	3
NR_E	3	3	3	1	2	3	3	1	3
AR_E	5	0	0	1	1	1	6	0	3
NAR_E	4	0	0	6	1	1	6	1	3
Constant weight									
NA_C	7	1	3	4	2	5	5	0	3
NR_C	1	3	3	2	1	2	3	0	3
AR_C	3	0	0	1	0	0	4	0	2
NAR_C	4	0	0	4	1	2	5	1	3
Markov-switching weight									
NA_{MS}	7	0	0	3	2	2	5	1	1
NR_{MS}	4	3	3	2	3	3	5	1	3
AR_{MS}	3	0	0	1	0	0	6	0	2
NAR_{MS}	8	0	0	5	1	1	6	0	3

Note: We present the frequency of inclusion in the MCSs across eight different maturities for each model combination given a forecasting horizon. We calculate these frequencies for three different forecasting evaluation periods: conventional monetary policy period only ('Con.'); unconventional monetary policy period only ('Uncon.'); and both conventional and unconventional monetary policy periods ('All'). For example, the number 8 for the model 'R' in the column of 'All' under '1-month-ahead' means that the RW model is included across in the MCSs for all the maturities at one-month-ahead forecasting horizon when evaluating the forecasting performance of the competing models over both conventional and unconventional monetary policy periods. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively. More details about the MCS p-values and MSFEs are reported in Tables C.1– C.9 in Appendix C.

casting horizons, we find that the RW model outperforms the other mixture models for all maturities. The performance of the RW model is likely to originate from its superiority during the unconventional monetary policy period. This discrepancy in the forecasting results of the mixture models before and after the crisis is consistent with those for the best model selection based on the MSFEs, as reported in Sections 4.2.

In short, regardless of the forecasting horizon and maturity, we find similar patterns in best model selection and MCS procedures. That is, the mixtures of DNS, AFNS, and RW models perform well, and those mixture models always include the AFNS in the MCSs during the conventional monetary policy period. These results demonstrate that no-arbitrage restrictions in the AFNS are useful in improving the forecasting performance of the mixture models during the conventional monetary policy period. However, this is not the case during the unconventional monetary policy period and the RW model dominates the other models for all maturities.

5 Understanding the Yield Curve during the Unconventional Monetary Policy Period

In the previous section, we showed that the MCSs include the AFNS and its mixtures with other models in most maturity and forecasting horizon pairs during the conventional monetary policy period. During the period of unconventional monetary policy, however, the RW model dominates the mixture models and the other individual models. This section discusses potential reasons for the differing roles of the AFNS model (i.e., no-arbitrage restriction) in forecasting the yield curves and the performance of the mixture models in relation to changes in monetary policy between the two subsamples. To do so, we calculate correlations across different maturities and standard deviations of changes in yields and then relate the changes in the statistics of bond yields to monetary policy. We also examine the forecasting performance of key models over time in detail.

5.1 Correlations and Changes in Yields over Conventional and Unconventional Monetary Policy Periods

Table 5 calculates the sample correlations across maturities for the two subsamples we used for the forecasting evaluation. The correlations between short- and long-term bond yields significantly decreased during the unconventional monetary policy period (2009–2013) compared to the conventional policy period (2004–2008), while correlations between long-term

Table 5: Correlations across Maturities for the Two Subsamples

	3m	6m	12m	24m	36m	60m	84m
6m	1.00						
12m	0.99	1.00					
24m	0.97	0.98	0.99				
36m	0.95	0.96	0.97	1.00			
60m	0.91	0.92	0.93	0.97	0.99		
84m	0.85	0.85	0.88	0.92	0.95	0.99	
120m	0.74	0.75	0.78	0.83	0.87	0.94	0.98

(a) 2004:M1–2008:M12 (conventional monetary policy)

	3m	6m	12m	24m	36m	60m	84m
6m	0.91						
12m	0.80	0.94					
24m	0.63	0.75	0.91				
36m	0.56	0.67	0.84	0.99			
60m	0.45	0.54	0.72	0.92	0.97		
84m	0.42	0.51	0.69	0.89	0.95	0.99	
120m	0.40	0.46	0.63	0.85	0.92	0.98	0.99

(b) 2009:M1–2013:M12 (unconventional monetary policy)

Note: We calculate the sample correlations across maturities for two subsamples: 2004:M1–2008:M12 and 2009:M1–2013:M12. These subsamples are used to examine the effects of conventional and unconventional monetary policy on forecasting the yield curves in Sections 4.2 and 4.3.

bond yields remain to be very high. For example, the correlations between long-term yields are close to one for both subsamples ranging from 0.98 to 0.99, but the correlations between 3-month yield and 120-month yield show a substantial difference in the two subsamples, decreasing from 0.74 to 0.40.

Table 6 presents the model-implied correlations for the DNS and AFNS models. Here, we estimate the models for the full sample (i.e., February 1994–December 2013) and simulate the yield curve data at the parameter estimates. Note that the AFNS generates high correlations, ranging from 0.80 to 0.99, which are similar to the sample correlations in the first subsample period. Meanwhile, the correlations from the DNS ranges from 0.32 to 0.98. Given that the DNS produces relatively lower correlations, especially between short- and long-term bond yields, no-arbitrage restrictions in the AFNS appear to be more closely associated with the high correlations between short- and long-term bond yields. In both models, only a small

Table 6: Model-implied bond yield correlations

	3m	6m	12m	24m	36m	60m	84m
6m	0.89						
12m	0.68	0.81					
24m	0.55	0.77	0.88				
36m	0.47	0.70	0.84	0.98			
60m	0.39	0.62	0.77	0.93	0.94		
84m	0.35	0.58	0.74	0.90	0.92	0.94	
120m	0.32	0.53	0.69	0.86	0.89	0.94	0.98

(a) DNS

	3m	6m	12m	24m	36m	60m	84m
6m	0.93						
12m	0.87	0.88					
24m	0.89	0.92	0.94				
36m	0.88	0.90	0.92	0.99			
60m	0.85	0.86	0.88	0.95	0.96		
84m	0.81	0.82	0.83	0.91	0.92	0.93	
120m	0.81	0.80	0.80	0.88	0.91	0.93	0.95

(b) AFNS

Note: We calculate the model-implied correlation using the simulated yield data from the DNS and AFNS models.

number of factors are responsible for explaining the entire yield curve dynamics so that high correlations across different maturities are expected, but this is not the case for the correlations between short- and long-term bond yields in the DNS compared to the AFNS. This is mainly because the factor loadings in the AFNS are more tightly constrained by no-arbitrage restrictions and therefore these additional restrictions of no-arbitrage significantly improve forecasts of the yield curve during the conventional monetary policy period.

We also measure the variation in the bond yields over time. Here, small variations indicate that the RW model is preferred, because this model implies there is no difference between the forecasts and the current yields. Table 7 reports the standard deviations of the changes in the yields for the same subsamples using $SD(\Delta y^O_{t+h,t}(\tau))$ for $h = 1, 4, 12$, where $\Delta y^O_{t+h,t}(\tau) = y^O_{t+h}(\tau) - y^O_t(\tau)$. We find that the variation in the yields with 36 months or less to maturity have decreased significantly since 2009, whereas the variation in the yields with 60 months or longer to maturity have not changed considerably. For example, the

Table 7: Standard deviations of yield changes

	3 m	6 m	12 m	24 m	36 m	60 m	84 m	120 m
One-month-ahead	0.33	0.30	0.29	0.30	0.31	0.29	0.28	0.27
Four-month-ahead	0.82	0.81	0.79	0.77	0.74	0.62	0.55	0.48
12-month-ahead	1.88	1.83	1.68	1.45	1.28	0.96	0.80	0.64

(a) 2004:M1-2008:M12 (conventional monetary policy)

	3 m	6 m	12 m	24 m	36 m	60 m	84 m	120 m
One-month-ahead	0.04	0.04	0.06	0.12	0.17	0.24	0.26	0.26
Four-month-ahead	0.11	0.18	0.19	0.24	0.34	0.52	0.57	0.57
12-month-ahead	0.53	0.55	0.54	0.46	0.47	0.66	0.75	0.77

(b) 2009:M1–2013:M12 (unconventional monetary policy)

Note: We calculate the standard deviations of the changes in the yields $SD(\Delta y^O_{t+h,t}(\tau))$ for $h = 1, 4, 12$, where $\Delta y^O_{t+h,t}(\tau) = y^O_{t+h}(\tau) - y^O_t(\tau)$ for two subsamples: January 2004–December 2008 and January 2009–December 2013. These are used for the subsample analysis of the forecasting evaluations in Sections 4.2 and 4.3.

standard deviation of the one-month changes in the yields with three months to maturity ($SD(\Delta y^O_{t+1,t}(\tau = 3m))$ decreased from 0.33 to 0.04, while that of the one-month changes in the yields with 120 months to maturity remained stable, changing from 0.27 to 0.26. As a result, the RW model tends to perform well in terms of predicting yields with 36 months or less to maturity during the second subsample period.

