Forecasting Interest Rates and Inflation: Blue Chip Clairvoyants or Econometrics?

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Abstract

This is the first study to examine the forecasting performance of the individual participants in the Blue Chip Financial Forecasts - a unique collection of cross-sectional time series survey data on interest rates and inflation. An empirical examination reveals that fed funds futures prices best predict the fed funds rate at very short horizons, and that survey forecasters are competitive at short horizon forecasts of short to medium maturity interest rates. The Diebold-Li model with VAR(3) dynamics, enhanced by shrinking the parameter estimates toward the long run mean using the Qrinkage estimator, emerges as the best performing model for long horizon forecasts of yields up to 2 years. For forecasting 5 and 10-year maturity yields, autoregressive Qrinkage models dominate. Individual survey forecasters, including the mean forecaster, do particularly well at forecasting inflation.

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1 Introduction

The art of clairvoyance has been around long before the first tasseographer glared into an empty teacup and saw the curvature in the leaves pointing to signs of the future. Like the tea watcher, traders, monetary policy makers and trend spotters are keenly focused on changes in the shape of a particular curve. A new twist, shift or turn in the yield curve may signal a change in expected prices or a downturn in economic growth, thus serving as a harbinger of the future path of monetary policy and the future state of the macroeconomy. Accurately predicting interest rates is tantamount to accurately predicting future prices. Hence accurate forecasts of the term structure of interest rates is of fundamental importance to the decision making process of central banks, speculative traders, firms and households.

This research examines a world of competing clairvoyants, both human forecasters and those purely econometric in nature, and strives to say something about which one produces superior forecasts. We do so by evaluating the forecasting performance of the individual analysts in the Blue Chip Financial Forecasts survey against a set of econometric forecasting models. We extract a unique data set that comprises the individual time series of the participants in the Blue Chip Financial Forecasts from January of 1993 to January of 2006. Competing forecasts for interest rates and inflation are generated by various econometric forecasting models. Included in this set are models using the Qrinkage, or criteria-based shrinkage estimator of Hansen (2006), that can be specified to shrink the estimated parameters so as to pull the model's forecasts toward a specific prior, such as the long run mean or the random walk forecast. We also take the Nelson and Siegel (1987) model of Diebold and Li (2005), allow for more general dynamics on the underlying factors, and apply Qrinkage to the estimated parameters. Additionally, for the federal funds rate, financial market-based forecasts are constructed using futures prices. In addition to reporting the root mean squared forecast errors (RMSFE), we consider the information content of the data and use Model Confidence Set p-values, introduced in Hansen, Lunde, and Nason (2003, 2005), as a statistical measure for evaluating the performance of each forecasting model.

The large literature on optimal forecast combination suggests that using the average or consensus forecast leads, in general, to greater forecasting precision by diversifying across different forecasting techniques and by drawing on information from different sources. For example, Zarnowitz and Braun (1992) show that combining forecasts of macroeconomic variables results in large gains in accuracy. A similar conclusion is reached by Bauer, Eisenbeis, Waggoner, and Zha (2003), who study the forecasting performance of the individuals in the Blue Chip Economic Indicators, a related survey focusing mostly on macroeconomic variables. Although this points to strong evidence for only considering the mean forecasts of macroeconomic variables, it is not clear that the same would be true for forecasts of interest rates. If there are a large number of forecasters who are not providing their true forecasts, or if the forecasters have asymmetric loss functions, then aggregating across the entire set of forecasts may not necessarily improve forecasting performance. This begs the question: does a particular forecaster stand out from the crowd by consistently outperforming the average or consensus forecaster? Moreover, how do individual survey forecasters perform when compared with a set of econometric benchmarks? Do certain forecasters posses superior predictive ability? These and similar questions uniquely motivate the study of the time series of individual forecasters in the Blue Chip Financial Forecasts. This is the only known survey that encompasses forecasts of essentially the entire term structure of US interest rates and the macroeconomic variables that influence them. Accurate forecasts of interest rates and inflation are of importance to traders, financial managers and monetary policy makers, many of whom subscribe to and depend on these forecasts to anchor important decisions. Our collection of individual-level forecast data is unique in the world of academia, and enables us to study the forecasting performance of the individual participants in this survey. In addition, econometric forecasts are susceptible to in-sample over-fitting, thus an important question concerns the choice of gravity point to which to shrink the parameters for out-of-sample forecasting. Should we shrink the forecasts toward the long run mean or toward the random walk forecast?

The finance literature is full of studies that examine the relevance of analysts' forecasts in assessing valuation in the equity markets. The literature linking survey forecasts to bond markets is much less extensive, yet to the extent that forecasts provide information on market expectations about macro-variables and the future path of interest rates, they are important for bond pricing. Chun (2006) incorporates information from the Blue Chip Financial Forecasts into a dynamic term structure model via a forward-looking monetary policy reaction function. Kim and Orphanides (2005) leverage information from the Blue Chip Financial Forecasts to help overcome estimation issues relating to small samples.[1] Recent studies using the Blue Chip surveys include Chernov and Müller (2007), Orphanides and Wei (2008) and Piazzesi and Schneider (2008). The recent proliferation of articles employing the Blue Chip surveys suggests that evaluating and examining the performance of the survey participants is an important and topical research question. The shared common thread among these prior studies is their use of the mean or consensus survey forecast, yet as we demonstrate in this study, looking at individual level data may contain important information for predicting interest rates and inflation.

The literature on forecast evaluation is large and extensive. Studies that examine interest rate forecasting using parametric models include Diebold and Li (2005) and Almeida and Vicente (2007). Other studies are based on traditional dynamic arbitrage-free models, such as Duffee (2002), or models including macroeconomic information, such as Ang and Piazzesi (2004), Favero, Niu, and Sala (2007) and Mönch (2007). Focusing on inflation, Ang, Bekaert, and Wei (2005) compare the forecasting performance of surveys with a set of econometric forecasts and find that mean survey forecasts do the best at forecasting.[2] Although many studies have evaluated the forecasting performance of the mean survey forecaster against a set of econometric models, very few studies have used individual-level forecast data. Batchelor (1997) is an early study that evaluates the individual forecasters in the Blue Chip Financial Forecasts over the period 1983 to 1992, but only looks at the forecasting performance of the 3-month Treasury yield. Batchelor and Dua (1991) study the individual forecasters in the Blue Chip Economic Indicators survey, and find that forecasters who incorporate individual judgement tend to produce more rational forecasts than forecasters who rely on pure econometric models. Gavin and Mandal (2001) find that for forecasting both output and inflation, that the mean survey forecast from the Blue Chip Economic Indicators is a good proxy for the expectations of Fed policymakers.

Our empirical investigation uncovers new insights into the relative forecasting ability of the individual

[1]Several other studies have used survey forecasts within a dynamic asset pricing framework. Pennacchi (1991) and Brennan, Wang, and Xia (2004) both augment their asset pricing models with survey forecasts of inflation from the Livingston data set.

[2]Studies that focus on forecasting inflation include Swidler and Ketcher (1990), Keane and Runkle (1990), Mehra (2002), Capistran and Timmerman (2005, 2006), Thomas (1999), Romer and Romer (2000), Hansen, Lunde, and Nason (2003) and Stock and Watson (1999).

participants in the Blue Chip Financial Forecasts vis-a-vis a set of benchmark forecasting models. Firstly, financial market-based forecasts of the federal funds rate extracted from federal funds futures prices prove to be superior at forecasting the funds rate at the 1 and 2-month ahead forecast horizons. Secondly, we find that for short horizon forecasts of short to medium maturity yields, several of the individual survey forecasters perform extremely well. However, for forecasting short to medium maturity yields over longer forecast horizons, the best performing model is the dynamic Nelsen-Siegel model of Diebold and Li (2005), enhanced with VAR(3) dynamics and where Qrinkage is applied to shrink the forecasts of the underlying factors toward their long run means. Finally, for predicting long maturity yields, we find that the statistical evidence points to a Qrinkage version of an $AR(2)$ model. Owing to the mean reverting nature of long yields, one might suspect that shrinking the model's forecasts toward the long run mean aids in forecasting over longer horizons, whereas shrinking toward the random walk forecast would only help over very short horizons. Our results are consistent with this intuition. We also find that for long maturity yields, econometric models consistently outperform the survey forecasters.

For forecasting inflation, the survey forecasters perform exceptionally well. In stark contrast to forecasting interest rates, the mean survey forecaster is very competitive at predicting inflation across all horizons. This is also roughly consistent with the findings of Ang, Bekaert, and Wei (2005). We find that although transient forecasters appear to add noise to the interest rate forecasts, they add useful information for forecasting inflation.

2 The Competing Clairvoyants

This section describes in detail the set of competing forecasting models evaluated in this study including the individual survey analysts in the Blue Chip Financial Forecasts, market-based forecasts of the federal funds rate taken from futures prices, univariate and vector autoregressive time-series models, the Nelson and Siegel (1987) model of Diebold and Li (2005) with generalized dynamics, and the criteria-based shrinkage (Qrinkage) versions of the aforementioned econometric models.

The set of econometric forecasts used in the study include the martingale forecast (random walk),[3] autoregressive (AR) and vector autoregressive (VAR) models with up to 3 lags. VAR models employ lags of other variables in the system to explain a variable's dynamics, whereas an AR model uses only its own lags. We also generalize the Diebold and Li (2005) model to allow for the dynamics of the 3 underlying factors to follow any one of the AR and VAR specifications with up to 3 lags. Finally, to adjust for the in-sample over-fit of the data, we estimate Qrinkage versions of all of the above models. Table 3 lists the econometric models considered in this study. All of the models are estimated using both a recursive, expanding window beginning in January of 1988 and with a 5-year rolling window. $AR(p)$ models that use a rolling window are denoted as ARpr models, with p referring to the number of lags. VAR models are either estimated using all maturity yields in the study, denoted as $VARp$ models, or including both yields and the percentage change in the CPI, denoted as $VARpc$ models. When these models are estimated with a rolling window, we will refer to them as $VARpcr$ models. Naturally,

[3] This is simply the no-change forecast. The martingale forecast of X_{t+s} with respect to the time t information set equals X_t. The random walk is always a martingale, the converse isn't necessarily true, although they produce identical forecasts.

when generating forecasts of CPI, only VAR models that include CPI are used. At each month t, the models are estimated using historical data and then iterated forward using the estimated parameters to generate 1-month ahead forecasts that are then used as data to generate 2-month ahead forecasts, and so on. To match the format of the Blue Chip surveys, forecasts for a particular calender quarter are generated by averaging over the 3 iterated monthly forecasts that fall within that quarter.

2.1 Blue Chip Financial Forecasts

A salient contribution of this study is the construction of an individual-level cross-sectional time series data set consisting of the forecasts of *every* participant in the Blue Chip Financial Forecasts survey from January 1993 to January 2006. Although forecasters from over 100 different firms have participated in the Blue Chip survey, only a total of 13 firms made consistent forecasts over this sample period. Many forecasters are excluded due to them missing a significant part of the survey, for example all of 1993, or for not making at least 120 forecasts over the sample period. Table 1 lists these 13 firms along with the names of the individual participants. For the few firms where the individual forecaster names changed over time, it may be reasonable to assume the existence of a firm-specific forecasting methodology that ties the time series together across the different individual participants. In addition to these 13 participating firms, when it can be ascertained that a particular forecaster moved to a different firm, a new time series is created by piecing together the individual time series. Table 2 lists the 8 additional individuals forecasters who consistently participated in the survey along with the names of the firms they were associated with. In this way a total of 21 individual forecasters are evaluated in this study.

The participants in the Blue Chip Financial Forecasts are surveyed around the 25th of each month and the results published a few days later on the 1st of the following month. The forecasters are asked to forecast the average over a particular calender quarter, beginning with the current quarter and extending 4 to 5 quarters into the future. In this study, we look at a subset of the forecasted variables. The interest rate forecasts examined are the federal funds rate, and the set of H.15 Constant Maturity Treasuries (CMT) of the following maturities: 3-month, 6-month, 1-year, 2-year, 5-year and 10-year. To enable comparisons, historical data is obtained from the US Treasury.[4] The survey also includes a set of macroeconomic variables that are linked to movements in interest rates. These variables are percentage changes in Real GDP, the GDP Price Index and the Consumer Price Index. These macroeconomic forecasts are listed as "Key Assumptions" and provide, for each forecaster, a unique insight into the perceived relationship between interest rates and the macroeconomy. In this version of the study, we focus only on inflation as measured by the quarter-over-quarter percentage change in the average CPI, the definition of inflation used by the Blue Chip survey.[5] Thus, when computing historical inflation for use in an econometric model, the level of inflation is defined as the percentage change in the average CPI over a particular calender quarter relative to the average CPI over the preceding 3 months.[6] The Blue

[4]Source: http://www.federalreserve.gov. CMT yields were download at a daily frequency and converted to quarterly averages for use in this study. The maturities used are the 3m, 6m, 1y, 2y, 5y and 10y yields; also included is the federal funds rate.

[5]The Blue Chip surveys also forecast GDP growth and the GDP price deflator. The difficulty with evaluating GDP growth forecasts lies with real-time data issues due to revisions in the GDP data. Issues related to data revisions notwithstanding, constructing econometric forecasts using the quarterly frequency of available GDP data requires special treatment and we have thus chosen to omit these variables from this study.

[6] Seasonally adjusted, CPI-U, US City Average, All Items. Source: http://data.bls.gov/ Series Id: CUSR0000SA0

Table 1: Forecasting Firms and Their Individual Forecasters

	Company Model	Individual Forecasters	Dates
1	Bear Stearns Co.	Lawerence Kudlow	Jan 93 - Mar 94
		John Ryding	Apr 94
		Wayne D. Angell	May 94 - Apr 96
		Wayne D. Angell and John Ryding	May 96 - Dec 01
		John Ryding and Conrad DeQuadros	Jan 02 - Jan 06
2	Comerica	David L. Littmen	Jan 93
		David L. Littmen and David L. Sowerby	Feb 93 - Jun 93
		David L. Littmen	Jul 93 - Oct 94
		David L. Littmen and James W. Bills	Nov 94 - Feb 97
		David L. Littmen and David L. Sowerby	Mar 97 - Apr 97
		David L. Littmen	Sep 99 - Feb 05
3	Cycle Data	Robert S. Powers	1993 - 2006
4	De Prince	Albert E. DePrince Jr.	1993 - 2006
5	Fannie Mae	David W. Berson	1993 - 2006
6	La Salle	Carl R. Tannenbaum	1993 - 2006
7	Natl City Bank Cleveland	Theodore H. Tung	Jan 93 - Oct 99
		Richard J. DeKaser	Nov 99 - Jan 06
8	Nomura	David H. Resler	Jan 93 - Feb 93
		David H. Resler and Carol Stone	Mar 93 - Jun 03
		David H. Resler and Parul Jain	Nov 03 - Jun 05
		David H. Resler and Gerald Zukowski	Jul 05 - 2006
9	Scotia Bank/ Bank of Nova Scotia	Aron Gampel and Warren Jestin	1993 - 2006
10	Standard and Poors	David M. Blitzer	Jan 93 - Jan 04
		David M. Blitzer and David Wyss	Feb 04 - Jan 06
11	US Trust Co.	Thomas W. Synnott III	Jan 93 - Oct 02
		Robert T. McGee and Nora C. Mirshafii	Nov 02 - Jan 06
12	Wayne Hummer Co.	William B. Hummer	1993 - 2006
13	Wells Fargo/Capital Management	Gary Schlossberg	1993 - 2006
		Gary Schlossberg and Mark Green	Feb 93 - Jun 94

This table lists the 13 forecasting firms who participated in the survey every year from January 1993 until January 2006. Although the names of the individual forecasters change over time, the construction of a time-series for each firm hinges on the assumption of a firm specific forecasting model.