All of these changes are potentially associated with changes in the transmission of monetary policy through interest rate, which affect the term structure of interest rates in different ways.

In the period of conventional policy, the Fed uses a short-term policy rate as a monetary policy instrument (i.e., the federal funds rate) and changes in the short-term rate affect the entire path of expected future short-term interest rates, resulting in changes to long-term bond yields through this channel. This implies that conventional monetary policy leads to high correlations between short- and long-term bond yields and considerable variations in the yields across all the different maturities so that the cross-equation restrictions such as no-arbitrage restrictions would be useful in improving the model's forecasting ability. Thus, the AFNS model would play an important role in improving forecasting ability in mixture models. Many studies in the literature (e.g., Ang and Piazzesi (2003), Almeida and Vicente (2008), Moench (2008), Carriero and Giacomini (2011), and Christensen, Diebold and Rudebusch (2011)) also report the similar findings that imposing no-arbitrage restrictions on a broader class of yield curve models improve their forecasting abilities using the data sets before the global financial crisis. In addition, the standard deviation of 12-month-ahead changes in yields with 120 months to maturity is much smaller than that of three-month yields during the conventional monetary policy period because short-term interest rates are more sensitive to the policy rate. This implies that the RW model would be more useful in predicting long-term yields at long forecasting horizons than it would in predicting short-term yields at short forecasting horizons. This conjecture is confirmed by Table 3 (b), which shows that the RW model is chosen as the best model when forecasting yields with 84 and 120 months to maturity at longer forecasting horizons.

Since the global financial crisis, the U.S. economy had showed a drastic slowdown with the federal funds rates at nearly zero. To stimulate household and business spending and support economy recovery, the Fed made a series of large-scale asset purchases, the so-called 'Quantitative Easing', between December 2008 and October 2014. During the period of unconventional monetary policy, the Fed purchased long-term Treasuries and other long-term bonds and these purchases put downward pressure on the yields of a wide range of longer-term securities, while short-term yields were constrained by the zero lower bound. In addition, in September 2011 the Fed announced that a Maturity Extension Program, the so called "Operation Twist", involving purchases of longer-term Treasury securities and the liquidation of an equivalent amount of shorter-term securities not to increase the total size of the Fed's balance sheet. Thus, unconventional monetary policy is directly associated with changes in long-term bond yields, resulting in low correlations between short- and long-term bond yields and little variation in short-term bond yields.

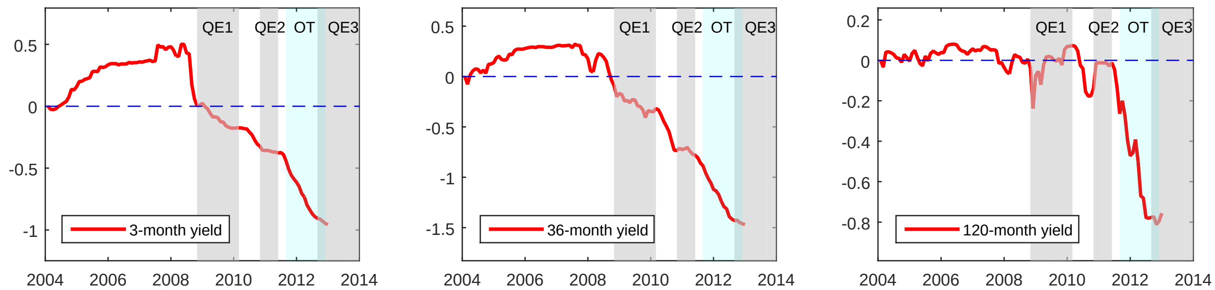
The effects of unconventional monetary policy on the yield curve have been studied in the literature. For example, Swanson and Williams (2014) estimate the time-varying sensitivity of yields to macroeconomic news using high-frequency data and compare the sensitivity measures during the unconventional monetary policy period to those for the period 1990–2000 associated with conventional monetary policy. They find that yields with six months or less to maturity have been severely constrained since early 2009, whereas medium- and longer-term yields (e.g., 5- and 10-year Treasury yields) have essentially been unconstrained by the zero bound during the same period. In addition, Inoue and Rossi (2018) compare how monetary policy shocks affect the yield curve during the conventional and unconventional monetary policy periods. They construct the monetary policy shocks following the traditional approach in Romer and Romer (2004) and calculate the shocks' correlations with yields during two subsamples for conventional and unconventional monetary policy. They show that the correlation during the conventional monetary policy period is highest for short-term maturities, while the correlation is highest for the longest-term maturities during the unconventional monetary policy period. Thus, these empirical findings documented in the literature are also consistent with our finding that monetary policy affects the yield curve in different ways during the conventional and unconventional monetary policy periods.

Based on the findings in this paper as well as in the literature, we argue that these stylized facts explain why the AFNS (i.e., no-arbitrage restrictions) plays an important role in forecasting the yield curve during the period of conventional policy, but not during the period of unconventional policy. To confirm this relationship between monetary policy and its effects on forecasting yields curve, we further examine our explanation by looking at the forecasting performance of several forecasting models over time in the next section.

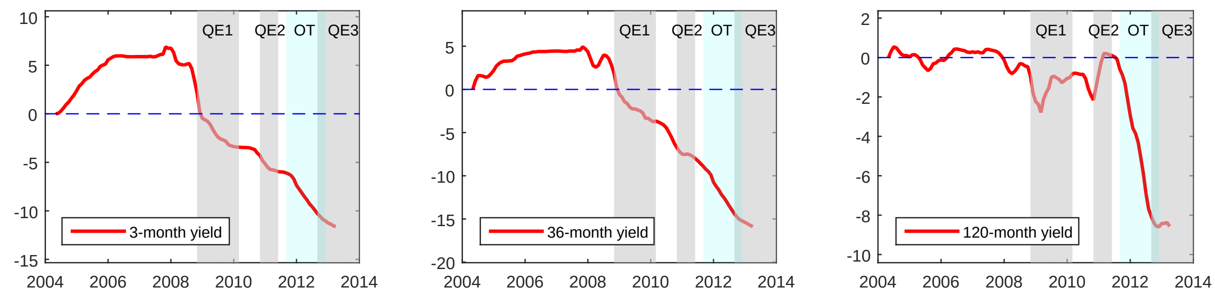
5.2 Forecasting Performance over Time: Cumulative Squared Forecasting Errors

To examine the relative importance of models at each point in time in detail, we plot the cumulative squared forecasting errors of the RW model (benchmark) minus the cumulative squared forecasting errors of the AFNS model over time. The cumulative squared forecasting error at time t for yields with τ months to maturity at the forecasting horizon h is given by $\sum_{s=1}^{t}\left[L_{R,s}(\tau,h) - L_{A,s}(\tau,h)\right]$. Whenever a line increases, the AFNS model forecasts better; whenever it decreases, the RW forecasts better. We choose the AFNS model for the comparison to verify the role of no-arbitrage restrictions in forecasting the yield curves. Plotting the cumulative squared forecasting errors is a useful graphical device to help identify periods in which no-arbitrage restrictions are useful in forecasting the yield curve relative to

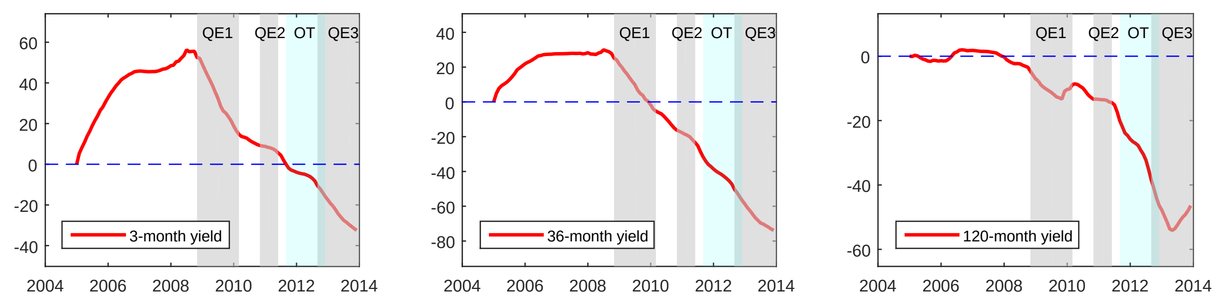
Figure 2: AFNS vs. RW: Difference in cumulative mean squared errors