Table 2: Individual Forecasters and Their Firms

	Individual Forecaster	Companies	Dates
14	Irwin L. Kellner	Chemical Banking Corp	Jan 93 - Feb 97
		Kellner Economics Associates	Mar 97 - Jan 06
15	James W. Coons	Huntington Natl Bank	Jan 93 - Feb 03
		JW Coons	Mar 03 - Jan 06
16	Jay N. Woodworth	Bankers Trust Economics	Jan 93 - Feb 94
		Woodsworth Holdings	Mar 94 - Jan 06
17	Jeff K. Thredgold	Key Corp	Jan 93 - Jan 97
		Thredgold Economic Assoc	Feb 97 - Jan 06
18	Joel L. Naroff	First Fidelity Bank Corp	Jan 93 - Mar 99
		Naroff Economics Advisors	Apr 99 - Jan 06
19	Mickey Levy	CRT Govt Securities Inc	Jan 93 - Jul 93
		Nations Bank Montgomery Sec	Aug 93 - Apr 99
		Bank of America	May 99 - Jan 06
20	Robert T. McGee	Tokai Bank Ltd	Jan 93 - Jan 02
		UBJ Bank	Feb 02 - Oct 02
		US Trust Company	Nov 02 - Jan 06
21	James M. Griffin Jr.	Aetna Life Casualty	1993 - 1994
		Aeltus Investment	1995 - 2003
		ING Aeltus Investment Management	2003 - 2006

This table lists the 8 additional time-series that were constructed by tracing an individual forecaster across different forecasting firms. Each of the above forecasters made at least 120 forecasts, and also consistently participated in the survey every year from January 1993 until January 2006.

Chip Financial Forecasts report the cross-sectional average as the "consensus forecast." In this study, the mean forecast (*MHL*) is constructed manually by first removing the high and the low forecasts before computing the cross-sectional average. The mean across only the 21 forecasters (*M21*) who participated consistently during the sample period from 1993 to 2006 is also considered.[7] The difference between these two measures of the consensus forecast captures the effect of those transient forecasters who were only active during some fraction of the sample period, hence any sample selection bias in the forecast data would be reflected in this difference.

2.2 Federal Funds Futures Forecasts

The Chicago Board of Trade (CBT) introduced the federal funds futures contract in October of 1988. Several previous studies have extracted forecasts of the federal funds rate using futures prices, see for example Kuttner (2001) and Piazzesi and Swanson (2006). To extract the 2 quarter ahead forecast (of the average over the subsequent calender quarter), we need futures contracts that are traded up to 9 months ahead. Since these contracts are not consistently available, we only extract forecasts up to 1 quarter ahead, that is the 1, 2 and 3-month ahead forecasts. Each forecast constructed from a specific

[7] For some months, the number of forecasters over which the average is taken may be less than 21, as not every one of the 21 forecasters made forecasts in every month for every series.

Table 3: Summary of Forecasting Models

Qrinkage AR(p) Models		**AR(p) Models**	
Qrnk(α)AR1	Recursive Estimation	AR1	Recursive Estimation
Qrnk(α)AR2	Window begins in Jan 1988	AR2	Window begins in Jan 1988
Qrnk(α)AR3		AR3	
Qrnk(α)AR1r	Rolling Estimation	AR1r	Rolling Estimation
Qrnk(α)AR2r	5 Year window	AR2r	5 Year window
Qrnk(α)AR3r		AR3r	
Qrinkage VAR(p) Models		**VAR(p) Models**	
Qrnk(α)VAR1	Recursive Estimation	VAR1	Recursive Estimation
Qrnk(α)VAR2	Window begins in Jan 1988	VAR2	Window begins in Jan 1988
Qrnk(α)VAR3	Excludes CPI	VAR3	Excludes CPI
Qrnk(α)VAR1r	Rolling Estimation	VAR1r	Rolling Estimation
Qrnk(α)VAR2r	5 Year window	VAR2r	5 Year window
Qrnk(α)VAR3r	Excludes CPI	VAR3r	Excludes CPI
Qrnk(α)VAR1c	Recursive Estimation	VAR1c	Recursive Estimation
Qrnk(α)VAR2c	Window begins in Jan 1988	VAR2c	Window begins in Jan 1988
Qrnk(α)VAR3c	Includes CPI	VAR3c	Includes CPI
Qrnk(α)VAR1cr	Rolling Estimation	VAR1cr	Rolling Estimation
Qrnk(α)VAR2cr	5 Year window	VAR2cr	5 Year window
Qrnk(α)VAR3cr	Includes CPI	VAR3cr	Includes CPI
Other Models		**Survey-Based Models**	
MART	Random Walk Forecast	MHL	Mean survey forecast (without high and low)
FFF	Fed Funds Futures	M21	Mean of the 21 individual forecasters in this paper
DL-	A DL prefix indicates a version of Diebold and Li's specification of the Nelson-Siegel Model.		

In addition to 21 individual forecasting models, this table outlines the set of forecasting models used in the study. AR(p) and VAR(p) versions of the models are estimated with lag lengths $p = 1$, $p = 2$ and $p = 3$, so that, for example, the $Qrnk(\alpha)VAR3r$ model above is a VAR version of the Qrinkage model estimated with 3 lags and a rolling estimation window. For the above Qrinkage models, α defines the gravity point, so $\alpha = 0$ shrinks toward the long run mean, and $\alpha = 1$ shrinks toward the random walk forecast. The prefix DL denotes Diebold and Li's specification of the Nelson-Siegel Model, where the dynamics of the factors follows one of the above econometric specifications. For example, $DLQrnk(\alpha)VAR2$ is version of the Nelson-Siegel model where the 3 factors are forecast using a Qrinkage VAR(2) with a recursive estimation window.

futures contract is an approximation and taken to be 100 minus the futures price.[8] The futures-based forecast for a particular quarter is constructed by averaging the futures forecasts using the 3 separate futures contracts that expire within that quarter.

[8]The issue of risk premia and discounting is ignored for the time being. The price of a futures contract on the settlement date is equal to 100 minus the average daily funds rate over the settlement month. See Piazzesi and Swanson (2006) for risk-adjusted forecasts using futures prices. These issues will be addressed in a future version of this research. The source of the federal funds futures prices is Datastream.

2.3 Criteria Based Shrinkage

Criteria-based shrinkage, or "Qrinkage" forecasting models are introduced in Hansen (2006).[9] Hansen (2008), motivates Qrinkage, by discussing the issue of how in-sample overfitting can often lead to out-of-sample underfitting when making forecasts.[10] We estimate and forecast using Qrinkage versions of the following econometric models - $AR(1)$, $AR(2)$, $AR(3)$, $VAR(1)$, $VAR(2)$ and $VAR(3)$. The Qrinkage-based models are defined using both recursive and rolling estimation windows denoted in subsequent tables as *Qrnk(α)p* and *Qrnk(α)VARp* models, where p is the number of lags and α is the parameter characterizing the gravity point. In addition, we take the Nelson and Siegel (1987) model of Diebold and Li (2005), allow for more general dynamics on the underlying factors, and apply Qrinkage to the estimated parameters. Additional details on the Qrinkage estimator are available in Appendix A.

2.4 Univariate and Vector Autoregressive Models

We propose a general framework for applying shrinkage across a set of time-series models. Assume an autoregressive AR(p) process

$$x_t = \beta_0 \bar{x} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + \epsilon_t. \tag{1}$$

where ϵ_t is a Gaussian white noise process (independently distributed with zero mean) and $\bar{x}$ is the long run mean of x_t over the estimation window.

Suppose we want to shrink the parameters so as to pull the forecasts toward the random walk. We could estimate the following equivalent model

$$x_t - x_{t-1} = \beta_0 \bar{x} + (\beta_1 - 1) x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + \epsilon_t \tag{2}$$

and shrink the estimated coefficients toward 0. By shrinking each one of the estimated coefficients toward 0, we are in effect shrinking β_1 toward 1, and as a consequence shrinking the forecasts of x_t toward the random walk forecast, x_{t-1}. Likewise if we wanted to shrink the parameters so as to pull the forecasts toward the long run mean, we could estimate the following equivalent model

$$x_t - \bar{x} = (\beta_0 - 1)\bar{x} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + \epsilon_t \tag{3}$$

and shrink the estimated coefficients toward 0. By shrinking each one of the estimated coefficients toward 0, we are in effect shrinking β_0 toward 1, consequently we are shrinking forecasts of x_t toward the long run mean, $\bar{x}$. Depending on the degree of mean reversion in the underlying series, and depending also on the forecast horizon, forecasting performance may be improved by either shrinking towards the

[9] As of yet this document is still a work in progress. The exposition in this section is based on Peter's presentation at the 2006 Stanford Institute for Theoretical Economics Summer Workshop on Economic Forecasting Under Uncertainty. I thank him for suggesting that I include these forecasts in this study. Any errors in interpretation or implementation are solely my responsibility.

[10] Shrinkage-based models are often employed in Bayesian econometrics to pull estimated parameters toward a set of priors. These techniques have been used in finance to estimate portfolio weights, for example in Vasicek (1973), Jorion (1986), Karolyi (1992) and Baks, Metrick, and Wachter (2001). In forecasting, shrinkage methods have been employed by Zellner and Hong (1989), Brav (2000) and Tobias (2001). Giacomini and White (2006) find that the shrinkage employed by Bayesian VARs outperform simple factor models and unrestricted AR models across all forecast horizons.

random walk forecast or shrinking towards the long run mean. Naturally, for some series forecasting performance might be best improved by shrinking towards a point that is a linear combination of x_t and $\bar{x}$. Suppose we would like to shrink toward a gravity point defined by $g_{t-1}(\alpha) = \alpha\bar{x} + (1-\alpha)x_{t-1}$, we could estimate the following equivalent model

$$x_t - \alpha\bar{x} - (1-\alpha)x_{t-1} = (\beta_0 - \alpha)\bar{x} + (\beta_1 - (1-\alpha))x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + \epsilon_t. \tag{4}$$

By shrinking the estimated coefficients toward 0, we are in effect shrinking B_0 towards α and $\mathcal{B}_1$ towards $1-\alpha$, and as a result we are shrinking forecasts of x_t toward $\alpha\bar{x} + (1-\alpha)x_t$. Letting $y_t = x_t - g(\alpha)$, $\boldsymbol{\beta} = [(\beta_0 - \alpha)\ (\beta_1 - 1 + \alpha)\ \beta_2 \ldots \beta_p]'$ and $\mathbf{x}_t = [\bar{x}\ x_{t-1} \ldots x_{t-p}]$. Define $\mathbf{y}$ as an m-vector and $\mathbf{X}$ as an m by $(p+1)$ matrix, where the tth row of each is y_t and $\mathbf{x}_t$, respectively and m denotes the number of observations within the estimation window. Expressed in matrix notation

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \tag{5}$$

where $\boldsymbol{\epsilon}$ is normally distributed vector of errors with mean $\mathbf{0}$ and $E(\boldsymbol{\epsilon}\boldsymbol{\epsilon}') = \sigma_\epsilon^2\mathbf{I}$. The coefficients are estimated via an OLS regression and the estimated coefficients are pulled toward 0 using the Qrinkage technique of Hansen (2006).[11]

Vector autoregressive (VAR) models have been previously employed in the interest rate forecasting literature, yet due to the large number of parameters that need to estimated, they are susceptible to in-sample over-fitting, leading to poor out-of-sample forecasting performance. To address this issue, we specify a general VAR framework that facilitates the application of shrinkage techniques. Assume an n-dimensional vector autoregressive process

$$\mathbf{x}_t = \boldsymbol{\beta}_0\bar{\mathbf{x}} + \boldsymbol{\beta}_1\mathbf{x}_{t-1} + \boldsymbol{\beta}_2\mathbf{x}_{t-2} + \cdots + \boldsymbol{\beta}_p\mathbf{x}_{t-p} + \boldsymbol{\epsilon}_t. \tag{6}$$

where $\mathbf{x}_t = [x_{1t}\ x_{2t}\ \ldots\ x_{nt}]'$ is an $n \times 1$ vector, $\boldsymbol{\beta}_0$ is an $n \times n$ diagonal matrix, $\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_p$ are $n \times n$ matrices, $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of white noise error terms and $\bar{\mathbf{x}}$ is an $n \times 1$ vector of the mean of $\mathbf{x}_t$ over the estimation window.

As with the univariate case, we propose a equivalent expression that permits parameter shrinkage towards a vector that is a linear combination of $\mathbf{x}_{t-1}$ and $\bar{\mathbf{x}}$. Suppose we would like to shrink to a gravity vector defined by $\mathbf{g}_{t-1}(\boldsymbol{\alpha}) = \boldsymbol{\alpha}\bar{\mathbf{x}} + (\mathbf{I} - \boldsymbol{\alpha})\mathbf{x}_{t-1}$, where $\boldsymbol{\alpha}$ is a diagonal matrix with $[\alpha_1\ \ldots\ \alpha_n]$ on the diagonal. Then we could estimate the following equivalent model

$$\boldsymbol{x}_t - \boldsymbol{\alpha}\bar{\mathbf{x}} - (\mathbf{I} - \boldsymbol{\alpha})\mathbf{x}_{t-1} = (\boldsymbol{\beta}_0 - \boldsymbol{\alpha})\bar{\mathbf{x}} + (\boldsymbol{\beta}_1 - (\mathbf{I} - \boldsymbol{\alpha}))\mathbf{x}_{t-1} + \boldsymbol{\beta}_2\mathbf{x}_{t-2} + \cdots + \boldsymbol{\beta}_p\mathbf{x}_{t-p} + \boldsymbol{\epsilon}_t. \tag{7}$$

By shrinking the estimated coefficients toward 0, we are in effect shrinking the diagonal matrix $\boldsymbol{\beta_0}$ toward $\boldsymbol{\alpha}$ and $\boldsymbol{\beta_1}$ toward $\mathbf{I} - \boldsymbol{\alpha}$, whereby shrinking the time $t-1$ conditional forecasts of $\mathbf{x}_t$ toward the gravity vector given by $\boldsymbol{\alpha}\bar{\mathbf{x}} + (\mathbf{I} - \boldsymbol{\alpha})\mathbf{x}_{t-1}$. Note that as in the univariate case, α_k controls, for the kth equation, the weight distributed across the random walk forecast and the long run mean when computing the gravity point. This allows for added flexibility in forecasting by allowing for each variable in the system to have a different gravity point. Although this description provides for a general framework using any $\boldsymbol{\alpha}$, to limit the number of models in this study, we only examine models with $\boldsymbol{\alpha} = \mathbf{1}$ or $\mathbf{0}$.

[11] This version of the paper only sets $\alpha = 0$ and 1.

The coefficients in (7) are estimated equation by equation using OLS regressions, as this yields both consistent and efficient estimators in this setting. The estimated coefficients in each equation are pulled toward 0 using the Qrinkage technique of Hansen (2006).

2.5 Nelson-Siegel Model of Diebold and Li with Extended Dynamics

Diebold and Li (2005) propose a dynamic interpretation of the 3 factor model of Nelson and Siegel (1987) and find this model outperforms standard benchmarks at the 12-month ahead forecast horizon. As this model has itself become a benchmark model in the literature, we incorporate this into our study. The advantage of this model over a VAR lies in the parsimony with which 3 factors are used to capture the dynamics of the entire yield curve. The yield on an n-period bond is modeled as

$$y_t(n) = \beta_{1t} + \beta_{2t}\left(\frac{1-e^{-\lambda n}}{\lambda n}\right) + \beta_{3t}\left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right) \tag{8}$$

where the 3 latent factors are given by β_{1t}, β_{2t} and β_{3t}, representing the level, slope and curvature of the yield curve, respectively. In their study, Diebold and Li (2005) focus primarily on the AR(1) dynamics of these 3 underlying dynamic factors, while also reporting the results obtained from using a multivariate VAR(1) structure for comparative purposes. They argue that the imposition of richer dynamic structures would tend to over-fit the data in-sample, leading to diminished forecasting performance out-of-sample. In our study, we generalize their model to allow for a wider set of possible underlying factor dynamics, including both autoregressive and vector autoregressive structures with up to 3 lags. The trick that permits this generalization to be effective for out-of-sample forecasting is the application of Qrinkage to the dynamic process governing the underlying factors. The estimation involves 3 steps. In the first step, at every point in time t, the latent factors $\mathbf{x}_t = [\beta_{1t}\ \beta_{2t}\ \beta_{3t}]'$ are estimated from the panel of yields via OLS. As in Diebold and Li (2005) we set $\lambda = .0609$. For forecasting the funds rate, the maturity is set to .003 as an approximation. In the second step, for each AR and VAR specification of the factor dynamics, the coefficients governing the evolution of $\mathbf{x}_t$ are estimated via OLS. Finally, Qrinkage is applied in exactly the same manner discussed in the earlier sections. By employing Qrinkage and shrinking the parameter estimates of the process governing the underlying factors to account for the in-sample overfit, we minimize the out-of-sample underfit. This permits the model to embed richer factor dynamics by incorporating information in additional lags, while effectively offsetting the negative impact of overfitting via an application of Qrinkage. This improvement in forecasting the 3 underlying factors is important, as the ability to forecast yields is based primarily on our ability to forecast the underlying factors. To our knowledge, this is the first paper to apply parameter shrinkage within this class of models.

To preview the out-of-sample forecasting results in the next section, Figure 1 shows for the 6 month and 2 year maturity yields, the root mean squared forecast errors (RMSFE) of several models divided by the RMSFE of the random walk forecast. We are clearly able to improve upon the prior performance of the Diebold-Li class of models. In all the plots, there is clear evidence of the benefits of parameter shrinkage. The upper panel shows the performance of the two specifications that are studied in Diebold and Li (2005). As mentioned in their study, the top right plot shows the VAR(1) specification under performing the more parsimonious AR(1) model when estimated using a recursive window. However, when the models are estimated using a rolling estimation window, this issue only appears to be

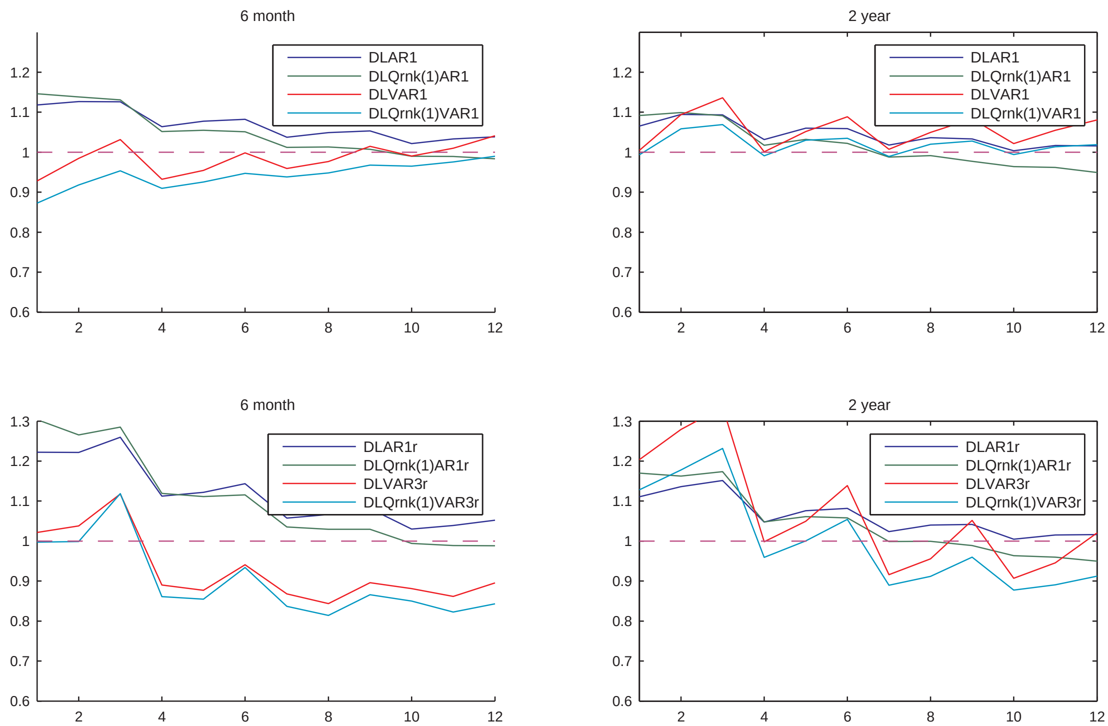

Figure 1: **Comparison of Various Diebold and Li Models.** All plots show the forecasting performance of several Diebold and Li models relative to the random walk forecast. The models in the top panel are estimated using a recursive, expanding estimation window while the models in the bottom panel use a 5 year rolling estimation window. The dashed line corresponds to the random walk forecast (MART).

present for short horizon forecasts of longer maturity yields. Over longer horizons, the performance of the DLQrnk(1)VAR3r model with VAR(3) dynamics, a 5-year rolling estimation window and Qrinkage toward the long run mean, is superior to both the random walk and the aforementioned AR(1) and VAR(1) specifications. The bottom plots clearly show the full benefits of parameter shrinkage when combined with a richer structure for the underlying dynamics. The gains from Qrinkage are apparent when comparing the performance of the DLQrnk(1)VAR3r model with the DLVAR3r model, which is the identical model without parameter shrinkage.

3 Out-of-Sample Forecasting Results

According to a quadratic loss function, the model with the smallest root mean squared forecast error (RMSFE), may be crowned as the 'best' forecasting model over a particular sample period. However, in general, there may other competing models that are equally good, and whose RMSFE performance might have been superior conditioned on a different realization of the data. Thus rather than searching for a single 'best' model, one might be interested in constructing a subset of models that contain the 'best' model(s) with a certain level of confidence. Hansen, Lunde, and Nason (2003, 2005) introduce

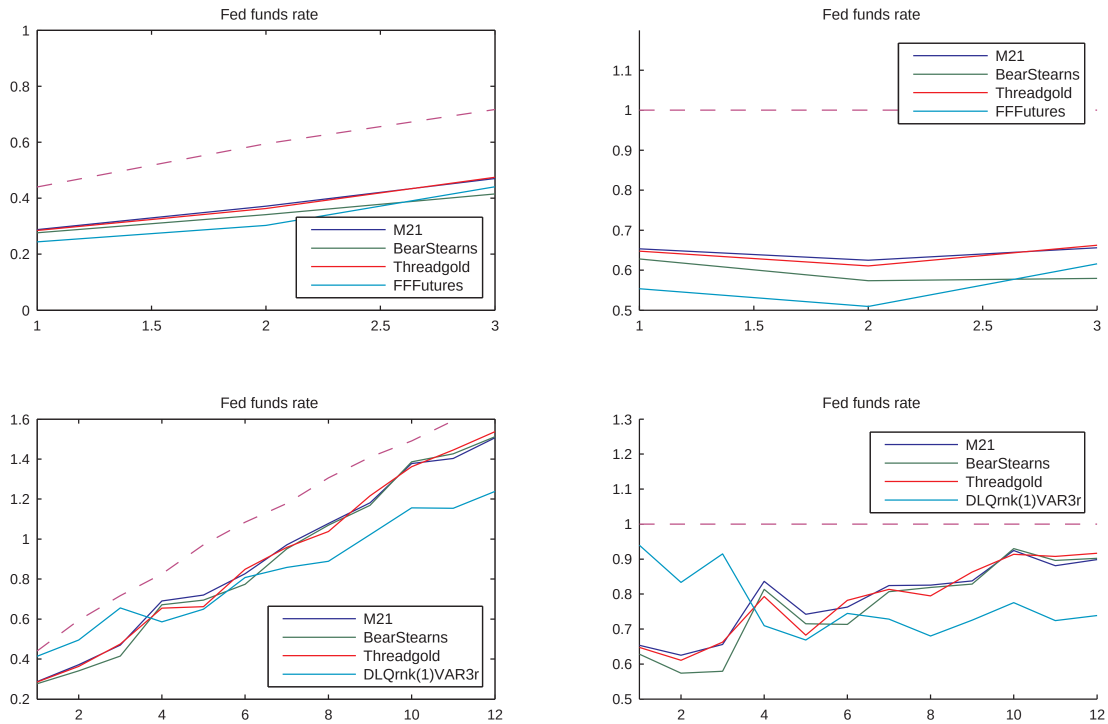

Figure 2: **Out of Sample Forecast Errors - Fed Funds Rate.** The left plots show out of sample forecast errors for several selected models. The right plots show the forecasting performance relative to the random walk forecast. The dashed line corresponds to the random walk forecast (MART). The top plots show RMSE up to 3 months ahead to highlight the performance of the fed funds futures forecast.

the idea of Model Confidence Sets (MCSs). A MCS is a random data-dependent set that contains the set of 'best' forecasting model(s) with a pre-specified level of probability. Thus a MCS is analogous to the idea of a confidence interval when estimating a parameter. In the same way a confidence interval contains the true parameter with a certain level of probability, a MCS contains the set of best forecasting model(s).

The Model Confidence Sets in this study suggest that for many of the forecasted variables the information content of the data is rather fuzzy and we find that the MCSs computed using any conventional significance levels are rather large. For the most part, there is simply not enough information in the data to reduce the competing set of models down to a reasonably small subset. So rather than reporting all the models in a particular MCS, we will focus on reporting MCS p-values. The MCS procedure generates MCS p-values that can be taken as a metric for ranking the various forecasting models. The higher the MCS p-value the more likely that the model belongs to a set of 'best' forecasting models. By looking at the models with the largest MCS p-values, it is possible to reach some broad conclusions. Tables 4 and 5 report average MCS p-values, for forecast horizons 1 through 4 quarters ahead. By construction, the model with the lowest RMSFE will always have a MCS p-value equal to 1. Please see Appendix B for a brief overview of MCSs, and refer to Hansen, Lunde, and Nason (2003, 2005) for additional details.

Table 4: Model Confidence Set P-values

FedFunds		**3month**		**6month**		**1year**	
FFFutures	1	BearStearns	1	BearStearns	1	Qrnk(0)AR2	1
BearStearns	0.7167	Nomura	0.8931	J.K.Thredgold	0.9259	Nomura	0.9916
WellsFargo	0.3917	USTrust	0.8931	USTrust	0.8736	J.K.Thredgold	0.9916
J.K.Thredgold	0.3917	WellsFargo	0.8931	WellsFargo	0.8736	R.T.McGee	0.9916
Nomura	0.3011	J.K.Thredgold	0.8931	M.Levy	0.8736	AR2	0.9916
USTrust	0.2656	R.T.McGee	0.8931	R.T.McGee	0.8736	Qrnk(0)AR3	0.9916
M21	0.2087	M21	0.8931	M21	0.8736	Qrnk(1)AR2	0.9916
MHL	0.1973	MHL	0.8931	Qrnk(0)VAR1c	0.8736	Qrnk(1)AR3	0.9916
DLVAR3	0.1973	VAR1c	0.8931	Qrnk(0)VAR1	0.8736	Qrnk(0)VAR1c	0.9916
R.T.McGee	0.1763	Qrnk(0)VAR1c	0.8931	StandardPoors	0.8721	Qrnk(0)VAR1	0.9916
J.N.Woodworth	0.1654	Qrnk(1)VAR1c	0.8931	MHL	0.8721	Qrnk(1)VAR1	0.9916
Qrnk(0)VAR1c	0.1393	VAR1	0.8931	VAR1c	0.8721	M21	0.9911
DLVAR3r	1	Nomura	1	DLQrnk(0)VAR3r	1	Qrnk(0)VAR1	1
BearStearns	0.9829	USTrust	1	BearStearns	0.9998	StandardPoors	0.9995
WellsFargo	0.9829	WellsFargo	1	Nomura	0.9998	USTrust	0.9995
J.K.Thredgold	0.9829	J.K.Thredgol d	1	StandardPoors	0.9998	J.K.Thredgold	0.9995
Qrnk(0)VAR1	0.9829	VAR1c	1	USTrust	0.9998	AR2	0.9995
DLVAR3	0.9829	Qrnk(0)VAR1c	1	J.K.Thredgold	0.9998	Qrnk(0)AR2	0.9995
DLQrnk(0)VAR3r	0.9829	Qrnk(0)VAR3c	1	M.Levy	0.9998	Qrnk(1)AR2	0.9995
DLQrnk(1)VAR1r	0.9829	VAR1	1	VAR1c	0.9998	Qrnk(1)AR3	0.9995
DLQrnk(1)VAR2r	0.9829	Qrnk(0)VAR1	1	Qrnk(0)VAR1c	0.9998	Qrnk(0)VAR1c	0.9995
DLQrnk(1)VAR3r	0.9829	Qrnk(1)VAR1	1	VAR1	0.9998	DLQrnk(0)VAR2	0.9995
DLVAR2r	0.9726	DLVAR3r	1	Qrnk(0)VAR1	0.9998	DLQrnk(0)VAR1r	0.9995
DLQrnk(1)VAR3	0.97	DLQrnk(0)VAR 1r	1	Qrnk(1)VAR1	0.9998	DLQrnk(0)VAR2r	0.9995
DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
USTrust	0.2782	USTrust	0.763	StandardPoors	0.6946	DePrince	0.796
J.N.Woodworth	0.2782	VAR1c	0.763	USTrust	0.6946	USTrust	0.796
J.K.Thredgold	0.2782	Qrnk(0)VAR3c	0.763	J.K.Thredgold	0.6946	J.K.Thredgold	0.796
VAR1c	0.2782	VAR1	0.763	VAR1c	0.6946	Qrnk(0)AR2	0.796
Qrnk(0)VAR3c	0.2782	DLVAR3r	0.763	VAR1	0.6946	Qrnk(1)AR2	0.796
VAR1	0.2782	DLQrnk(0)VAR3r	0.763	Qrnk(0)VAR1	0.6946	Qrnk(1)AR3	0.796
Qrnk(0)VAR1	0.2782	DLQrnk(1)VAR 1r	0.763	DLVAR2r	0.6946	VAR1c	0.796
Qrnk(0)VAR3	0.2782	DLQrnk(1)VAR 2r	0.763	DLVAR3r	0.6946	Qrnk(0)VAR3c	0.796
DLVAR3	0.2782	Qrnk(0)VAR1	0.7564	DLQrnk(0)VAR3r	0.6946	VAR1	0.796
DLVAR1r	0.2782	DLVAR2r	0.7564	DLQrnk(1)VAR1r	0.6946	Qrnk(0)VAR1	0.796
DLVAR2r	0.2782	StandardPoors	0.7443	DLQrnk(1)VAR2r	0.6946	DLVAR2r	0.796
DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
VAR1	0.1127	Comerica	0.3782	USTrust	0.1905	USTrust	0.5151
Qrnk(0)VAR3	0.1127	USTrust	0.3782	J.N.Woodworth	0.1905	DLQrnk(1)VAR2r	0.5151
DLVAR2r	0.1127	VAR1c	0.3782	J.K.Thredgold	0.1905	DePrince	0.3045
DLVAR3r	0.1127	Qrnk(0)VAR3c	0.3782	M.Levy	0.1905	I.L.Keller	0.3045
DLQrnk(0)VAR3r	0.1127	VAR1	0.3782	Qrnk(0)AR2	0.1905	J.N.Woodworth	0.3045
DLQrnk(1)VAR1r	0.1127	Qrnk(1)VAR2	0.3782	Qrnk(1)AR2	0.1905	J.K.Thredgold	0.3045
DLQrnk(1)VAR2r	0.1127	DLVAR2r	0.3782	Qrnk(1)AR3	0.1905	M.Levy	0.3045
Qrnk(0)VAR3c	0.1087	DLVAR3r	0.3782	VAR1c	0.1905	Qrnk(0)AR2	0.3045
USTrust	0.088	DLQrnk(0)VAR3r	0.3782	Qrnk(0)VAR3c	0.1905	Qrnk(1)AR2	0.3045
J.N.Woodworth	0.088	DLQrnk(1)VAR 1r	0.3782	Qrnk(1)VAR2c	0.1905	Qrnk(1)AR3	0.3045
Qrnk(1)AR3	0.088	DLQrnk(1)VAR2r	0.3782	VAR1	0.1905	VAR1c	0.3045

For each quarter ahead forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. The top panel gives the MCS p-values for the 1-quarter ahead forecasts, the 2nd panel for the 2-quarter ahead forecasts, the 3rd panel for the 3-quarter ahead forecasts and the bottom panel for the 4-quarter ahead forecasts.