(a) 1-month-ahead forecasts



(b) 4-month-ahead forecasts



(c) 12-month-ahead forecasts

Note: We plot the cumulative mean squared forecasting errors of the random-walk model (R) minus the cumulative mean squared forecasting errors of the arbitrage-free Neslon-Siegel Model (A): $\sum_{s=1}^{t} [L_{R,s}(\tau, h) - L_{A,s}(\tau, h)]$. The x-axis indicates time $t + h$. Whenever a line increases, the arbitrage-free Nelson-Siegel model forecasts better; whenever it decreases, the random-walk model forecasts better. The grey shaded areas correspond to three quantitative easing programs QE1, QE2, and QE3; and the blue shaded area corresponds to the Maturity Extension Program, also known as the second "Operation Twist (OT)." There is overlap between OT and QE3 from September 2012 to December 2012.

the RW benchmark and to determine whether these periods are consistent with those under conventional monetary policy.[19]

Figure 2 presents the difference in the cumulative squared forecasting errors for three-month, 36-month, and 120-month yields.[20] The differences for three-month and 36-month yields show an upward drift (i.e., the AFNS performs better) during the conventional monetary policy period, while they exhibit a downward drift since QE1 started. For the 120-month yield, two models perform similarly during the conventional monetary policy period, but the downward drift is more pronounced during Operation Twist period in 2011–2012. Operation Twist essentially sells or redeems shorter-term Treasury securities and uses the proceeds to buy longer-term Treasury securities extending the average maturity of the securities in the Federal Reserve's portfolio. For example, the Federal Open Market Committee announced a $400 billion program in September 2011 and an additional $267 billion program in June 2012 through the end of 2012, As a result, it increases short-term bond yields, but lowers long-term bond yields. As we discussed in the previous section, the AFNS, which are associated with high correlations across different maturities, would not perform well during the period of Operation Twist and our empirical evidence confirms this conjecture.

We also consider the relative forecasting performance of NAR_{MS} against the RW benchmark model because NAR_{MS} has the highest frequency of being included in the MCSs across different maturities at different forecasting horizons during the conventional monetary policy period. Figure 3 shows very similar patterns as depicted in Figure 2 that the RW performed very well during the unconventional monetary policy period.

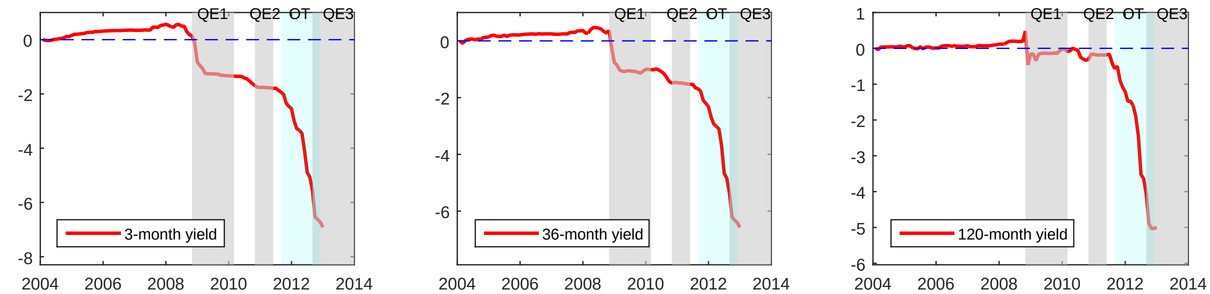
6 Conclusion

Compared with conventional monetary policy, the unconventional policy in the low-interest rate environment since the Great Recession has a different transmission mechanism to the term structure of interest rates. We study how conventional and unconventional monetary policies affect the forecasting performance of individual yield curve models and their mixtures.

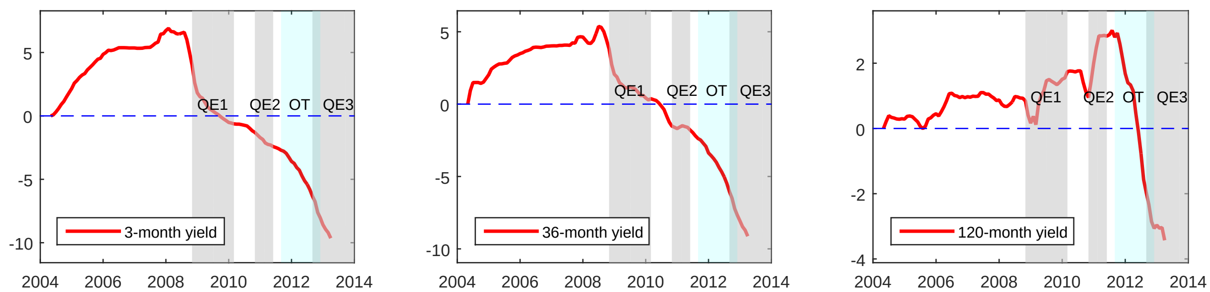
[19] Note that a starting date for the cumulation does not alter this pattern because it will only shift the graph up or down so that the results should be robust to the choice of forecasting evaluation sample.

[20] We find similar patterns for yields to other maturities. The complete figures are available upon request.

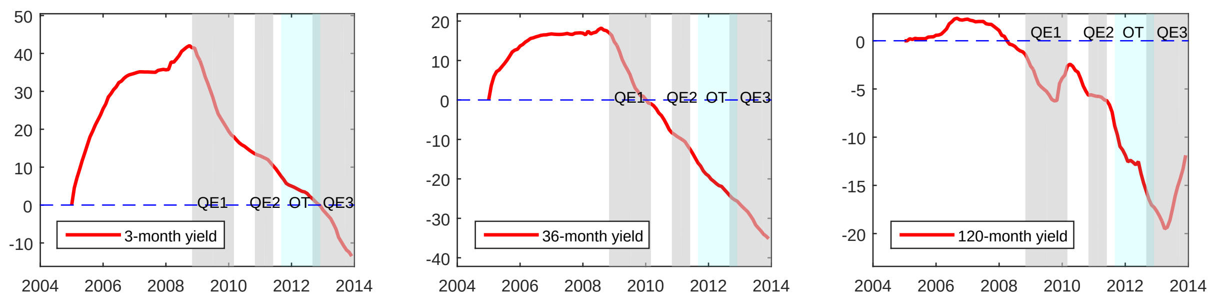
Figure 3: NAR_{MS} vs. RW: Difference in cumulative mean squared errors



(a) 1-month-ahead forecasts



(b) 4-month-ahead forecasts



(c) 12-month-ahead forecasts

Note: We plot the cumulative mean squared forecasting errors of the random-walk model (R) minus the cumulative mean squared forecasting errors of the Markov-switching mixture of three models (NAR_{MS}): $\sum_{s=1}^{t} [L_{R,s}(\tau, h) - L_{NAR_{MS},s}(\tau, h)]$. The x-axis indicates time $t + h$. Whenever a line increases, NAR_{MS} forecasts better; whenever it decreases, R forecasts better. The grey shaded areas correspond to three quantitative easing programs QE1, QE2, and QE3; and the blue shaded area corresponds to the Maturity Extension Program, also known as the second "Operation Twist (OT)." There is overlap between OT and QE3 from September 2012 to December 2012.

We consider three individual models: the dynamic Nelson-Siegel model, the arbitrage-free Nelson-Siegel model, and the random-walk model. The mixtures of two or three models are included to avoid the case that our forecasting results are driven by any potential model specifications. We evaluate forecasting performance based on the MSFE by choosing the best model and constructing the MCSs for each maturity at each forecasting horizon. Out-of-sample forecasts for U.S. bond yields show that the arbitrage-free Nelson-Siegel model and its mixtures perform well in the period of conventional monetary policy, whereas the random-walk model outperforms all the individual models and their mixtures in the period of unconventional monetary policy period.

We show that the tightly constrained cross-equation restrictions of the no-arbitrage condition are associated with high correlations of bond yields across different maturities, whereas the random-walk model performs well when the yields are less correlated and exhibit little variation over time. The diminishing role of no-arbitrage restrictions in forecasting the yield curve since 2009 can be attributed to unconventional monetary policy, which involved direct purchases of long-term bonds while the short-term bond yields were stuck near zero, resulting in low correlations between short- and long-term bond yields and little variation in short-term bond yields. In addition, the more pronounced superiority of the random-walk model forecasts during the maturity extension program period supports our finding that the program moved short- and long-term bond yields in opposite directions.

Finally, we would like to emphasize that although our mixture model is preferable during periods of conventional policy, we do not argue that it is the best option. There are numerous variants of the DNS and AFNS models; our findings simply suggest that whatever the set of candidate models is, combinations of these models may provide better forecasting outcomes, especially during periods of conventional monetary.

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Appendices

A Likelihood

This section presents the step-by-step procedure for the log-likelihood calculation. Suppose that $\boldsymbol{\psi}$ is the set of all model parameters and the log-likelihood $\log L$ is initialized to zero. At time 1, $p(s_{t-1}|Y_{t-1}, \boldsymbol{\psi})$ is given at the unconditional probability of regime s_t. For $t = 1, 2, .., T$, the following steps are repeated sequentially.