Table 5: Model Confidence Set P-values

2year		**5year**		**10year**		**CPI**	
J.K.Thredgold	1	Qrnk(0)AR2r	1	Qrnk(1)AR2r	1	J.L.Naroff	1
Qrnk(0)AR2	0.9826	MART	0.9836	MART	0.9879	J.N.Woodworth	0.9511
Qrnk(1)AR2	0.9826	AR2r	0.9836	AR2r	0.9879	I.L.Keller	0.8315
Qrnk(0)VAR1	0.9826	Qrnk(0)AR2	0.9836	Qrnk(0)AR2r	0.9879	J.W.Coons	0.8315
AR2	0.9621	Qrnk(1)AR1	0.9836	Qrnk(1)AR1	0.9879	Qrnk(1)AR1r	0.8315
Qrnk(1)AR3	0.9621	Qrnk(1)AR2	0.9836	Qrnk(1)AR1r	0.9879	M21	0.7984
Nomura	0.9554	Qrnk(1)AR3	0.9836	Qrnk(0)VAR1c	0.9879	MHL	0.7984
Qrnk(0)VAR1c	0.9352	Qrnk(1)AR2r	0.9836	Qrnk(0)AR1	0.9748	AR3r	0.7984
Qrnk(0)AR2r	0.9325	Qrnk(0)VAR1c	0.9836	Qrnk(1)AR2	0.9748	Qrnk(1)AR3	0.7867
MART	0.9248	Qrnk(0)VAR1	0.9836	Qrnk(0)AR2	0.9723	Nomura	0.782
Qrnk(1)AR1	0.9117	DLQrnk(0)AR2	0.9836	Qrnk(0)VAR1	0.966	J.K.Thredgold	0.782
DLQrnk(0)VAR2	0.9117	DLQrnk(0)AR1r	0.9836	Qrnk(1)AR3r	0.9498	Qrnk(1)AR3r	0.782
J.K.Thredgold	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	J.N.Woodworth	1
Nomura	0.9959	Nomura	0.9934	J.K.Thredgold	0.8278	J.W.Coons	0.7921
Qrnk(0)AR2	0.9959	J.K.Thredgold	0.9934	MART	0.8278	J.L.Naroff	0.7921
Qrnk(1)AR2	0.9959	MART	0.9934	AR2r	0.8278	Qrnk(1)AR1	0.7609
Qrnk(0)VAR1	0.9959	AR2r	0.9934	Qrnk(0)AR2r	0.8278	MHL	0.7425
DLQrnk(0)VAR2	0.9959	Qrnk(0)AR2r	0.9934	Qrnk(1)AR1	0.8278	Qrnk(1)AR1r	0.7351
DLQrnk(1)VAR2r	0.9959	Qrnk(1)AR1	0.9934	Qrnk(1)AR1r	0.8278	J.K.Thredgold	0.7252
Qrnk(0)VAR1c	0.9921	Qrnk(1)AR2	0.9934	Qrnk(1)AR3r	0.8278	M.Levy	0.7252
Qrnk(1)AR3	0.9867	Qrnk(1)AR1r	0.9934	Qrnk(0)VAR1c	0.8278	AR1r	0.7252
DLQrnk(0)VAR2r	0.9845	Qrnk(0)VAR1c	0.9934	Qrnk(0)AR1	0.8196	Qrnk(1)AR3r	0.7252
AR2	0.9785	Qrnk(0)VAR2c	0.9934	Qrnk(1)AR2	0.8196	Nomura	0.7197
MART	0.9784	Qrnk(0)VAR1	0.9934	Qrnk(0)VAR2c	0.8196	M21	0.7197
DLQrnk(1)VAR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	J.L.Naroff	1
Nomura	0.8438	J.K.Thredgold	0.9439	J.K.Thredgold	0.6292	M.Levy	0.9535
I.L.Keller	0.8438	AR2r	0.9439	M.Levy	0.6292	J.W.Coons	0.863
J.K.Thredgold	0.8438	Qrnk(0)AR2r	0.9439	MART	0.6292	J.N.Woodworth	0.863
Qrnk(0)AR2	0.8438	Qrnk(1)AR2	0.9439	AR2r	0.6292	WellsFargo	0.8616
Qrnk(0)AR2r	0.8438	Qrnk(1)AR1r	0.9439	Qrnk(0)AR1	0.6292	MHL	0.8616
Qrnk(1)AR2	0.8438	Qrnk(1)AR3r	0.9439	Qrnk(0)AR2	0.6292	AR3r	0.8616
Qrnk(1)AR3	0.8438	Qrnk(0)VAR2c	0.9439	Qrnk(0)AR2r	0.6292	Qrnk(1)AR1	0.8616
Qrnk(0)VAR1c	0.8438	Qrnk(0)VAR3c	0.9439	Qrnk(1)AR1	0.6292	Qrnk(1)AR3r	0.8616
Qrnk(0)VAR2c	0.8438	Qrnk(0)VAR1	0.9439	Qrnk(1)AR2	0.6292	J.K.Thredgold	0.8549
Qrnk(0)VAR3c	0.8438	Qrnk(0)VAR2	0.9439	Qrnk(1)AR1r	0.6292	Qrnk(1)AR2r	0.8217
Qrnk(0)VAR1	0.8438	DLAR2r	0.9439	Qrnk(1)AR3r	0.6292	Qrnk(1)AR1r	0.8119
DLQrnk(1)VAR3r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	J.L.Naroff	1
DLQrnk(1)VAR2r	0.9096	Cycledata	0.7816	J.K.Thredgold	0.4028	J.W.Coons	0.797
Cycledata	0.6208	J.K.Thredgold	0.7816	Cycledata	0.2803	M.Levy	0.797
Nomura	0.6208	AR2r	0.7816	DePrince	0.2803	DePrince	0.6084
USTrust	0.6208	Qrnk(0)AR2r	0.7816	FannieMae	0.2803	BearStearns	0.5912
I.L.Keller	0.6208	Qrnk(1)AR3r	0.7816	I.L.Keller	0.2803	Comerica	0.5912
J.N.Woodworth	0.6208	Qrnk(0)VAR2c	0.7816	M.Levy	0.2803	Cycledata	0.5912
J.K.Thredgold	0.6208	Qrnk(0)VAR2	0.7816	MART	0.2803	WayneHummer	0.5912
Qrnk(0)AR2	0.6208	DLAR2r	0.7816	AR2r	0.2803	I.L.Keller	0.5912
Qrnk(0)AR2r	0.6208	DLQrnk(1)AR1	0.7816	Qrnk(1)AR1	0.2803	M21	0.5912
Qrnk(1)AR2	0.6208	DLQrnk(1)AR2	0.7816	Qrnk(1)AR1r	0.2803	MHL	0.5912
Qrnk(0)VAR2c	0.6208	DLQrnk(1)AR3	0.7816	Qrnk(1)AR3r	0.2803	AR2r	0.5912

For each quarter ahead forecast horizon the 12 models with the highest Model Confidence Set(MCS) p-values are given. The top panel gives the MCS p-values for the 1-quarter ahead forecasts, the 2nd panel for the 2-quarter ahead forecasts, the 3rd panel for the 3-quarter ahead forecasts and the bottom panel for the 4-quarter ahead forecasts.

3.1 Forecasting the Fed Funds Fate

Over very short horizons, several individual forecasters including Bear Stearns, Nomura, J.K.Threadgold and Wells Fargo exhibit RMSFEs that are very competitive with the federal funds futures forecast (FFF). Figure 2 depicts the RMSFEs for a few of these individual forecasters. The models clearly have little difficulty in beating the random walk. The top panel highlights the fact that the fed funds futures forecast outperforms all the individual forecasters at predicting the funds rate 1 and 2 months ahead. How significant are these differences between the 'best' forecaster and the set of 'next best' forecasters? Table 4 lists the 12 models with the highest average MCS p-values for each forecast horizon from 1 through 4 quarters ahead. The results for the fed funds rate are reported in the first column. Based on the MCS p-values, the null of equal predictive ability between the federal funds futures forecast (FFF) and Bear Stearns and the set of 'next best' models can be rejected at the 39.17% level. That is, Bear Stearns and FFF form a MCS at a level of 39.17% when averaging over the 1-quarter ahead forecasts. Although this is much larger than standard significance levels traditionally used to test statistical hypothesis, it does paint a general picture of a model's performance given the information content of the data. The statistical evidence for the 2-quarter ahead forecast horizon is much less conclusive as the Model Confidence Sets, at any reasonable level of significance, encompass a bevy of econometric and survey forecasters.

The bottom panel of Figure 2 shows that as the forecast horizon increases, one particular model emerges as the strongest performer - the Qrinkage version of the Diebold-Li model with VAR(3) dynamics estimated over a 5-year rolling window - DLQrnk(1)VAR3r. As α (the parameter governing the choice of gravity point) equals 1, the Qrinkage procedure pulls the forecasts of the underlying factor dynamics toward their long run means. The statistical evidence in favor of the DLQrnk(1)VAR3r model is most apparent at the 4 quarter ahead forecast horizon. From Table 4, we see that the 'next best' model only has a MCS p-value equal to .1127, and the best individual survey forecasters only have MCS p-values equal to .088! So although many individual survey forecasters are competitive at short forecast horizons, at longer horizons they are less so, and the evidence points to DLQrnk(1)VAR3r as the best forecasting model.

3.2 Forecasting Short to Medium Maturity Yields

Columns 2 and 3 of Table 4 list MCS p-values for the 3-month and 6-month yield forecasts. Note that for shorter forecast horizons many of the MCS p-values are quite large, implying that the Model Confidence Sets computed using any reasonable significance level are also large. In other words, there simply isn't enough information in the data to distinguish between a large subset of competing models. Note the presence of numerous top performing survey forecasters including Bear Stearns, US Trust, Nomura, Threadgold, Wells Fargo and Levy. The mean survey forecasters MHL and M21, are also competitive over short forecast horizons, along with several Qrinkage vector autoregressive models of order 1. Figure 3 highlights the RMSFE performance of few of these individual forecasters, and it is evident that although they easily outperform the random walk, they cannot match the performance of the DLQrnk(1)VAR3r model over longer forecast horizons. At the 4-quarter ahead forecast horizon, the MCS p-value for the 'next best' performing model is .3782 for the 3-month yield and .1905 for the

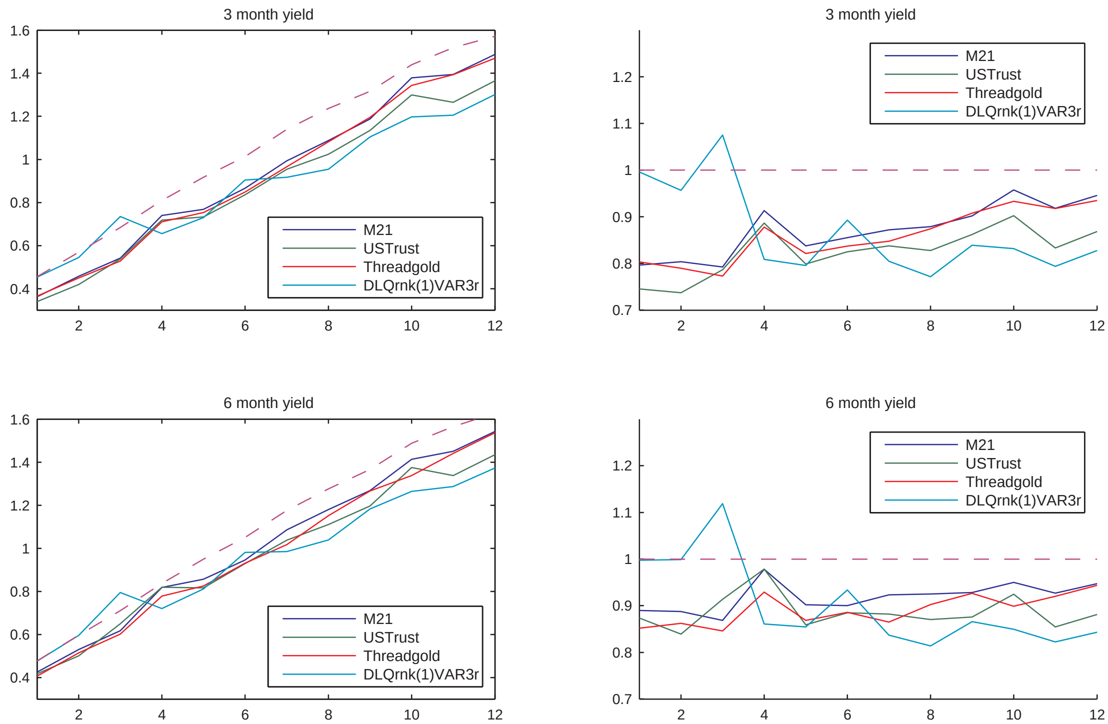

Figure 3: **Out of Sample Forecast Errors - 3 and 6 month yields** The left plots show out of sample forecast errors for several selected models. The right plots show the forecasting performance relative to the random walk forecast. The dashed line corresponds to the random walk forecast (MART).

6-month yield, lending strong statistical support in favor of the DLQrnk(1)VAR3r model.

The 4th column of Table 4 and the first column of Table 5 list the MCS p-values for the 1 and 2-year yield forecasts. For shorter horizon forecasts, we see that a mixture of individual participants and econometric models have MCS p-values that are once again close to 1. The data are again not informative enough to sharply differentiate from among the top set of forecasters. However as the forecast horizon increases, it is once again the DLQrnk(1)VAR3r model that emerges as the strongest performer. Figure 4 illustrates how this advantage over the random walk and the Qrinkage AR(2) class of models grows with the forecast horizon. In addition, note that both Qrinkage AR(2) models are consistently able to outperform the random walk. Comparing the performance of Qrnk(0)AR2 with Qrink(1)AR2, the figures show that shrinking toward the long run mean may offer a slight advantage when forecasting over longer horizons.

3.3 Forecasting Long Yields

MCS p-values for the 5-year and 10-year yield forecasts are displayed in the 2nd and 3rd columns of Table 5. The statistical evidence points to the dominance of the Qrinkage AR(2) model that shrinks the forecasts toward the long run mean over a 5-year rolling window (Qrnk(1)AR2r). Figure 5 illustrates the increasing advantage of shrinking toward the long run mean as the forecast horizon increases.