Algorithm 2: Log-likelihood calculation

- Step 1: The predictive probability of regime s_t, $p(s_t = j|Y_{t-1}, \boldsymbol{\psi})$ is computed as

$$\begin{aligned} p(s_t &= j|Y_{t-1}, \boldsymbol{\psi}) \\ &= \sum_{i=1}^{2} \Pr[s_t = j|s_{t-1} = i, \boldsymbol{\psi}] \times \Pr(s_{t-1} = i|Y_{t-1}, \boldsymbol{\psi}) \\ &= \sum_{i=1}^{2} q_{ij} \times p(s_{t-1} = i|Y_{t-1}, \boldsymbol{\psi}), \;\; j = 1, 2. \end{aligned}$$

- Step 2: The predictive model weight on $\mathcal{M}_1$, w_{1,s_t} is given by

$$W_{1,t} = \sum_{s_t=1}^{2} w_{1,s_t} \times p(s_t|Y^o_{t-1}, \boldsymbol{\psi}),$$

  such that the predictive model weight on $\mathcal{M}_2$ is $W_{2,t} = 1 - W_{1,t}$.

- Step 3: We now have the conditional likelihood density $p(\mathbf{y}_t|Y_{t-1}, \boldsymbol{\psi})$, given by

$$W_{1,t} \times p(\mathbf{y}_t|Y_{t-1}, \Theta_1, \mathcal{M}_1) + W_{2,t} \times p(\mathbf{y}_t|Y_{t-1}, \Theta_2, \mathcal{M}_2),$$

  and $\log L = \log L + \log p(\mathbf{y}_t|Y_{t-1}, \boldsymbol{\psi})$.

- Step 4: The updated probability of regime s_t, $p(s_t = i|Y_t, \boldsymbol{\psi})$ is calculated and retained as

$$\begin{aligned} p(s_t &= i|Y_t, \boldsymbol{\psi}) \\ &= p(s_t = i|Y_{t-1}, \boldsymbol{\psi}, \mathbf{y}_t) \\ &= \frac{p(s_t = i, \mathbf{y}_t|Y_{t-1}, \boldsymbol{\psi})}{p(\mathbf{y}_t|Y_{t-1}, \boldsymbol{\psi})} \\ &= \frac{p(\mathbf{y}_t|Y_{t-1}, \boldsymbol{\psi}, s_t = i)p(s_t = i|Y_{t-1}, \boldsymbol{\psi})}{p(\mathbf{y}_t|Y_{t-1}, \boldsymbol{\psi})} \text{ for } i = 1, 2, \end{aligned}$$

where the predictive density of y_t given s_t is simply given by

$$\begin{aligned} & p(y_t|Y_{t-1}, \boldsymbol{\psi}, s_t) \\ = \ & w_{1,s_t} \times p(\mathbf{y}_t|Y_{t-1}, \Theta_1, \mathcal{M}_1) + (1 - w_{1,s_t}) \times p(\mathbf{y}_t|Y_{t-1}, \Theta_2, \mathcal{M}_2). \end{aligned}$$

- Step 5: Set $t = t + 1$ and go to Step 1 if $t \leq T$.

B MCMC Sampling

B.1 Prior

In this appendix, we discuss our prior distributions in detail.

We assume that the ϕ for the DNS and G for the AFNS are diagonal, because these restrictions help to improve the predictive accuracy and reduces the computational burden, as shown in Christensen, Diebold and Rudebusch (2011).

For the regime identification, we impose the restriction that for any Markov-switching combinations involving the DNS model, the weight on the DNS model $\mathcal{M}_{NS}$, denoted by w_{NS,s_t}, should be higher in regime 2 than it is in regime 1:

$$0 < w_{NS,s_t=1} < w_{NS,s_t=2} < 1,$$

where w_{AF,s_t} is the weight on the AFNS model. For the AR_{MS} model, which does not include the DNS model, the restriction is replaced by

$$0 < w_{AF,s_t=1} < w_{AF,s_t=2} < 1.$$

All of the restrictions, including those on the factor identification and regime identification, are imposed through the prior. Table 2 summarizes our prior.

Table B.1: Prior distributions

Parameter	Density	Mean	S.D.
$1200 \times \kappa$	Normal	(0.2, -0.1, -0.1)'	(0.01, 0.01, 0.01)'
diag(ϕ)	Normal	(0.9, 0.9, 0.9)'	(0.05, 0.05, 0.05)'
1200×diag(V_{NS})	Inv. Gamma	1.000	0.200
$\rho_{NS,ij}$ $(i \neq j,\, i,j = 1,2,3)$	Uniform	0.000	0.580
$1.4 \times 10^4 \times diag(\Sigma_{NS})$	Inv. Gamma	2.000	0.300

(a) DNS

Parameter	Density	Mean	S.D.
$\bar{\boldsymbol{\gamma}}$	Normal	(-0.15, -0.07, 0)'	(0.01, 0.01, 0.01)'
$\boldsymbol{g}^Q$	Normal	0.067	0.031
diag(G)	Normal	(0.9, 0.9, 0.9)'	(0.05, 0.05, 0.05)'
10^4×diag(V_{AF})	Inv. Gamma	(2, 2.5, 5)'	(0.25, 0.25, 0.25)'
$\rho_{AF,ij}$ $(i \neq j,\, i,j = 1,2,3)$	Uniform	0.000	0.580
$1.4 \times 10^4 \times diag(\Sigma_{AF})$	Inv. Gamma	2.000	0.300

(b) AFNS

Parameter	Density	Mean	S.D.
$1.4 \times 10^4 \times diag(\Sigma_{RW})$	Inv. Gamma	2.000	0.300

(c) Random-walk

Parameter	Density	Mean	S.D.
w_{i,s_t} $(s_t = 1,2)$	Uniform	0.500	0.29

(d) Model weight

Parameter	Density	Mean	S.D.
q_{ii} $(i = 1,2)$	Beta	0.900	0.05

(e) Transition probability

Note: For the DNS and AFNS models, $\rho_{NS,ij}$ $and \rho_{AF,ij}$ are the (i,j) elements of Γ_{NS} and Γ_{AF}, respectively.

B.2 Posterior Simulation

Here, we present the posterior sampling scheme for the most general model among the competing ones, namely, the NAR_{MS} model. The others can be estimated as special cases of the NAR_{MS} model by using alternative approaches to determine the weights.

In the Bayesian context, the posterior density for the dynamic mixture model with Markov regime-switching weights is proportional to the product of the likelihood function of the yield curves ($\mathbf{Y} = \{\mathbf{y}_t\}_{t=1}^T$) and the joint prior density of the regime indicators ($\mathbf{S} = \{s_t\}_{t=1}^T$), latent variables ($\mathbf{X} = \{\mathbf{x}_t\}_{t=1,2,..,T}$ and $\mathbf{F} = \{\mathbf{f}_t\}_{t=1,2,..,T}$)), and model parameters ($\boldsymbol{\psi}$= $\{\Theta_{NS}$, Θ_{AF}, Θ_{RW}, Q, $w\}$).

Thus, the posterior density is given by

$$\pi\left(\boldsymbol{\psi}, \mathbf{X}, \mathbf{F}, \mathbf{S} | \mathbf{Y}\right) \propto f\left(\mathbf{Y} | \boldsymbol{\psi}, \mathbf{X}, \mathbf{F}, \mathbf{S}\right) \times f\left(\mathbf{X}, \mathbf{F} | \boldsymbol{\psi}\right) \times p\left(\mathbf{S} | \boldsymbol{\psi}\right) \times \pi(\boldsymbol{\psi}), \tag{B.1}$$

where $\pi\left(\boldsymbol{\psi}\right)$ is the prior density of the parameters, and $p\left(\mathbf{S}|\boldsymbol{\psi}\right)$ is the prior density of the regime-indicators, given the parameters where it is specified as a discrete two-state Markov-switching process. In addition, $f\left(\mathbf{X}, \mathbf{F}|\mathbf{S},\boldsymbol{\psi}\right)$ is the prior density of the factors and $f\left(\mathbf{Y}|\boldsymbol{\psi}, \mathbf{X}, \mathbf{F}, \mathbf{S}\right)$ is the likelihood function.

Given the joint density, our objective is to simulate the posterior distribution of $(\boldsymbol{\psi}, \mathbf{X}, \mathbf{F}, \mathbf{S})$ conditioned on the observed yield curves $\mathbf{Y}$**.** Because the joint posterior distribution in equation (B.1) is not analytically tractable, we rely on an MCMC simulation. Then, we sample the parameters, factors, regimes, and predictive yield curves recursively from the joint posterior distribution, as follows.

Algorithm: MCMC sampling

- Step 1: Sample $\Theta_{NS}, \Theta_{AF}, \Theta_{RW}, w|\mathbf{Y}$,$Q$.
  - Step 1(a): Sample $\Theta_{NS}, \Theta_{AF}, \Theta_{RW}, w|\mathbf{Y}$,$Q$.
  - Step 1(b): Sample $Q|\mathbf{Y}, \mathbf{S}$,$\Theta_{NS}, \Theta_{AF}, \Theta_{RW}, w$.
- Step 2: Sample $\mathbf{S}|\mathbf{Y}$,$\boldsymbol{\psi}$.
- Step 3: Sample $\mathbf{X}|\mathbf{Y}$,$\boldsymbol{\psi}$ and $\mathbf{F}|\mathbf{Y}$,$\boldsymbol{\psi}$.
- Step 4: Sample $\{\mathbf{y}_{T+h}\}_{h=1}^{H}|\mathbf{Y}, \mathbf{X}, \mathbf{F}, \mathbf{S}$,$\boldsymbol{\psi}$.

We now discuss the details of each MCMC step. The burn-in is 1,000 and the MCMC simulation size beyond the burn-in is 10,000.

Parameter Sampling First, $\Theta = (\Theta_{NS}, \Theta_{AF}, \Theta_{RW}, w)$ are simulated using a tailored randomized blocking Metropolis–Hastings algorithm (TaRB-MH, Chib and Ramamurthy (2010)). Note that the posterior density of Θ is proportional to the product of the likelihood and the prior because

$$\pi\left(\Theta|\mathbf{Y},Q\right) \propto f\left(\mathbf{Y}|\boldsymbol{\psi}\right) \times \pi(\Theta). \tag{B.2}$$

We simulate $\Theta|\mathbf{Y}$,Q rather than $\Theta|\mathbf{Y}, \mathbf{S}, \mathbf{X}$,$Q$ by integrating out the regimes and the latent factors because the former is more efficient than the latter. The likelihood computation is illustrated in Appendix A.

In every MCMC iteration, we apply the TaRB-MH method and sample Θ given ($\mathbf{Y}$,Q). This algorithm is particularly useful when the posterior density is high-dimensional and its surface is possibly irregular. For the technical details, refer to Chib and Ramamurthy (2010) or Chib and Kang (2013).

Next, because the transition probability Q is independent of ($\mathbf{Y}$,Θ), given the regimes $\mathbf{S}$, it is sampled from

$$Q|\mathbf{S}.$$

Moreover, its prior is conjugate and the transition probabilities are sampled from a beta distribution.

Regime Sampling The time-series of the regimes $\mathbf{S}$ is simulated in one block using the multi-move method (Chib (1998)). This method consists of two stages. The first stage calculates the filtered probabilities, $\Pr(s_t|Y_t, \boldsymbol{\psi})$, as follows:

$$\begin{aligned}\Pr(s_t &= j|Y_t, \boldsymbol{\psi}) = \frac{\sum_{i=1}^{2} p(\mathbf{y}_t|Y_{t-1}, s_t = j, \boldsymbol{\psi}) \times \Pr(s_t = j|s_{t-1} = i, \boldsymbol{\psi})}{\sum_{j=1}^{2}\left[\sum_{i=1}^{2} p(\mathbf{y}_t|Y_{t-1}, s_t = j, \boldsymbol{\psi}) \times \Pr(s_t = j|s_{t-1} = i, \boldsymbol{\psi})\right]} \\ &= \frac{\sum_{i=1}^{2} p(\mathbf{y}_t|Y_{t-1}, s_t = j, \boldsymbol{\psi}) \times q_{ij}}{\sum_{j=1}^{2}\left[\sum_{i=1}^{2} p(\mathbf{y}_t|Y_{t-1}, s_t = j, \boldsymbol{\psi}) \times q_{ij}\right]},\end{aligned}$$

for $j = 1, 2$. Then, the conditional density of $\mathbf{y}_t$ $p(\mathbf{y}_t|Y_{t-1}, s_t, \boldsymbol{\psi})$ is computed as a linear combination of the model-specific conditional densities of $\mathbf{y}_t$: $p(\mathbf{y}_t|Y_{t-1}, \Theta_{NS}, \mathcal{M}_{NS})$, $p(\mathbf{y}_t|Y_{t-1}, \Theta_{AF}, \mathcal{M}_{AF})$, and $p(\mathbf{y}_t|Y_{t-1}, \Theta_{RW}, \mathcal{M}_{RW})$. That is,

$$\begin{aligned}& p(\mathbf{y}_t|Y_{t-1}, s_t, \boldsymbol{\psi}) \\ =\; & w_{NS,s_t} \times p(\mathbf{y}_t|Y_{t-1}, \Theta_{NS}, \mathcal{M}_{NS}) + w_{AF,s_t} \times p(\mathbf{y}_t|Y_{t-1}, \Theta_{AF}, \mathcal{M}_{AF}) \\ & +(1 - w_{NS,s_t} - w_{AF,s_t}) \times p(\mathbf{y}_t|Y_{t-1}, \Theta_{RW}, \mathcal{M}_{RW}).\end{aligned}$$

These model-specific conditional densities are already given in equations (5), (15), and (17).

In the second stage, $\{s_t\}_{t=1}^{T}$ is sampled using backward recursion. The regime at time T, s_T, is first drawn with the filtered probability $\Pr(s_T|Y_T, \boldsymbol{\psi})$. Then, conditioned on s_{t+1}, we compute $\Pr(s_t|Y_t, s_{t+1}, \boldsymbol{\psi})$ using the filtered probabilities, as follows:

$$\begin{aligned}& \Pr(s_t = i|Y_t, s_{t+1}, \boldsymbol{\psi}) \\ & \quad = \frac{q_{ij} \times \Pr[s_t = i|Y_t, \boldsymbol{\psi}]}{\sum_{i=1}^{2} q_{ij} \times \Pr[q_t = i|Y_t, \boldsymbol{\psi}]},\; i = 1, 2.\end{aligned} \tag{B.3}$$

Now, given s_{t+1}, s_t is sampled with the probability $\Pr(s_t|Y_t, s_{t+1}, \boldsymbol{\psi})$ for $t = T-1, T-2, .., 1$, which completes the regime sampling.

Factor Sampling The latent factors $\mathbf{X}$ in the DNS model are sampled independently of $(\Theta_{AF}, \Theta_{RW}, w, Q)$. Given (Θ_{NS}, Y), $\mathbf{X}$ is typically simulated using the Carter and Kohn approach (Carter and Kohn (1994)). However, we can compute the factors $\mathbf{F} = \{\mathbf{f}_t\}_{t=1}^{T}$ precisely in the AFNS model as

$$\mathbf{f}_t = (\mathbf{b}_B)^{-1} \times \left(\mathbf{y}_t^B - \mathbf{a}_B\right)$$

using the basis yields and the model parameters.

Predictive Yield Curve Sampling Each MCMC cycle is completed by sampling the posterior predictive draws, given ($\mathbf{Y}$, $\mathbf{X}$, $\mathbf{F}$, $\mathbf{S}$, $\boldsymbol{\psi}$). For each posterior draw, $(\mathbf{y}_T, \mathbf{x}_T, \mathbf{f}_T, s_T, \boldsymbol{\psi})$, and a forecast horizon of $h = 1, 2, .., H$, we first simulate the predictive draws of the factors $\{\mathbf{x}_{T+h},\ \mathbf{f}_{T+h}\}_{h=1}^{H}$. Given the factors and parameters, the model-specific predictive bond yields are generated within the individual model specifications. Next, the predictive regime $\{s_{T+h}\}_{h=1}^{H}$ is sampled using the Markov-switching process. This regime determines the model weights for each forecast horizon. Finally, the predictive yield curve is computed as a linear combination of the model-specific predictive yield curves and is retained as a posterior predictive draw. The following algorithm summarizes the predictive yield curve simulation.

Algorithm 3: Posterior predictive distribution simulation

- Step 1: Sample the factors $\{\mathbf{x}_{T+h}\}_{h=1}^{H}|\mathbf{X},\Theta_{NS}$ and $\{\mathbf{f}_{T+h}\}_{h=1}^{H}|\mathbf{F},\Theta_{AF}$.
- Step 2: Sample the model-specific predictive yields

$$\{\mathbf{y}_{NS,T+h}\}_{h=1}^{H}|\mathbf{X},\Theta_{NS}, \quad \{\mathbf{y}_{AF,T+h}\}_{h=1}^{H}|\mathbf{F},\Theta_{AF}, \text{ and } \{\mathbf{y}_{RW,T+h}\}_{h=1}^{H}|\mathbf{Y},\Theta_{RW}.$$

- Step 3: Sample the predictive regimes, $\{s_{T+h}\}_{h=1}^{H}|\mathbf{S},Q$.
- Step 4: For $h = 1, 2, .., H$, compute the predictive yield curve as

$$\begin{aligned}\mathbf{y}_{T+h} &= w_{NS,s_{T+h}} \times \mathbf{y}_{NS,T+h} + w_{AF,s_{T+h}} \times \mathbf{y}_{AF,T+h} \\ &\quad +(1 - w_{NS,s_{T+h}} - w_{AF,s_{T+h}}) \times \mathbf{y}_{RW,T+h}.\end{aligned}$$

- Step 5: Retain $\{\mathbf{y}_{T+h}\}_{h=1}^{H}$ as a posterior predictive draw.