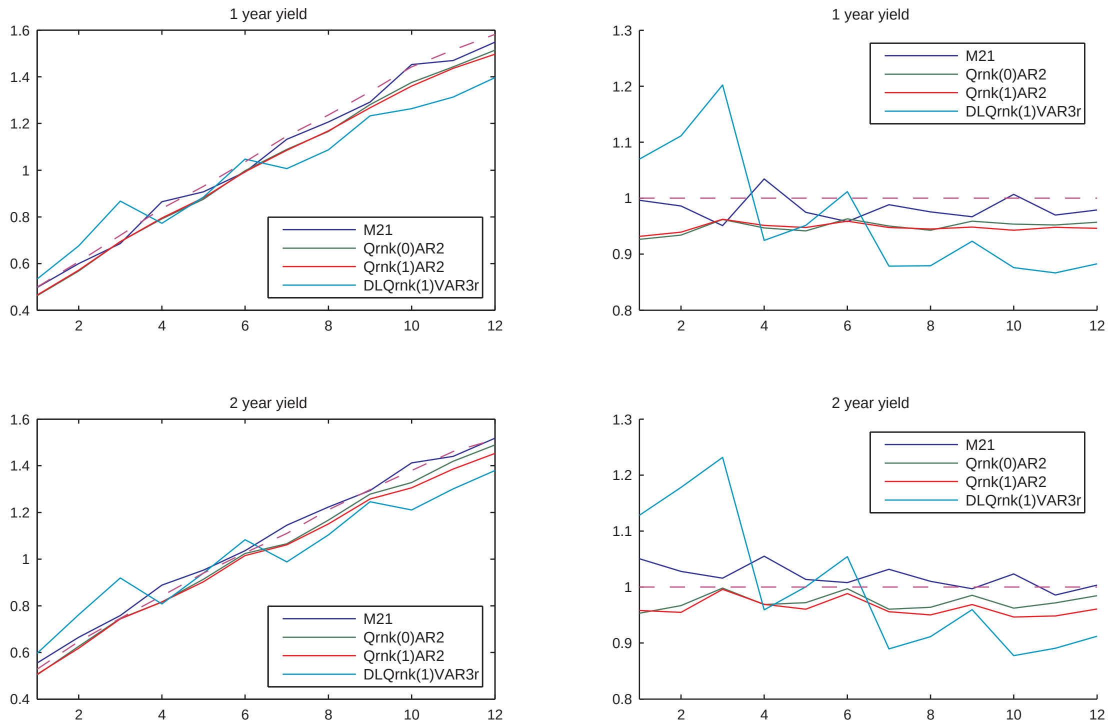

Figure 4: **Out of Sample Forecast Errors - 1 and 2 year yields** The left plots show out of sample forecast errors for several selected models. The right plots show the forecasting performance relative to the random walk forecast. The dashed line corresponds to the random walk forecast (MART).

Intuitively, when forecasting over longer horizons the underlying process will on average drift away from the random walk and back toward its long run mean. However, one might expect that shrinking toward the random walk forecast would be advantageous over shorter forecast horizons. This intuition is consistent with the strong short-horizon performance of model Qrnk(1)AR2r.

What may be surprising is the evidence that the individual survey participants could dramatically improve their forecasting performance by simply providing the random walk forecast (MART). From other studies we know that the random walk is a difficult benchmark to beat and from Table 5 we see that only a few of the individual survey participants are competitive with the random walk. The mean survey forecaster clearly under performs the random walk forecast, as do most of the econometric forecasting models. However, note from Figure 5 that the mean survey forecaster converges toward the random walk forecast as the horizon increases. In light of these findings, it is somewhat remarkable that the Qrnk(1)AR2r model arises as the one model that is clearly able to outperform the random walk forecast over longer forecast horizons.

3.4 Forecasting Inflation

The final column of Table 5 displays the MCS p-values for forecasting percentage change in the CPI. Note that across all 4 forecast horizons, it is the individual forecasters who are on top - Naroff for 1,

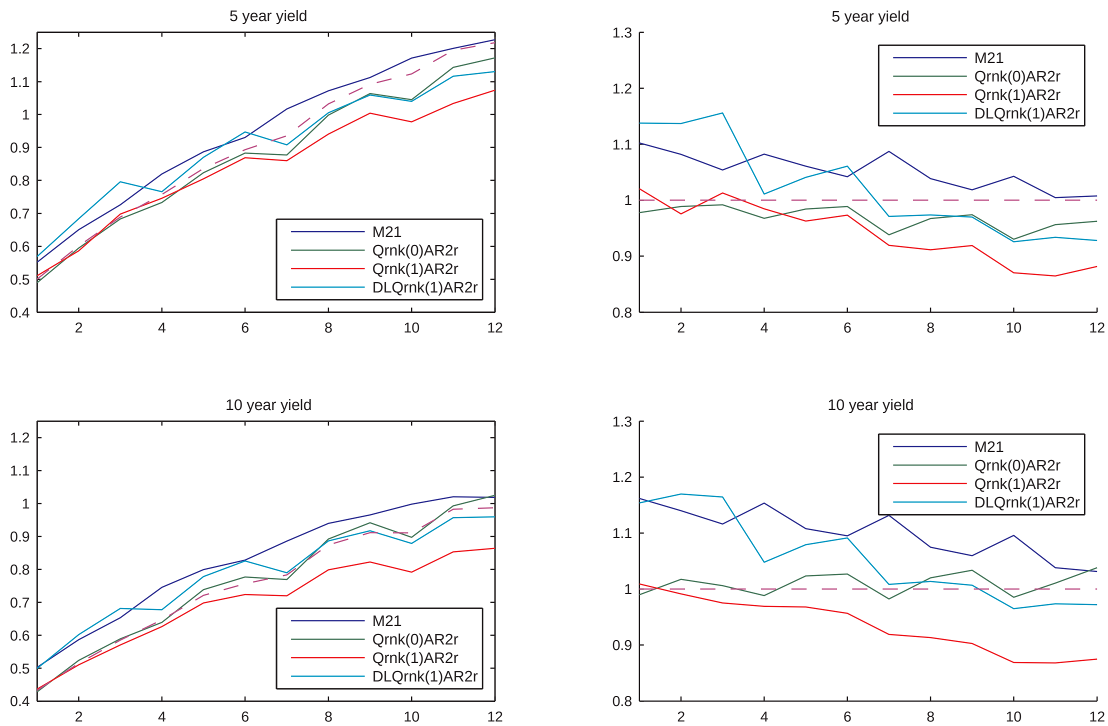

Figure 5: **Out of Sample Forecast Errors - 5 and 10 year yields.** The left plots show out of sample forecast errors for several selected models. The right plots show the forecasting performance relative to the random walk forecast. The dashed line corresponds to the random walk forecast (MART).

3 and 4 quarters ahead, and Woodsworth for 2 quarters ahead. Also note the presence of the mean survey forecasters, M21 and MHL, sprinkled across the lists for all 4 horizons. Although never the forecaster with the highest MCS p-value, in contrast to how they perform at forecasting long term interest rates, they do quite well at forecasting inflation. This suggests that the mean survey forecasts are a potentially valuable source of information about future inflation. This is illustrated in Figure 6 which shows the RMSFE performance for a few of the survey participants. Note unlike the case of long term interest rates the surveys forecasters have no problems outperforming the random walk over all forecast horizons.

How do the pure econometricians do? For both the 2 and 3 quarter ahead forecast horizons, econometric forecasters constitute a significant portion of the 'next best' performing models. The Qrinkage AR family of models appears to be the best econometric models suited for forecasting inflation.

4 Discussion

Why might some survey forecasters perform relatively well at forecasting inflation and short maturity yields, yet under perform at forecasting long maturity yields? Suppose the forecasters are using an optimal linear forecasting model, then when using with a quadratic loss function, which posits the desirability of minimizing mean squared forecast errors, they would provide their true expectations

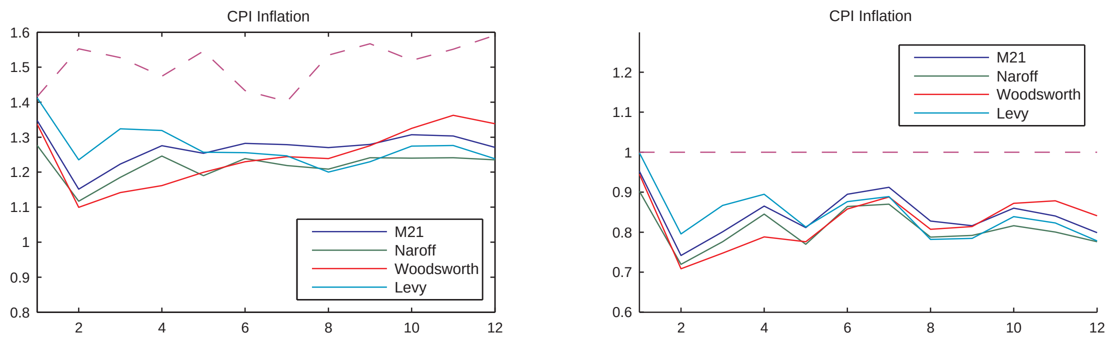

Figure 6: **Out of Sample Forecast Errors - CPI Inflation.** The left plots show out of sample forecast errors for several selected models. The right plots show the forecasting performance relative to the random walk forecast. The dashed line corresponds to the random walk forecast (MART).

(conditioned on their information sets). Given a symmetric distribution of the random variable of interest, minimizing the mean absolute error yields the identical optimal forecast as minimizing the mean squared error. Yet when the distribution is skewed these forecasts will differ. Several studies, including Gu and Wu (2003) and Basu and Markov (2004), find evidence in favor of evaluating forecasters using mean absolute forecasts errors. Hong and Kubrik (2002) show that forecast accuracy as measured using absolute forecast errors is consistent with analysts' career objectives. Others studies, including Patton and Timmerman (2003) and Elliot, Komunger, and Timmermann (2004) show that forecast rationality can be preserved if the forecasters are assumed to have asymmetric loss functions.

Although we use the quadratic loss function as a benchmark, the true loss functions of the survey participants are unobserved, and may certainly reflect their underlying career motives and concerns. As with the large literature focusing on the forecasts of equity analysts, one may be able to argue that some forecasters are biasing forecasts of long term interest rates with the intent of influencing the investment behavior of their clients. However, misreporting their information with a biased forecast might be optimal even when the forecasters are not interested in altering investors' investment decisions. Ottaviani and Sorensen (2006) develop an equilibrium theory of forecasting where strategically altering the forecasts toward the prior mean improves their reputation as forecasters; a second theory, under a contest setting, leads to excessively differentiated forecasts. Moreover, some forecasters may opt take a conservative stance rather than chance standing out from the crowd, especially if they believe that the consensus forecast efficiently aggregates information in the market. For macroeconomic variables, Bauer, Eisenbeis, Waggoner, and Zha (2003) study the individual participants in the Blue Chip Economic Indicators survey and find evidence that the consensus forecast performs better than any individual forecaster. Due to forecasts of financial variables likely having a larger impact than macroeconomic variables on the business concerns of a forecaster's firm and hence the career concerns of the forecaster, one might conjecture that some forecasters adopt a different loss function for long term interest rates than they do for forecasting inflation. If this is the case, forecast comparison under a quadratic loss function may result in the surveys performing better at forecasting inflation than they would at forecasting long bond yields.

The literature on forecast combination suggests that an inferior forecasting model may be useful when

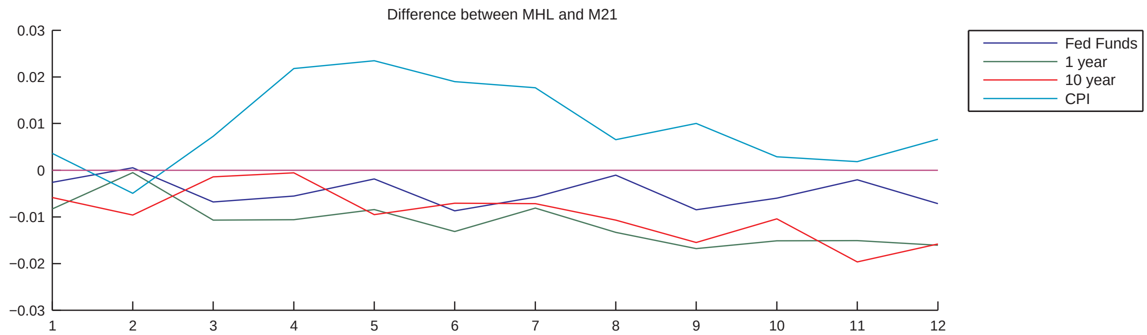

Figure 7: **Information Content of Transient Forecasters.** The difference between the root mean square errors of M21, the mean across the 21 forecasters who consistently participated in the survey and MHL, the mean across all survey participants (purged of high and low forecasts), as a measure of the information content of the transient forecasters.

forming a combination as it might still contain relevant information for forecasting. Yet, the existence of individual forecasters that consistently outperform the mean may be taken as evidence against a naive combination strategy of averaging survey data. Returning to Tables 4 and 5, we see that for inflation and for short horizon forecasts of short maturity yields, both of the mean survey forecasts, *M21* and *MHL*, occasionally appear on the list of top performing models. They are never the model with the lowest root mean squared forecast errors, as they are consistently outperformed by several individual forecasters. Interestingly for interest rate forecasts, the *M21* forecast always outperforms the *MHL* forecast, suggesting a marginal benefit from looking only at the 21 forecasters who are consistently in the survey. Figure 7 plots the difference between *M21* and *MHL*. This difference represents the impact of the transient forecasters, who may have exited the survey due to reasons linked to their lack of forecasting ability, leading to a survivorship bias. In other words, the transient forecasters appear to be adding noise to the consensus forecasts. On the contrary, for forecasting inflation, the *MHL* forecast outperforms the *M21* forecast. This suggests that for inflation the transient forecasters do provide useful information for forecasting.

5 Conclusion

In the end we fail to uncover a single magical model that best predicts interest rates and inflation, however, we do discover a set of broad patterns as well as valuable insights for assessing the performance of various models depending on the variable and forecast horizon of interest. We find that for forecasting the federal funds rate up to 1 quarter ahead, market-based forecasts extracted from federal funds futures contracts is the best performing model. Survey forecasters are, in general, quite good at forecasting short maturity yields over short forecast horizons. Over longer forecast horizons, the Qrinkage version of the Diebold-Li model with VAR(3) dynamics is the dominant model at forecasting short to medium maturity yields. We find that the class of Diebold-Li models can be significantly enhanced by enriching the underlying dynamics in combination with parameter shrinkage. For long maturity interest rates, simple univariate Qrinkage autoregressive models consistently outperform the survey forecasters. The

Qrinkage AR(2) model that shrinks toward to long run mean and estimated with a rolling window is the best model for predicting long maturity yields. However, for very short horizon forecasts, the statistical evidence points favorably toward the Qrinkage-AR(2) model, that shrinks toward the random walk forecast.

Survey forecasters perform exceptionally well at forecasting inflation. One possibility may be that macroeconomic variables, including inflation, are subject to a different loss function than long maturity yields. In addition, transient forecasters appear to add noise to interest rate forecasts, while adding information to inflation forecasts. These findings may have implications for studies using consensus interest rate and inflation forecasts as a model input.

Current research involves further enhancing the forecasting performance of forecasting models, including no-arbitrage models as well as macro-based models, by utilizing shrinkage techniques. The relative under-performance of VAR generated forecasts and the effectiveness of parameter shrinkage should spark interest in applying shrinkage methods when estimating dynamic term structure models, which most certainly suffers from in-sample over-fitting. It only seems natural to apply criteria-based shrinkage methods to the linear forecasting equations generated by no-arbitrage yield curve models, including those that incorporate forecasts themselves as factors.