C Tables

Table C.1: Model confidence set results for one-month-ahead forecasts: Conventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.000	0.097	0.015	0.096	0.058	0.071	0.002	0.086	0.019	0.094	0.058	0.081	0.143	0.069	0.018	0.049	1
A	0.248	0.088	0.108	0.080	0.128	0.066	0.054	0.082	0.172	0.090	0.058	0.086	0.011	0.083	0.013	0.049	4
R	0.081	0.096	0.108	0.082	0.010	0.078	0.002	0.086	0.172	0.092	0.178	0.074	1.000	0.062	0.013	0.050	4
Equal weight																	
NA_E	0.110	0.095	0.108	0.079	0.435	0.061	0.054	0.084	0.000	0.106	0.058	0.082	0.000	0.117	0.000	0.059	3
NR_E	0.000	0.097	0.040	0.086	0.010	0.072	0.000	0.088	0.172	0.091	0.113	0.076	0.314	0.065	0.007	0.050	3
AR_E	0.110	0.095	0.108	0.082	0.058	0.071	0.002	0.085	0.172	0.089	0.178	0.074	0.143	0.068	0.018	0.049	5
NAR_E	0.224	0.089	1.000	0.073	1.000	0.061	0.054	0.083	0.000	0.097	0.113	0.076	0.003	0.086	0.004	0.055	4
Constant weight																	
NA_C	0.110	0.091	0.040	0.087	0.218	0.065	1.000	0.077	0.185	0.088	0.178	0.073	0.143	0.070	1.000	0.046	7
NR_C	0.000	0.097	0.015	0.092	0.015	0.072	0.002	0.087	0.060	0.092	0.092	0.078	0.226	0.066	0.050	0.048	1
AR_C	0.110	0.094	0.108	0.081	0.058	0.068	0.013	0.084	0.172	0.091	0.092	0.080	0.017	0.080	0.004	0.050	3
NAR_C	0.248	0.088	0.056	0.083	0.058	0.068	0.054	0.082	0.172	0.091	0.178	0.073	0.134	0.071	0.050	0.048	4
Markov-switching weight																	
NA_{MS}	0.110	0.091	0.035	0.090	0.128	0.066	0.109	0.080	0.185	0.088	0.236	0.071	0.162	0.068	0.148	0.047	7
NR_{MS}	0.110	0.095	0.035	0.090	0.033	0.071	0.002	0.086	0.172	0.089	0.113	0.075	0.317	0.064	0.018	0.049	4
AR_{MS}	0.081	0.096	0.108	0.082	0.058	0.069	0.002	0.087	0.172	0.091	0.113	0.078	0.031	0.078	0.007	0.050	3
NAR_{MS}	1.000	0.087	0.108	0.081	0.219	0.064	0.464	0.077	1.000	0.084	1.000	0.068	0.314	0.065	0.361	0.046	8

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of being included in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.2: Model confidence set results for one-month-ahead forecasts: Unconventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.000	0.028	1.000	0.006	0.333	0.009	0.000	0.039	0.000	0.112	0.002	0.170	0.005	0.144	0.142	0.099	3
A	0.000	0.046	0.000	0.037	0.000	0.029	0.000	0.060	0.000	0.114	0.003	0.087	0.005	0.155	0.060	0.111	0
R	1.000	0.020	0.233	0.018	0.130	0.020	1.000	0.029	1.000	0.044	1.000	0.069	1.000	0.085	0.441	0.097	8
Equal weight																	
NA_E	0.000	0.066	0.000	0.048	0.000	0.039	0.000	0.069	0.000	0.139	0.002	0.156	0.005	0.165	0.060	0.111	0
NR_E	0.000	0.025	0.233	0.010	0.130	0.012	0.001	0.035	0.000	0.072	0.003	0.106	0.005	0.108	1.000	0.096	3
AR_E	0.000	0.041	0.000	0.035	0.000	0.033	0.000	0.054	0.000	0.083	0.020	0.079	0.005	0.124	0.060	0.109	0
NAR_E	0.000	0.100	0.000	0.081	0.000	0.072	0.000	0.102	0.000	0.145	0.002	0.147	0.005	0.183	0.006	0.143	0
Constant weight																	
NA_C	0.000	0.047	0.000	0.022	0.130	0.019	0.000	0.052	0.000	0.110	0.002	0.120	0.005	0.140	0.091	0.102	1
NR_C	0.000	0.029	0.233	0.008	0.130	0.010	0.000	0.040	0.000	0.096	0.002	0.139	0.005	0.127	0.142	0.098	3
AR_C	0.000	0.061	0.000	0.053	0.000	0.046	0.000	0.074	0.000	0.119	0.003	0.097	0.005	0.160	0.006	0.125	0
NAR_C	0.000	0.101	0.000	0.071	0.000	0.065	0.000	0.106	0.000	0.171	0.002	0.193	0.005	0.206	0.006	0.148	0
Markov-switching weight																	
NA_{MS}	0.000	0.092	0.000	0.073	0.000	0.069	0.000	0.094	0.000	0.134	0.003	0.116	0.005	0.163	0.060	0.124	0
NR_{MS}	0.000	0.026	0.233	0.008	1.000	0.009	0.001	0.036	0.000	0.082	0.002	0.118	0.005	0.114	0.318	0.097	3
AR_{MS}	0.000	0.054	0.000	0.041	0.000	0.031	0.000	0.063	0.000	0.095	0.003	0.087	0.005	0.142	0.060	0.115	0
NAR_{MS}	0.000	0.157	0.000	0.135	0.000	0.128	0.000	0.160	0.000	0.213	0.001	0.218	0.002	0.254	0.001	0.193	0

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.3: Model confidence set results for one-month-ahead forecasts: Conventional and Unconventional monetary policy period

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.056	0.062	0.295	0.051	0.504	0.040	0.062	0.063	0.003	0.103	0.014	0.125	0.002	0.107	0.208	0.074	3
A	0.056	0.067	0.066	0.058	0.135	0.047	0.021	0.071	0.003	0.102	0.027	0.086	0.002	0.119	0.092	0.080	1
R	1.000	0.058	0.369	0.050	0.135	0.049	1.000	0.058	1.000	0.068	1.000	0.071	1.000	0.074	0.473	0.073	8
Equal weight																	
NA_E	0.014	0.081	0.051	0.063	0.083	0.050	0.021	0.077	0.003	0.122	0.014	0.119	0.002	0.141	0.092	0.085	0
NR_E	0.056	0.061	1.000	0.048	0.265	0.042	0.062	0.062	0.004	0.082	0.027	0.091	0.005	0.087	0.481	0.073	3
AR_E	0.025	0.068	0.066	0.059	0.070	0.052	0.021	0.069	0.004	0.086	0.055	0.076	0.002	0.096	0.092	0.079	0
NAR_E	0.011	0.094	0.051	0.077	0.070	0.067	0.010	0.093	0.003	0.121	0.014	0.112	0.002	0.135	0.026	0.099	0
Constant weight																	
NA_C	0.023	0.069	0.101	0.054	0.293	0.042	0.062	0.064	0.003	0.099	0.014	0.096	0.002	0.105	0.387	0.074	3
NR_C	0.056	0.063	0.321	0.050	0.293	0.041	0.062	0.064	0.003	0.094	0.014	0.109	0.002	0.097	0.395	0.073	3
AR_C	0.015	0.077	0.051	0.067	0.070	0.057	0.021	0.079	0.003	0.105	0.027	0.088	0.002	0.120	0.092	0.087	0
NAR_C	0.011	0.094	0.026	0.077	0.070	0.066	0.010	0.094	0.003	0.131	0.014	0.133	0.002	0.139	0.092	0.098	0
Markov-switching weight																	
NA_{MS}	0.014	0.092	0.006	0.081	0.070	0.067	0.021	0.087	0.003	0.111	0.027	0.093	0.002	0.115	0.092	0.085	0
NR_{MS}	0.056	0.061	0.380	0.049	1.000	0.040	0.062	0.061	0.004	0.086	0.014	0.096	0.005	0.089	1.000	0.073	3
AR_{MS}	0.015	0.075	0.051	0.061	0.083	0.050	0.021	0.075	0.004	0.093	0.027	0.082	0.002	0.110	0.092	0.083	0
NAR_{MS}	0.008	0.122	0.006	0.108	0.019	0.096	0.008	0.118	0.003	0.149	0.014	0.143	0.002	0.160	0.026	0.119	0

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.4: Model confidence set results for four-month-ahead forecasts: Conventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.001	0.632	0.013	0.584	0.003	0.517	0.003	0.524	0.006	0.486	0.001	0.329	0.190	0.253	0.095	0.172	1
A	0.080	0.575	0.013	0.519	0.005	0.464	0.025	0.486	0.067	0.470	0.584	0.284	0.000	0.296	0.022	0.187	1
R	0.001	0.639	0.000	0.628	0.000	0.579	0.003	0.538	0.006	0.513	0.001	0.329	0.430	0.250	0.095	0.178	1
Equal weight																	
NA_E	0.080	0.575	0.120	0.492	0.151	0.438	0.021	0.493	0.006	0.513	0.000	0.367	0.000	0.407	0.000	0.257	2
NR_E	0.000	0.640	0.000	0.613	0.000	0.558	0.000	0.543	0.006	0.500	0.000	0.331	0.190	0.254	0.022	0.179	1
AR_E	0.009	0.601	0.013	0.559	0.003	0.509	0.021	0.504	0.014	0.474	0.166	0.303	0.013	0.260	0.095	0.178	1
NAR_E	1.000	0.514	1.000	0.468	1.000	0.422	1.000	0.440	0.361	0.434	0.584	0.284	0.013	0.276	0.022	0.189	6
Constant weight																	
NA_C	0.009	0.578	0.065	0.514	0.091	0.449	0.093	0.459	0.181	0.438	0.262	0.288	0.544	0.240	1.000	0.157	4
NR_C	0.001	0.630	0.005	0.598	0.000	0.536	0.003	0.531	0.006	0.485	0.001	0.320	0.430	0.244	0.323	0.165	2
AR_C	0.009	0.601	0.013	0.538	0.003	0.486	0.021	0.503	0.014	0.483	0.262	0.298	0.000	0.301	0.004	0.195	1
NAR_C	0.080	0.560	0.020	0.515	0.006	0.460	0.049	0.465	0.115	0.440	0.262	0.289	1.000	0.236	0.391	0.157	4
Markov-switching weight																	
NA_{MS}	0.009	0.601	0.013	0.546	0.005	0.480	0.021	0.487	0.067	0.456	0.262	0.289	0.430	0.245	0.323	0.162	3
NR_{MS}	0.001	0.624	0.005	0.600	0.002	0.532	0.021	0.522	0.014	0.478	0.018	0.316	0.544	0.241	0.207	0.169	2
AR_{MS}	0.009	0.594	0.013	0.534	0.003	0.481	0.021	0.499	0.014	0.476	0.262	0.297	0.001	0.291	0.012	0.193	1
NAR_{MS}	0.080	0.546	0.065	0.502	0.025	0.450	0.194	0.456	1.000	0.433	1.000	0.279	0.544	0.238	0.323	0.161	5

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.5: Model confidence set results for four-month-ahead forecasts: Unconventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.000	0.183	0.103	0.141	0.040	0.151	0.000	0.258	0.000	0.431	0.019	0.589	0.056	0.540	0.276	0.428	2
A	0.000	0.389	0.000	0.428	0.000	0.417	0.000	0.502	0.000	0.628	0.073	0.473	0.010	0.696	0.087	0.543	0
R	1.000	0.109	1.000	0.129	1.000	0.139	1.000	0.155	1.000	0.215	1.000	0.334	1.000	0.376	1.000	0.392	8
Equal weight																	
NA_E	0.000	0.515	0.000	0.501	0.000	0.452	0.000	0.489	0.000	0.618	0.019	0.640	0.026	0.641	0.207	0.495	1
NR_E	0.000	0.161	0.021	0.151	0.000	0.164	0.000	0.229	0.000	0.332	0.073	0.460	0.106	0.456	0.553	0.401	2
AR_E	0.000	0.292	0.000	0.325	0.000	0.333	0.000	0.386	0.000	0.473	0.073	0.464	0.026	0.593	0.103	0.515	1
NAR_E	0.000	0.406	0.000	0.409	0.000	0.396	0.000	0.432	0.000	0.498	0.049	0.494	0.056	0.563	0.264	0.471	1
Constant weight																	
NA_C	0.000	0.319	0.000	0.282	0.000	0.260	0.000	0.324	0.000	0.439	0.073	0.466	0.106	0.500	0.553	0.402	2
NR_C	0.000	0.196	0.000	0.173	0.000	0.187	0.000	0.294	0.000	0.444	0.019	0.588	0.056	0.555	0.264	0.454	1
AR_C	0.000	0.455	0.000	0.499	0.000	0.500	0.000	0.579	0.000	0.692	0.034	0.586	0.009	0.777	0.057	0.635	0
NAR_C	0.000	0.338	0.000	0.312	0.000	0.304	0.000	0.375	0.000	0.485	0.034	0.537	0.056	0.558	0.264	0.455	1
Markov-switching weight																	
NA_{MS}	0.000	0.415	0.000	0.387	0.000	0.352	0.000	0.391	0.000	0.468	0.073	0.429	0.106	0.498	0.487	0.403	2
NR_{MS}	0.000	0.158	0.138	0.138	0.040	0.152	0.000	0.236	0.000	0.366	0.034	0.498	0.106	0.489	0.276	0.420	3
AR_{MS}	0.000	0.396	0.000	0.416	0.000	0.389	0.000	0.466	0.000	0.547	0.034	0.509	0.010	0.681	0.073	0.575	0
NAR_{MS}	0.000	0.381	0.000	0.368	0.000	0.354	0.000	0.406	0.000	0.500	0.034	0.519	0.036	0.571	0.207	0.473	1

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.6: Model confidence set results for four-month-ahead forecasts: Conventional and Unconventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.141	0.408	1.000	0.362	1.000	0.334	0.038	0.391	0.012	0.458	0.011	0.459	0.049	0.396	0.042	0.300	3
A	0.044	0.482	0.062	0.474	0.050	0.440	0.002	0.494	0.003	0.549	0.129	0.379	0.003	0.496	0.004	0.365	1
R	1.000	0.374	0.394	0.378	0.200	0.359	1.000	0.347	1.000	0.364	1.000	0.332	1.000	0.313	0.439	0.285	8
Equal weight																	
NA_E	0.026	0.545	0.051	0.496	0.050	0.445	0.003	0.491	0.003	0.566	0.011	0.503	0.003	0.524	0.004	0.376	0
NR_E	0.141	0.401	0.197	0.382	0.063	0.361	0.038	0.386	0.016	0.416	0.096	0.395	0.066	0.355	0.211	0.290	3
AR_E	0.141	0.446	0.094	0.442	0.050	0.421	0.005	0.445	0.006	0.474	0.096	0.384	0.015	0.427	0.004	0.346	1
NAR_E	0.141	0.460	0.163	0.438	0.063	0.409	0.033	0.436	0.012	0.466	0.096	0.389	0.034	0.420	0.023	0.330	1
Constant weight																	
NA_C	0.141	0.449	0.163	0.398	0.200	0.355	0.038	0.392	0.016	0.438	0.129	0.377	0.066	0.370	1.000	0.280	5
NR_C	0.141	0.413	0.163	0.386	0.063	0.362	0.033	0.413	0.012	0.465	0.011	0.454	0.049	0.399	0.042	0.310	2
AR_C	0.026	0.528	0.029	0.519	0.012	0.493	0.002	0.541	0.003	0.588	0.096	0.442	0.003	0.539	0.000	0.415	0
NAR_C	0.141	0.449	0.163	0.414	0.063	0.382	0.033	0.420	0.012	0.463	0.096	0.413	0.049	0.397	0.042	0.306	2
Markov-switching weight																	
NA_{MS}	0.026	0.508	0.062	0.467	0.050	0.416	0.005	0.439	0.012	0.462	0.129	0.359	0.063	0.371	0.439	0.283	2
NR_{MS}	0.141	0.391	0.394	0.369	0.200	0.342	0.038	0.379	0.016	0.422	0.096	0.407	0.066	0.365	0.099	0.295	3
AR_{MS}	0.034	0.495	0.062	0.475	0.050	0.435	0.003	0.482	0.003	0.512	0.096	0.403	0.006	0.486	0.000	0.384	0
NAR_{MS}	0.088	0.463	0.163	0.435	0.063	0.402	0.033	0.431	0.008	0.467	0.096	0.399	0.049	0.404	0.042	0.317	1