A Qrinkage

The Criteria Based Shrinkage (or Qrinkage) estimator is introduced in Hansen (2006). The idea behind Qrinkage is to construct out-of-sample forecasting models that shrink the estimated coefficients by an optimal amount to account for in-sample over-fitting of the data. It is optimal in the sense that the estimator minimizes the in-sample over-fit, whereby maximizing the out-of-sample under-fit. See Hansen (2008) for details. For the special case of linear forecasting models the Qrinkage estimator is constructed as follows. Let $\mathbf{S}_{XX} = \mathbf{X}'\mathbf{X}/k$ where $k = m-(p+1)$ is equal to the number of observations m minus the degrees of freedom. The matrix decomposition of this square matrix into eigenvalues and eigenvectors is given by $\mathbf{S}_{XX} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}'$ (also known as an eigen decomposition) where Λ is an $k \times k$ diagonal matrix containing the eigenvalues and Q is the $k \times k$ matrix of linearly independent eigenvectors such that $\mathbf{Q}' = \mathbf{Q}^{\mathbf{-1}}$ and $\mathbf{Q}\mathbf{Q}' = \mathbf{I}$. Thus, we can write equation (4) as

$$\begin{aligned} \mathbf{y} &= \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} && (9) \\ &= \mathbf{X}\mathbf{Q}\mathbf{Q}'\boldsymbol{\beta} + \boldsymbol{\epsilon} && (10) \\ &= \mathbf{Z}\boldsymbol{\gamma} + \boldsymbol{\epsilon} && (11) \end{aligned}$$

where $\mathbf{Z} = \mathbf{X}\mathbf{Q}$ and $\boldsymbol{\gamma} = \mathbf{Q}'\boldsymbol{\beta}$. Estimating $\boldsymbol{\gamma}$ by OLS we have $\hat{\boldsymbol{\gamma}} = (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{y}$ and $\mathbf{Z}$ is an orthogonal set of regressors.[12] Let $\hat{\gamma}_i$ denote the ith estimated coefficient in a regression of $\mathbf{y}$ on $\mathbf{Z}$.

[12] Note that $\mathbf{Z}'\mathbf{Z} = \mathbf{Q}'\mathbf{X}'\mathbf{X}\mathbf{Q} = n\mathbf{Q}'\mathbf{S}_{XX}\mathbf{Q} = n\mathbf{Q}'\mathbf{Q}\mathbf{\Lambda}\mathbf{Q}'\mathbf{Q} = n\mathbf{\Lambda}$, where the last step follows from the identity $\mathbf{Q}'\mathbf{Q} = \mathbf{Q}\mathbf{Q}' = \mathbf{I}$. Since $\mathbf{Z}$ is an orthogonal set of regressors, it follows that $\mathbf{\Lambda}$ is a diagonal matrix. The unbiased estimator of $\text{Var}(\hat{\boldsymbol{\gamma}})$ is known to be $\hat{\sigma}_\epsilon^2(\mathbf{Z}'\mathbf{Z})^{-1} = \hat{\sigma}_\epsilon^2(n\mathbf{\Lambda})^{-1}$, which is a diagonal matrix, hence the ith the t-statistic is given by $\hat{\gamma}/(\sqrt{\hat{\sigma}_\epsilon^2/n\lambda_i})$. Using orthogonal regressors is not necessary, however we employ them to be consistent with Hansen's work.

The Qrinkage estimator is given by

$$\tilde{\gamma_i} = \hat{\gamma}_i max(0, 1 - \frac{1}{|t_i|}) \quad (12)$$

where

$$t_i = \hat{\gamma}_i \frac{\sqrt{n\lambda_i}}{\hat{\sigma}_\epsilon}. \quad (13)$$

where $\hat{\sigma}_\epsilon^2 = \hat{\boldsymbol{\epsilon}}'\hat{\boldsymbol{\epsilon}}/n$ is the sample estimate for σ_ϵ^2 and λ_i is the ith element of the diagonal matrix $\boldsymbol{\Lambda} = \mathbf{Z}'\mathbf{Z}/n$. Finally, it follows from $\boldsymbol{\gamma} = \mathbf{Q}'\boldsymbol{\beta}$ and $\mathbf{Q}' = \mathbf{Q}^{-1}$, that the Qrinkage estimate of $\boldsymbol{\beta}$ is $\tilde{\boldsymbol{\beta}} = Q\tilde{\boldsymbol{\gamma}}$.

The quick intuition behind the procedure is to shrink the parameter estimates toward zero in relation to the uncertainty inherent in the estimates. The greater the uncertainty the greater the shrinkage where the maximum shrinkage is constrained so that the sign of the parameter estimate remains unchanged. The larger the t_i, the closer the term $1 - 1/|t_i|$ is to 1 and the less shrinkage that is applied to the estimated parameters. The expression for t_i, which corresponds to the ith t statistic, provides intuition behind the procedure as it increases (implying less shrinkage) when n increases (more data), the regressor variance λ_i is large (more variation in the $\mathbf{Z}$ variables leads to better estimates) or the noise $\hat{\sigma}_\epsilon$ decreases (more precise estimates). For further details, please see Hansen (2006), yet as his research is still a work in progress the details of this procedure are subject to refinement.

B Model Confidence Sets

Econometric methods for determining equal predictive ability between competing models were developed by West (1996) and Diebold and Mariano (1995). White (2000) provides a formal method for testing the superiority of a set of forecasting models over a benchmark model. Hansen (2005) modifies this framework in developing a new test for superior predictive ability and applies this method for evaluating forecasts of inflation. However, what if the data are not informative enough to differentiate the ‘best’ forecasting model from the set of ‘good’ forecasting models with significant precision? Hansen, Lunde, and Nason (2003, 2005) propose a procedure for reducing the set of all competing models to a smaller subset that includes the best forecasting model(s) with a pre-specified level of probability. In the same way that a confidence interval is a random data-dependent set that covers a population parameter, a Model Confidence Set (MCS) is a random data-dependent set that covers the best forecasting model(s). The number of models remaining in a MCS are reflective of the information content of the data, hence uninformative data will result in relatively large model confidence sets. Compared with tests of superior predictive ability, as in White (2000) or Hansen (2005), the MCS approach has the advantage of selecting a set of models as opposed to focusing on the relative performance of a single model. The determination of such a set may be useful for forecast combination, as the ‘second’ or ‘third’ best model may contain valuable information for forecasting. In evaluating competing forecasts, we focus on model confidence set p-values as a way of statistically measuring the performance of a particular forecasting model.

Suppose there are N competing forecasters. We are interested in evaluating if these N forecasters are equally good at forecasting in terms of a particular loss function. The evaluation criteria we impose is that of minimizing the expected loss function, $E[L_{i,t}]$, where the time t loss for forecaster i is given by $L_{i,t}$. The loss function is assumed to be quadratic. Denote by $\mathbf{M}_0 = \{1, .., N\}$ the set of all forecasting models under consideration. If a subset of these forecasters is equally good at forecasting, then for this subset of models one would not reject the null hypothesis of equal predictive ability. Such a test is provided by Diebold and Mariano (1995) and West (1996) where under the null hypothesis the set of competing forecasts each have the same level of expected loss. Define the set of superior models by $\mathbf{M}^* \equiv \{i \in \mathbf{M}_0 : E(d_{ij,t}) \leq 0,\ \forall j \in \mathbf{M}_0\}$, where $d_{ij,t} = L_{i,t} - L_{j,t}$ is the loss differential between models i and j. If a set of models rejects the null of equal predictive ability, then it is clear that at least one of the models in the set is, in a statistical sense, inferior to the best performing model(s). Hansen, Lunde, and Nason (2005) introduce the idea of a Model Confidence Set (MCS). The MCS is a random set of models that contains the set of superior forecasting models, $\mathbf{M}^*$, with a pre-specified level of probability. Define $\hat{\mathbf{M}}^*_\alpha$ as the Model Confidence Set with confidence level $1 - \alpha$. For example, the set $\hat{\mathbf{M}}^*_{.05}$ contains the set of 'best' forecasting model(s) with 95% probability.

The MCS procedure is iterative and removes the worst performing model from the set until the test accepts the null of equal predictive ability, $H_0 : E(d_{ij,t}) = 0$ for all $i, j \in \mathbf{M} \subset \mathbf{M}_0$, where $\mathbf{M}$ is a trimmed subset of the candidate models still under consideration in the current step of the procedure. We employ a test referred to as the *deviation from the common average* that is constructed as follows. Let $\bar{d_{ij}} = n^{-1}\Sigma_{t=1}^{n}\bar{d}_{ij,t}$ and $\bar{d}_i = m^{-1}\Sigma_{j\in\mathbf{M}}\bar{d}_{ij}$, the test statistic is given by $T_D = \Sigma_{j\in\mathbf{M}}t_i^2$ where $t_i = \bar{d}_i/\hat{\sigma}(\bar{d}_i)$. This statistic has the advantage of having the fewest pairwise comparisons. Due to the presence of nuisance parameters, the asymptotic distribution of T_D is non-standard and estimated using bootstrap methods. At each step, if the null is rejected, a model is eliminated from $\mathbf{M}$ and the procedure is repeated until the null is 'accepted' at which point the set of surviving models defines the model confidence set. For more details on the computational aspects of generating MCSs using MULCOM 1.00 *Econometric Toolkit for Multiple Comparisons*, please see Hansen and Lunde (2007).

This iterative procedure generates Model Confidence Set p-values, that can be used to evaluate the probability that a model belongs to a MCS at a given level. So low MCS p-values indicate that during the iterative MCS building procedure the model will be eliminated from consideration at an earlier step than a model with a higher MCS p-value. For example, a test on a candidate set of models $\mathbf{M}$, that contains a model with a MCS p-value of .09 will reject the null of equal predictive ability at the 10% significance level. Thus, the iterative procedure will eventually remove this model when constructing a MCS with a level of $\alpha = 10\%$. If model i has a MCS p-value equal to $\hat{p}_i$, then i is in $\hat{\mathbf{M}}^*_\alpha$ if and only if $\hat{p}_i > \alpha$. If $\hat{p}_i \leq \alpha$ then the model will be eliminated at some stage of the iterative process used to compute $\hat{\mathbf{M}}^*_\alpha$. When evaluating the forecasting properties of a model we focus on the MCS p-value as a statistical indicator of the model's performance, as forecasting models with high MCS p-values are more likely to be a member of $\mathbf{M}^*$.

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Supplementary Tables
Not for Publication

Table 6: Root Mean Squared Forecast Errors - Fed Funds Rate

1 – quarter		**1 – month**		**2 – month**		**3 – month**	
FFFutures	0.340	FFFutures	0.243	FFFutures	0.303	BearStearns	0.415
BearStearns	0.349	USTrust	0.260	BearStearns	0.341	J.K.Thredgold	0.437
J.K.Thredgold	0.367	BearStearns	0.276	J.K.Thredgold	0.345	FFFutures	0.441
Nomura	0.382	Nomura	0.284	WellsFargo	0.352	M21	0.469
WellsFargo	0.383	Qrnk(0)VAR1r	0.286	Nomura	0.363	DLVAR3	0.474
M21	0.384	M21	0.287	USTrust	0.370	Nomura	0.474
MHL	0.387	Qrnk(0)VAR1rc	0.289	MHL	0.371	MHL	0.476
USTrust	0.390	MHL	0.290	M21	0.371	WellsFargo	0.477
J.N.Woodworth	0.397	VAR1r	0.292	J.N.Woodworth	0.372	J.W.Coons	0.479
DLVAR3	0.398	WellsFargo	0.296	Qrnk(0)VAR1c	0.376	R.T.McGee	0.481
R.T.McGee	0.400	J.N.Woodworth	0.298	Qrnk(0)VAR1	0.379	DLQrnk(0)VAR3	0.484
J.W.Coons	0.405	VAR1cr	0.301	M.Levy	0.383	DLVAR2	0.488
2 – quarter		**4 – month**		**5 – month**		**6 – month**	
DLVAR3r	0.686	DLQrnk(1)VAR3r	0.585	DLQrnk(1)VAR3r	0.649	BearStearns	0.773
DLQrnk(1)VAR3r	0.687	DLQrnk(1)VAR2r	0.597	WellsFargo	0.662	WellsFargo	0.775
DLVAR3	0.697	Qrnk(1)VAR1	0.599	DLVAR3r	0.662	DLVAR3	0.779
DLQrnk(0)VAR3r	0.702	Qrnk(0)VAR1	0.599	Nomura	0.662	DLVAR3r	0.779
WellsFargo	0.704	DLVAR3	0.599	DLQrnk(1)VAR2r	0.673	J.K.Thredgold	0.783
DLQrnk(1)VAR1r	0.706	Qrnk(0)VAR1c	0.602	J.K.Thredgold	0.678	DLQrnk(0)VAR3r	0.793
DLQrnk(1)VAR2r	0.707	DLQrnk(1)VAR3	0.604	Qrnk(0)VAR1c	0.683	DLQrnk(1)VAR3r	0.807
J.K.Thredgold	0.708	DLVAR3r	0.606	DLQrnk(1)VAR1r	0.683	DLQrnk(0)VAR3	0.809
BearStearns	0.714	DLQrnk(1)VAR1r	0.607	Qrnk(0)VAR1	0.684	J.N.Woodworth	0.809
DLVAR2r	0.715	Qrnk(0)VAR1r	0.607	DLQrnk(0)VAR3r	0.690	DLQrnk(1)VAR3	0.813
DLQrnk(1)VAR3	0.720	DLQrnk(0)VAR3r	0.612	BearStearns	0.694	DLQrnk(1)VAR1r	0.814
3 – quarter		**7 – month**		**8 – month**		**9 – month**	
DLQrnk(1)VAR3r	0.925	DLQrnk(1)VAR3r	0.858	DLQrnk(1)VAR3r	0.888	DLQrnk(1)VAR3r	1.022
DLVAR3r	0.966	VAR1	0.874	DLVAR3r	0.938	DLVAR3r	1.038
DLQrnk(1)VAR2r	0.970	VAR1c	0.878	DLQrnk(1)VAR2r	0.940	DLQrnk(1)VAR2r	1.061
DLQrnk(1)VAR1r	0.992	DLQrnk(1)VAR2r	0.900	DLQrnk(1)VAR1r	0.967	DLQrnk(1)VAR1r	1.084
DLQrnk(0)VAR3r	1.004	Qrnk(0)VAR1	0.907	DLQrnk(0)VAR3r	0.983	DLQrnk(0)VAR3r	1.085
DLVAR2r	1.021	DLVAR3r	0.916	VAR1	0.997	DLVAR2r	1.109
Qrnk(0)VAR3	1.031	DLQrnk(1)VAR1r	0.917	DLVAR2r	0.999	DLVAR3	1.118
J.K.Thredgold	1.038	Qrnk(0)VAR3	0.921	VAR1c	1.008	DLQrnk(1)VAR3	1.118
DLQrnk(1)VAR3	1.041	J.K.Thredgold	0.921	Qrnk(0)VAR1	1.011	DLVAR1r	1.138
Qrnk(0)VAR3c	1.041	Qrnk(1)VAR1	0.928	Qrnk(0)VAR3	1.023	Qrnk(0)VAR3	1.138
DLVAR3	1.044	Qrnk(0)VAR1c	0.929	Qrnk(0)VAR1c	1.026	DLQrnk(1)VAR2	1.141
4 – quarter		**10 – month**		**11 – month**		**12 – month**	
DLQrnk(1)VAR3r	1.183	VAR1	1.152	DLQrnk(1)VAR3r	1.153	DLQrnk(1)VAR3r	1.238
DLQrnk(1)VAR2r	1.233	DLQrnk(1)VAR3r	1.155	DLQrnk(1)VAR2r	1.214	DLQrnk(1)VAR2r	1.279
DLVAR3r	1.255	VAR1c	1.162	DLVAR3r	1.233	DLVAR3r	1.303
DLQrnk(1)VAR1r	1.279	DLQrnk(1)VAR2r	1.203	DLQrnk(1)VAR1r	1.258	DLQrnk(1)VAR1r	1.343
DLQrnk(0)VAR3r	1.303	DLVAR3r	1.229	DLQrnk(0)VAR3r	1.281	DLQrnk(0)VAR3r	1.367
DLVAR2r	1.324	Qrnk(0)VAR3	1.230	DLVAR2r	1.306	DLVAR2r	1.388
Qrnk(0)VAR3	1.345	DLQrnk(1)VAR1r	1.231	VAR1	1.315	J.N.Woodworth	1.395
Qrnk(0)VAR3c	1.347	Qrnk(0)VAR1	1.233	Qrnk(0)VAR3c	1.323	DLQrnk(1)VAR3	1.409
DLQrnk(1)VAR3	1.355	Qrnk(0)VAR3c	1.244	J.N.Woodworth	1.326	DLQrnk(0)VAR1r	1.418
J.N.Woodworth	1.358	DLQrnk(0)VAR3r	1.257	VAR1c	1.331	DLVAR3	1.426
DLVAR1r	1.360	Qrnk(1)VAR2	1.260	Qrnk(0)VAR3	1.333	DLQrnk(0)VAR2	1.426