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.7: Model confidence set results for 12-month-ahead forecasts: Conventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.050	3.944	0.064	3.560	0.050	2.967	0.077	2.378	0.085	1.888	0.032	1.162	0.119	0.812	0.098	0.518	1
A	1.000	3.370	1.000	3.068	1.000	2.572	1.000	2.116	1.000	1.735	1.000	0.900	0.119	0.929	0.074	0.615	7
R	0.050	4.024	0.028	3.761	0.025	3.157	0.245	2.333	0.367	1.781	0.116	1.004	1.000	0.644	1.000	0.417	5
Equal weight																	
NA_E	0.318	3.423	0.495	3.093	0.413	2.609	0.245	2.229	0.078	1.908	0.032	1.255	0.030	1.163	0.015	0.777	4
NR_E	0.050	3.984	0.035	3.679	0.028	3.093	0.148	2.372	0.225	1.853	0.032	1.114	0.119	0.772	0.098	0.509	3
AR_E	0.092	3.686	0.128	3.399	0.117	2.865	0.245	2.235	0.367	1.767	0.116	0.993	0.119	0.803	0.098	0.531	6
NAR_E	0.375	3.421	0.212	3.164	0.134	2.693	0.283	2.169	0.379	1.748	0.057	1.037	0.119	0.847	0.085	0.567	6
Constant weight																	
NA_C	0.092	3.734	0.128	3.346	0.117	2.774	0.259	2.210	0.379	1.759	0.032	1.057	0.119	0.781	0.098	0.506	5
NR_C	0.050	3.904	0.064	3.583	0.050	3.006	0.127	2.372	0.152	1.876	0.032	1.154	0.119	0.809	0.098	0.529	3
AR_C	0.092	3.498	0.128	3.195	0.117	2.713	0.245	2.222	0.279	1.814	0.057	1.019	0.090	0.960	0.051	0.647	4
NAR_C	0.092	3.621	0.128	3.298	0.117	2.783	0.245	2.230	0.282	1.785	0.032	1.087	0.119	0.799	0.098	0.520	5
Markov-switching weight																	
NA_{MS}	0.092	3.793	0.128	3.440	0.117	2.868	0.245	2.287	0.279	1.812	0.032	1.048	0.119	0.808	0.098	0.527	5
NR_{MS}	0.092	3.836	0.128	3.526	0.117	2.965	0.245	2.328	0.279	1.835	0.032	1.116	0.119	0.773	0.098	0.506	5
AR_{MS}	0.092	3.603	0.128	3.280	0.117	2.733	0.259	2.200	0.367	1.774	0.116	0.984	0.119	0.906	0.057	0.615	6
NAR_{MS}	0.166	3.464	0.149	3.175	0.134	2.709	0.283	2.191	0.379	1.752	0.032	1.043	0.119	0.789	0.098	0.510	6

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.8: Model confidence set results for 12-month-ahead forecasts: Unconventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.000	0.442	0.000	0.428	0.000	0.492	0.000	0.687	0.000	0.969	0.000	1.168	0.020	1.068	0.058	0.883	0
A	0.000	1.354	0.000	1.551	0.000	1.616	0.000	1.753	0.000	1.925	0.000	1.405	0.000	1.727	0.003	1.347	0
R	1.000	0.099	1.000	0.169	1.000	0.187	1.000	0.168	1.000	0.236	1.000	0.490	1.000	0.662	1.000	0.686	8
Equal weight																	
NA_E	0.000	1.390	0.000	1.440	0.000	1.364	0.000	1.307	0.000	1.421	0.000	1.289	0.005	1.246	0.038	1.009	0
NR_E	0.000	0.297	0.000	0.341	0.000	0.399	0.000	0.482	0.000	0.625	0.001	0.790	0.092	0.806	0.314	0.716	1
AR_E	0.000	0.651	0.000	0.786	0.000	0.854	0.000	0.902	0.000	0.991	0.001	0.869	0.020	1.047	0.051	0.887	0
NAR_E	0.000	0.850	0.000	0.939	0.000	0.962	0.000	0.938	0.000	0.954	0.001	0.796	0.048	0.867	0.304	0.723	1
Constant weight																	
NA_C	0.000	0.940	0.000	0.934	0.000	0.904	0.000	0.930	0.000	1.053	0.001	0.982	0.021	0.996	0.086	0.833	0
NR_C	0.000	0.422	0.000	0.453	0.000	0.543	0.000	0.720	0.000	0.946	0.000	1.112	0.020	1.035	0.058	0.858	0
AR_C	0.000	1.185	0.000	1.373	0.000	1.454	0.000	1.565	0.000	1.688	0.000	1.280	0.000	1.519	0.004	1.209	0
NAR_C	0.000	0.858	0.000	0.878	0.000	0.893	0.000	0.926	0.000	1.022	0.001	0.973	0.030	0.962	0.170	0.791	1
Markov-switching weight																	
NA_{MS}	0.000	1.051	0.000	1.065	0.000	1.023	0.000	1.008	0.000	1.080	0.001	0.905	0.030	0.966	0.117	0.807	1
NR_{MS}	0.000	0.319	0.000	0.341	0.000	0.422	0.000	0.580	0.000	0.794	0.001	0.981	0.030	0.950	0.117	0.807	1
AR_{MS}	0.000	1.019	0.000	1.131	0.000	1.117	0.000	1.179	0.000	1.231	0.001	0.975	0.002	1.256	0.016	1.042	0
NAR_{MS}	0.000	0.908	0.000	0.949	0.000	0.956	0.000	0.962	0.000	1.033	0.001	0.950	0.021	0.975	0.092	0.813	0

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of being included in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.

Table C.9: Model confidence set results for 12-month-ahead forecasts: Conventional and Unconventional monetary policy

	3 months		6 months		12 months		24 months		36 months		60 months		84 months		120 months		$\mathcal{M}_{90\%}$
	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	p_{MCS}	MSFE	freq.
Single model																	
N	0.158	2.193	0.284	1.994	0.173	1.730	0.016	1.533	0.002	1.428	0.002	1.165	0.004	0.940	0.012	0.701	3
A	0.146	2.362	0.111	2.309	0.059	2.094	0.006	1.935	0.002	1.830	0.011	1.153	0.000	1.328	0.001	0.981	1
R	1.000	2.061	0.469	1.965	1.000	1.672	1.000	1.251	1.000	1.008	1.000	0.747	1.000	0.653	1.000	0.551	8
Equal weight																	
NA_E	0.146	2.407	0.144	2.267	0.110	1.986	0.016	1.768	0.002	1.665	0.002	1.272	0.001	1.204	0.004	0.893	3
NR_E	0.209	2.140	0.284	2.010	0.173	1.746	0.016	1.427	0.002	1.239	0.011	0.952	0.014	0.789	0.096	0.613	3
AR_E	0.209	2.168	0.212	2.093	0.110	1.860	0.016	1.568	0.002	1.379	0.011	0.931	0.004	0.925	0.009	0.709	3
NAR_E	0.270	2.135	0.284	2.051	0.173	1.827	0.016	1.554	0.002	1.351	0.011	0.917	0.008	0.857	0.071	0.645	3
Constant weight																	
NA_C	0.158	2.337	0.149	2.140	0.110	1.839	0.016	1.570	0.002	1.406	0.011	1.020	0.008	0.889	0.023	0.670	3
NR_C	0.209	2.163	0.284	2.018	0.173	1.775	0.016	1.546	0.002	1.411	0.011	1.133	0.004	0.922	0.012	0.694	3
AR_C	0.158	2.341	0.130	2.284	0.060	2.083	0.006	1.894	0.002	1.751	0.011	1.150	0.000	1.240	0.001	0.928	2
NAR_C	0.158	2.239	0.212	2.088	0.110	1.838	0.016	1.578	0.002	1.404	0.011	1.030	0.008	0.880	0.052	0.655	3
Markov-switching weight																	
NA_{MS}	0.065	2.422	0.144	2.252	0.110	1.945	0.016	1.647	0.002	1.446	0.011	0.977	0.008	0.887	0.023	0.667	1
NR_{MS}	0.270	2.078	1.000	1.933	0.257	1.694	0.016	1.454	0.002	1.314	0.011	1.048	0.008	0.862	0.039	0.656	3
AR_{MS}	0.158	2.311	0.149	2.205	0.110	1.925	0.016	1.689	0.002	1.502	0.011	0.979	0.001	1.081	0.004	0.829	2
NAR_{MS}	0.208	2.186	0.215	2.062	0.136	1.832	0.016	1.576	0.002	1.392	0.011	0.997	0.008	0.882	0.039	0.661	3

Note: The MCS p-values and MSFEs are reported for maturities of 3, 6, 12, 24, 36, 60, 84, and 120 months. The last column shows the frequency of inclusion in the MCSs across different maturities for each model combination. The model indicators N, A, and R denote the DNS model, AFNS model, and RW model, respectively. The subscripts E, C, and MS denote equal weights, (estimated) constant weights, and Markov-switching weight combinations, respectively.