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 7: Model Confidence Set p-values - Fed Funds Rate

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
FFFutures	1	FFFutures	1	FFFutures	1	BearStearns	1
BearStearns	0.7167	USTrust	0.5053	BearStearns	0.2347	J.K.Thredgold	0.794
WellsFargo	0.3917	BearStearns	0.3067	USTrust	0.2347	FFFutures	0.794
J.K.Thredgold	0.3917	Nomura	0.3067	WellsFargo	0.2347	DLVAR3	0.6053
Nomura	0.3011	WellsFargo	0.3067	J.K.Thredgold	0.2347	Nomura	0.5526
USTrust	0.2656	J.N.Woodworth	0.3067	Nomura	0.2146	WellsFargo	0.5526
M21	0.2087	J.K.Thredgold	0.3067	J.N.Woodworth	0.2146	R.T.McGee	0.5526
MHL	0.1973	M21	0.3067	MHL	0.1837	M21	0.5526
DLVAR3	0.1973	MHL	0.3067	M21	0.1559	MHL	0.5526
R.T.McGee	0.1763	Qrnk(0)VAR1rc	0.3067	Qrnk(0)VAR1c	0.1559	DLQrnk(0)VAR3	0.5526
J.N.Woodworth	0.1654	VAR1r	0.3067	DLVAR3	0.1172	J.W.Coons	0.5503
Qrnk(0)VAR1c	0.1393	Qrnk(0)VAR1r	0.3067	M.Levy	0.1003	DLVAR2	0.5503
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
DLVAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	BearStearns	1
BearStearns	0.9829	VAR1c	0.9995	Nomura	0.9904	WellsFargo	0.9997
WellsFargo	0.9829	Qrnk(0)VAR1c	0.9995	WellsFargo	0.9904	J.K.Thredgold	0.9997
J.K.Thredgold	0.9829	Qrnk(0)VAR1	0.9995	J.K.Thredgold	0.9904	DLVAR3	0.9997
Qrnk(0)VAR1	0.9829	Qrnk(0)VAR1r	0.9995	Qrnk(0)VAR1	0.9904	DLVAR3r	0.9997
DLVAR3	0.9829	Qrnk(1)VAR1	0.9995	DLVAR3r	0.9904	DLQrnk(0)VAR3r	0.9994
DLQrnk(0)VAR3r	0.9829	DLVAR3	0.9995	DLQrnk(1)VAR2r	0.9904	DLQrnk(1)VAR3r	0.9965
DLQrnk(1)VAR1r	0.9829	DLVAR3r	0.9995	Qrnk(0)VAR1c	0.9891	J.N.Woodworth	0.9943
DLQrnk(1)VAR2r	0.9829	DLQrnk(0)VAR3r	0.9995	DLQrnk(0)VAR3r	0.9891	DLQrnk(0)VAR3	0.994
DLQrnk(1)VAR3r	0.9829	DLQrnk(1)VAR3	0.9995	DLQrnk(1)VAR1r	0.9891	DLQrnk(1)VAR3	0.994
DLVAR2r	0.9726	DLQrnk(1)VAR1r	0.9995	J.N.Woodworth	0.9884	DLQrnk(1)VAR1r	0.994
DLQrnk(1)VAR3	0.97	DLQrnk(1)VAR2r	0.9995	BearStearns	0.9861	Qrnk(0)VAR3c	0.9934
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
USTrust	0.2782	VAR1c	0.9051	VAR1c	0.5301	DLVAR3r	0.6589
J.N.Woodworth	0.2782	VAR1	0.9051	VAR1	0.5301	BearStearns	0.5266
J.K.Thredgold	0.2782	USTrust	0.8786	DLVAR3r	0.5301	USTrust	0.5266
VAR1c	0.2782	J.K.Thredgold	0.8786	DLQrnk(0)VAR3r	0.5301	WellsFargo	0.5266
Qrnk(0)VAR3c	0.2782	Qrnk(0)VAR1c	0.8786	DLQrnk(1)VAR1r	0.5301	J.N.Woodworth	0.5266
VAR1	0.2782	Qrnk(0)VAR3c	0.8786	DLQrnk(1)VAR2r	0.5301	J.K.Thredgold	0.5266
Qrnk(0)VAR1	0.2782	Qrnk(0)VAR1	0.8786	Qrnk(0)VAR3c	0.5073	M21	0.5266
Qrnk(0)VAR3	0.2782	Qrnk(0)VAR3	0.8786	Qrnk(0)VAR1	0.5073	MHL	0.5266
DLVAR3	0.2782	Qrnk(1)VAR1	0.8786	Qrnk(0)VAR3	0.5073	Qrnk(0)VAR3c	0.5266
DLVAR1r	0.2782	DLVAR3r	0.8786	DLVAR2r	0.5073	VAR1	0.5266
DLVAR2r	0.2782	DLQrnk(0)VAR3r	0.8786	Nomura	0.4232	Qrnk(0)VAR1	0.5266
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1	VAR1	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
VAR1	0.1127	DLQrnk(1)VAR3r	0.9795	VAR1c	0.4292	BearStearns	0.154
Qrnk(0)VAR3	0.1127	VAR1c	0.9748	VAR1	0.4292	Comerica	0.154
DLVAR2r	0.1127	Qrnk(1)AR3	0.8315	DLVAR3r	0.4292	DePrince	0.154
DLVAR3r	0.1127	Qrnk(0)VAR3c	0.8315	DLQrnk(0)VAR3r	0.4292	Nomura	0.154
DLQrnk(0)VAR3r	0.1127	Qrnk(0)VAR2rc	0.8315	DLQrnk(1)VAR1r	0.4292	StandardPoors	0.154
DLQrnk(1)VAR1r	0.1127	Qrnk(1)VAR2c	0.8315	DLQrnk(1)VAR2r	0.4292	USTrust	0.154
DLQrnk(1)VAR2r	0.1127	VAR2	0.8315	J.N.Woodworth	0.423	WellsFargo	0.154
Qrnk(0)VAR3c	0.1087	Qrnk(0)VAR1	0.8315	Qrnk(0)VAR3c	0.423	J.N.Woodworth	0.154
USTrust	0.088	Qrnk(0)VAR3	0.8315	Qrnk(0)VAR3	0.423	J.K.Thredgold	0.154
J.N.Woodworth	0.088	Qrnk(1)VAR2	0.8315	DLVAR2r	0.423	M.Levy	0.154
Qrnk(1)AR3	0.088	DLVAR3r	0.8315	USTrust	0.363	M21	0.154

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 8: Root Mean Squared Forecast Errors - 3 Month Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
BearStearns	0.437	USTrust	0.339	USTrust	0.419	BearStearns	0.505
USTrust	0.440	Qrnk(1)VAR1	0.344	BearStearns	0.439	J.K.Thredgold	0.528
J.K.Thredgold	0.453	VAR1c	0.346	Qrnk(0)VAR1c	0.440	R.T.McGee	0.532
Qrnk(1)VAR1	0.458	Qrnk(1)VAR1c	0.349	Qrnk(0)VAR1	0.442	USTrust	0.537
R.T.McGee	0.459	BearStearns	0.350	DLQrnk(0)VAR1r	0.444	M21	0.541
M21	0.460	VAR1	0.351	Qrnk(1)VAR1	0.444	MHL	0.545
Qrnk(0)VAR1c	0.461	Qrnk(0)VAR1c	0.353	Nomura	0.444	WellsFargo	0.547
MHL	0.462	Qrnk(0)VAR1	0.356	Qrnk(1)VAR1c	0.446	J.W.Coons	0.553
Qrnk(0)VAR1	0.464	VAR1r	0.359	R.T.McGee	0.448	Qrnk(1)VAR1	0.557
Qrnk(1)VAR1c	0.466	M21	0.362	J.K.Thredgold	0.449	StandardPoors	0.558
WellsFargo	0.469	DLQrnk(0)VAR2r	0.363	M.Levy	0.449	Qrnk(0)VAR1c	0.563
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(0)VAR1	0.759	VAR1c	0.616	Nomura	0.713	USTrust	0.835
Qrnk(0)VAR1c	0.762	VAR1	0.622	Qrnk(0)VAR1c	0.719	BearStearns	0.840
Qrnk(1)VAR1	0.763	Qrnk(0)VAR1	0.638	Qrnk(0)VAR1	0.719	J.K.Thredgold	0.848
USTrust	0.763	Qrnk(0)VAR1c	0.640	VAR1	0.727	WellsFargo	0.850
DLQrnk(0)VAR3r	0.766	Qrnk(1)VAR1	0.643	VAR1c	0.728	StandardPoors	0.856
Nomura	0.769	DLQrnk(1)VAR3r	0.654	DLQrnk(1)VAR3r	0.729	Qrnk(0)VAR3c	0.863
DLQrnk(1)VAR3r	0.770	Qrnk(1)VAR1c	0.655	USTrust	0.732	M21	0.866
DLVAR3r	0.771	DLQrnk(1)VAR1r	0.664	DLVAR3r	0.735	DLQrnk(0)VAR3r	0.866
J.K.Thredgold	0.772	Qrnk(0)VAR2	0.664	DLQrnk(0)VAR3r	0.743	Nomura	0.869
DLQrnk(1)VAR1r	0.775	DLQrnk(1)VAR2r	0.666	DLQrnk(1)VAR1r	0.743	MHL	0.872
Qrnk(0)VAR3c	0.777	Qrnk(0)VAR2c	0.667	DLQrnk(0)VAR1r	0.747	Qrnk(1)VAR1	0.872
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	0.995	VAR1	0.873	DLQrnk(1)VAR3r	0.954	DLQrnk(1)VAR3r	1.104
DLVAR3r	1.025	VAR1c	0.875	DLVAR3r	0.987	DLVAR3r	1.125
DLQrnk(1)VAR2r	1.032	DLQrnk(1)VAR3r	0.917	DLQrnk(1)VAR2r	0.997	USTrust	1.135
USTrust	1.040	Qrnk(0)VAR1	0.920	VAR1	1.007	DLQrnk(1)VAR2r	1.138
DLQrnk(1)VAR1r	1.044	Qrnk(0)VAR1c	0.939	DLQrnk(1)VAR1r	1.013	DLQrnk(0)VAR3r	1.142
DLQrnk(0)VAR3r	1.049	Qrnk(0)VAR3c	0.944	VAR1c	1.014	DLQrnk(1)VAR1r	1.152
Qrnk(0)VAR3c	1.060	DLQrnk(1)VAR2r	0.951	Qrnk(0)VAR1	1.018	Qrnk(0)VAR3c	1.160
DLVAR2r	1.064	Qrnk(0)VAR3	0.954	DLQrnk(0)VAR3r	1.018	DLQrnk(0)VAR1r	1.176
Qrnk(0)VAR1	1.068	USTrust	0.954	USTrust	1.024	DLVAR2r	1.177
Qrnk(0)VAR3	1.075	DLVAR3r	0.957	DLVAR2r	1.025	DLQrnk(0)VAR2	1.185
VAR1	1.076	Qrnk(1)VAR1	0.958	Qrnk(0)VAR1c	1.037	DLQrnk(0)VAR2r	1.186
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1.235	VAR1	1.153	DLQrnk(1)VAR3r	1.205	DLQrnk(1)VAR3r	1.301
DLQrnk(1)VAR2r	1.279	VAR1c	1.161	DLQrnk(1)VAR2r	1.257	DLQrnk(1)VAR2r	1.340
DLVAR3r	1.294	DLQrnk(1)VAR3r	1.197	DLVAR3r	1.263	USTrust	1.365
USTrust	1.310	Qrnk(0)VAR1	1.222	USTrust	1.265	DLVAR3r	1.366
DLQrnk(1)VAR1r	1.316	Qrnk(0)VAR3c	1.238	DLQrnk(1)VAR1r	1.293	DLQrnk(1)VAR1r	1.392
DLQrnk(0)VAR3r	1.328	DLQrnk(1)VAR2r	1.239	DLQrnk(0)VAR3r	1.299	DLQrnk(0)VAR3r	1.400
Qrnk(0)VAR3c	1.341	DLVAR3r	1.250	VAR1	1.317	Comerica	1.405
DLVAR2r	1.347	Qrnk(1)VAR2	1.255	DLVAR2r	1.317	Qrnk(1)AR3	1.423
Qrnk(1)VAR2	1.357	DLQrnk(1)VAR1r	1.261	Comerica	1.318	J.N.Woodworth	1.426
Comerica	1.361	Qrnk(0)VAR3	1.263	VAR1c	1.327	Qrnk(1)VAR2	1.429
Qrnk(1)VAR2c	1.364	Qrnk(0)VAR1c	1.266	Qrnk(0)VAR1	1.339	Qrnk(0)AR3	1.433

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 9: Model Confidence Set p-values - 3 Month Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
BearStearns	1	USTrust	1	USTrust	1	BearStearns	1
Nomura	0.8931	BearStearns	0.981	BearStearns	0.9991	Nomura	0.8776
USTrust	0.8931	VAR1c	0.981	Nomura	0.9991	StandardPoors	0.8776
WellsFargo	0.8931	Qrnk(1)VAR1	0.981	WellsFargo	0.9991	USTrust	0.8776
J.K.Thredgold	0.8931	Qrnk(1)VAR1c	0.98	J.K.Thredgold	0.9991	WellsFargo	0.8776
R.T.McGee	0.8931	Qrnk(0)VAR1c	0.9794	M.Levy	0.9991	FannieMae	0.8776
M21	0.8931	VAR1	0.9794	R.T.McGee	0.9991	J.W.Coons	0.8776
MHL	0.8931	VAR1r	0.9719	MHL	0.9991	J.N.Woodworth	0.8776
VAR1c	0.8931	Qrnk(0)VAR1	0.9719	VAR1c	0.9991	J.K.Thredgold	0.8776
Qrnk(0)VAR1c	0.8931	Comerica	0.9536	Qrnk(0)VAR1c	0.9991	R.T.McGee	0.8776
Qrnk(1)VAR1c	0.8931	VAR1cr	0.9328	Qrnk(1)VAR1c	0.9991	M21	0.8776
VAR1	0.8931	DLQrnk(0)VAR1r	0.913	Qrnk(0)VAR1	0.9991	MHL	0.8776
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Nomura	1	VAR1c	1	Nomura	1	USTrust	1
USTrust	1	Qrnk(0)VAR1c	0.9289	USTrust	0.9991	BearStearns	0.9991
WellsFargo	1	VAR1	0.9289	WellsFargo	0.9991	Nomura	0.9991
J.K.Thredgold	1	Qrnk(0)VAR1	0.9289	J.N.Woodworth	0.9991	StandardPoors	0.9991
VAR1c	1	Qrnk(1)VAR1	0.9289	VAR1c	0.9991	WellsFargo	0.9991
Qrnk(0)VAR1c	1	DLQrnk(1)VAR1r	0.9289	Qrnk(0)VAR1c	0.9991	J.N.Woodworth	0.9991
Qrnk(0)VAR3c	1	DLQrnk(1)VAR3r	0.9289	VAR1	0.9991	J.K.Thredgold	0.9991
VAR1	1	Qrnk(0)VAR2c	0.9273	Qrnk(0)VAR1	0.9991	M21	0.9991
Qrnk(0)VAR1	1	Qrnk(0)VAR3c	0.9273	DLVAR3r	0.9991	Qrnk(0)VAR3c	0.9991
Qrnk(1)VAR1	1	Qrnk(1)VAR1c	0.9273	DLQrnk(0)VAR1r	0.9991	Qrnk(1)VAR1	0.9991
DLVAR3r	1	VAR1r	0.9273	DLQrnk(0)VAR3r	0.9991	DLQrnk(0)VAR3r	0.9991
DLQrnk(0)VAR1r	1	Qrnk(0)VAR2	0.9273	DLQrnk(1)VAR1r	0.9991	MHL	0.9986
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	1	VAR1	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
USTrust	0.763	Comerica	0.9313	USTrust	0.8699	BearStearns	0.9248
VAR1c	0.763	StandardPoors	0.9313	VAR1c	0.8699	Comerica	0.9248
Qrnk(0)VAR3c	0.763	USTrust	0.9313	VAR1	0.8699	DePrince	0.9248
VAR1	0.763	J.K.Thredgold	0.9313	Qrnk(0)VAR1	0.8699	Nomura	0.9248
DLVAR3r	0.763	J.L.Naroff	0.9313	DLVAR3r	0.8699	StandardPoors	0.9248
DLQrnk(0)VAR3r	0.763	VAR1c	0.9313	DLQrnk(0)VAR3r	0.8699	USTrust	0.9248
DLQrnk(1)VAR1r	0.763	VAR2c	0.9313	DLQrnk(1)VAR1r	0.8699	WellsFargo	0.9248
DLQrnk(1)VAR2r	0.763	Qrnk(0)VAR1c	0.9313	DLQrnk(1)VAR2r	0.8699	J.N.Woodworth	0.9248
Qrnk(0)VAR1	0.7564	Qrnk(0)VAR2c	0.9313	DLVAR2r	0.8355	J.K.Thredgold	0.9248
DLVAR2r	0.7564	Qrnk(0)VAR3c	0.9313	Nomura	0.7829	J.L.Naroff	0.9248
StandardPoors	0.7443	Qrnk(1)VAR1c	0.9313	Qrnk(0)VAR1c	0.7829	M21	0.9248
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1	VAR1	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
Comerica	0.3782	USTrust	0.8886	Comerica	0.6863	Comerica	0.4477
USTrust	0.3782	VAR1c	0.8886	USTrust	0.6863	DePrince	0.4477
VAR1c	0.3782	VAR2c	0.8886	VAR1c	0.6863	USTrust	0.4477
Qrnk(0)VAR3c	0.3782	Qrnk(0)VAR1c	0.8886	VAR1	0.6863	J.N.Woodworth	0.4477
VAR1	0.3782	Qrnk(0)VAR3c	0.8886	DLVAR3r	0.6863	J.K.Thredgold	0.4477
Qrnk(1)VAR2	0.3782	Qrnk(1)VAR2c	0.8886	DLQrnk(0)VAR3r	0.6863	AR3	0.4477
DLVAR2r	0.3782	Qrnk(1)VAR2rc	0.8886	DLQrnk(1)VAR1r	0.6863	Qrnk(0)AR2	0.4477
DLVAR3r	0.3782	VAR2	0.8886	DLQrnk(1)VAR2r	0.6863	Qrnk(0)AR3	0.4477
DLQrnk(0)VAR3r	0.3782	Qrnk(0)VAR1	0.8886	DLVAR2r	0.6095	Qrnk(1)AR2	0.4477
DLQrnk(1)VAR1r	0.3782	Qrnk(0)VAR2	0.8886	J.N.Woodworth	0.5848	Qrnk(1)AR3	0.4477
DLQrnk(1)VAR2r	0.3782	Qrnk(0)VAR3	0.8886	Qrnk(0)VAR3c	0.5848	Qrnk(0)VAR3c	0.4477

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 10: Root Mean Squared Forecast Errors - 6 Month Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
BearStearns	0.512	VAR1c	0.398	USTrust	0.500	BearStearns	0.581
J.K.Thredgold	0.514	VAR1	0.402	BearStearns	0.509	R.T.McGee	0.600
M.Levy	0.528	Qrnk(0)VAR1	0.405	Qrnk(0)VAR1	0.512	J.K.Thredgold	0.601
M21	0.530	J.K.Thredgold	0.406	Qrnk(0)VAR1c	0.512	M.Levy	0.611
USTrust	0.531	Qrnk(1)VAR1	0.406	J.K.Thredgold	0.514	M21	0.617
R.T.McGee	0.533	Qrnk(0)VAR1c	0.408	WellsFargo	0.517	StandardPoors	0.619
Qrnk(0)VAR1	0.534	DLQrnk(1)VAR1	0.416	Nomura	0.522	MHL	0.627
Qrnk(0)VAR1c	0.535	USTrust	0.416	M.Levy	0.526	WellsFargo	0.632
WellsFargo	0.536	DLQrnk(0)VAR2r	0.417	Qrnk(1)VAR1	0.528	J.W.Coons	0.636
MHL	0.537	Qrnk(1)VAR1c	0.417	M21	0.529	Nomura	0.637
Qrnk(1)VAR1	0.540	DLQrnk(0)VAR1r	0.417	DLQrnk(0)VAR2	0.530	USTrust	0.649
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
DLQrnk(0)VAR3r	0.841	VAR1c	0.687	Qrnk(0)VAR1	0.804	M.Levy	0.900
Qrnk(0)VAR1	0.842	VAR1	0.694	Nomura	0.807	StandardPoors	0.915
DLQrnk(1)VAR3r	0.844	Qrnk(0)VAR1	0.706	DLQrnk(1)VAR3r	0.811	USTrust	0.929
J.K.Thredgold	0.846	Qrnk(0)VAR1c	0.717	Qrnk(0)VAR1c	0.812	J.K.Thredgold	0.930
StandardPoors	0.853	DLQrnk(1)VAR3r	0.720	USTrust	0.815	BearStearns	0.933
Qrnk(0)VAR1c	0.855	DLQrnk(1)VAR2r	0.737	VAR1c	0.816	DLQrnk(0)VAR3r	0.944
USTrust	0.856	DLQrnk(1)VAR1r	0.738	VAR1	0.817	M21	0.945
DLVAR3r	0.861	Qrnk(1)VAR1	0.741	DLQrnk(0)VAR3r	0.824	Nomura	0.956
DLQrnk(1)VAR2r	0.862	DLVAR1r	0.742	J.K.Thredgold	0.824	WellsFargo	0.957
Nomura	0.862	DLQrnk(0)VAR3r	0.743	DLQrnk(1)VAR2r	0.831	MHL	0.958
DLQrnk(1)VAR1r	0.864	Qrnk(0)VAR2	0.743	DLVAR3r	0.832	DLQrnk(0)VAR2	0.964
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	1.072	VAR1	0.961	DLQrnk(1)VAR3r	1.038	DLQrnk(1)VAR3r	1.183
DLQrnk(1)VAR2r	1.106	VAR1c	0.964	DLQrnk(1)VAR2r	1.075	USTrust	1.196
DLVAR3r	1.110	DLQrnk(1)VAR3r	0.984	DLVAR3r	1.076	M.Levy	1.206
USTrust	1.116	Qrnk(0)VAR1	0.997	DLQrnk(0)VAR3r	1.098	DLQrnk(1)VAR2r	1.214
DLQrnk(0)VAR3r	1.123	J.K.Thredgold	1.017	VAR1	1.103	DLQrnk(0)VAR3r	1.220
DLQrnk(1)VAR1r	1.132	DLQrnk(1)VAR2r	1.019	DLQrnk(1)VAR1r	1.104	DLVAR3r	1.224
StandardPoors	1.139	DLVAR3r	1.021	DLVAR2r	1.106	DLQrnk(1)VAR1r	1.248
DLVAR2r	1.145	StandardPoors	1.028	Qrnk(0)VAR1	1.108	StandardPoors	1.254
J.K.Thredgold	1.149	Qrnk(0)VAR1c	1.029	VAR1c	1.109	DLQrnk(0)VAR2	1.258
Qrnk(0)VAR1	1.156	DLQrnk(1)VAR1r	1.033	USTrust	1.110	DLQrnk(0)VAR2r	1.264
Qrnk(0)VAR3c	1.166	USTrust	1.038	StandardPoors	1.126	DLQrnk(0)VAR1r	1.265
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1.308	VAR1	1.247	DLQrnk(1)VAR3r	1.286	DLQrnk(1)VAR3r	1.372
DLQrnk(1)VAR2r	1.349	VAR1c	1.256	DLQrnk(1)VAR2r	1.331	DLQrnk(1)VAR2r	1.409
DLVAR3r	1.374	DLQrnk(1)VAR3r	1.264	USTrust	1.337	USTrust	1.434
USTrust	1.383	Qrnk(0)VAR1	1.301	DLVAR3r	1.348	DLVAR3r	1.458
DLQrnk(0)VAR3r	1.398	DLQrnk(1)VAR2r	1.304	DLQrnk(0)VAR3r	1.373	DLQrnk(0)VAR3r	1.471
DLQrnk(1)VAR1r	1.399	DLVAR3r	1.311	DLQrnk(1)VAR1r	1.380	M.Levy	1.479
DLVAR2r	1.420	VAR2	1.330	DLVAR2r	1.392	DLQrnk(1)VAR1r	1.480
Qrnk(1)VAR2	1.434	Qrnk(1)VAR2	1.332	StandardPoors	1.416	Qrnk(1)VAR2	1.502
J.K.Thredgold	1.440	DLQrnk(1)VAR1r	1.333	VAR1	1.420	Qrnk(1)AR2	1.505
Qrnk(1)VAR2c	1.441	J.K.Thredgold	1.337	DLQrnk(0)VAR1r	1.426	DLQrnk(0)VAR2	1.514
Qrnk(1)AR2	1.447	DLVAR2r	1.344	Nomura	1.428	DLQrnk(0)VAR2r	1.514

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 11: Model Confidence Set p-values - 6 Month Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
BearStearns	1	VAR1c	1	USTrust	1	BearStearns	1
J.K.Thredgold	0.9259	USTrust	0.9907	BearStearns	0.9976	StandardPoors	0.8861
USTrust	0.8736	J.K.Thredgold	0.9907	WellsFargo	0.9976	J.K.Thredgold	0.8861
WellsFargo	0.8736	AR3	0.9907	J.K.Thredgold	0.9976	M.Levy	0.8861
M.Levy	0.8736	Qrnk(0)VAR1c	0.9907	Qrnk(0)VAR1c	0.9976	R.T.McGee	0.8861
R.T.McGee	0.8736	VAR1	0.9907	Qrnk(0)VAR1	0.9976	M21	0.8391
M21	0.8736	Qrnk(0)VAR1	0.9907	Nomura	0.9972	WellsFargo	0.8274
Qrnk(0)VAR1c	0.8736	Qrnk(1)VAR1	0.9907	M.Levy	0.9972	Nomura	0.8142
Qrnk(0)VAR1	0.8736	DLQrnk(0)VAR1r	0.9907	DLQrnk(0)VAR1r	0.9972	MHL	0.7903
StandardPoors	0.8721	DLQrnk(0)VAR2r	0.9907	VAR1	0.997	J.W.Coons	0.7855
MHL	0.8721	DLQrnk(1)VAR1	0.9907	DLQrnk(0)VAR2	0.997	Qrnk(0)VAR1	0.7855
VAR1c	0.8721	Qrnk(1)AR3	0.9863	VAR1c	0.9944	USTrust	0.7259
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
DLQrnk(0)VAR3r	1	VAR1c	1	Qrnk(0)VAR1	1	M.Levy	1
BearStearns	0.9998	J.K.Thredgold	0.9436	Nomura	0.9996	BearStearns	0.9668
Nomura	0.9998	AR3	0.9436	StandardPoors	0.9996	StandardPoors	0.9668
StandardPoors	0.9998	Qrnk(0)VAR1c	0.9436	USTrust	0.9996	USTrust	0.9668
USTrust	0.9998	Qrnk(0)VAR2c	0.9436	J.K.Thredgold	0.9996	J.K.Thredgold	0.9668
J.K.Thredgold	0.9998	Qrnk(0)VAR3c	0.9436	VAR1c	0.9996	DLQrnk(0)VAR3r	0.9668
M.Levy	0.9998	Qrnk(0)VAR2rc	0.9436	Qrnk(0)VAR1c	0.9996	WellsFargo	0.9601
VAR1c	0.9998	VAR1	0.9436	VAR1	0.9996	Nomura	0.9421
Qrnk(0)VAR1c	0.9998	Qrnk(0)VAR1	0.9436	DLVAR3r	0.9996	M21	0.9421
VAR1	0.9998	Qrnk(0)VAR2	0.9436	DLQrnk(0)VAR1r	0.9996	Qrnk(0)VAR1	0.9421
Qrnk(0)VAR1	0.9998	Qrnk(0)VAR3	0.9436	DLQrnk(0)VAR3r	0.9996	DLQrnk(0)VAR2	0.9421
Qrnk(1)VAR1	0.9998	Qrnk(1)VAR1	0.9436	DLQrnk(1)VAR2r	0.9996	MHL	0.9206
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	1	VAR1	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
StandardPoors	0.6946	StandardPoors	0.9426	USTrust	0.8713	USTrust	0.949
USTrust	0.6946	USTrust	0.9426	VAR1c	0.8713	M.Levy	0.949
J.K.Thredgold	0.6946	J.K.Thredgold	0.9426	VAR1	0.8713	DLQrnk(0)VAR3r	0.949
VAR1c	0.6946	VAR1c	0.9426	Qrnk(0)VAR1	0.8713	DLQrnk(1)VAR2r	0.949
VAR1	0.6946	VAR2c	0.9426	DLVAR2r	0.8713	DLVAR3r	0.9432
Qrnk(0)VAR1	0.6946	Qrnk(0)VAR1c	0.9426	DLVAR3r	0.8713	StandardPoors	0.9093
DLVAR2r	0.6946	Qrnk(0)VAR3c	0.9426	DLQrnk(0)VAR3r	0.8713	Nomura	0.9086
DLVAR3r	0.6946	Qrnk(0)VAR1	0.9426	DLQrnk(1)VAR1r	0.8713	J.N.Woodworth	0.9086
DLQrnk(0)VAR3r	0.6946	DLVAR3r	0.9426	DLQrnk(1)VAR2r	0.8713	J.K.Thredgold	0.9086
DLQrnk(1)VAR1r	0.6946	DLQrnk(0)VAR3r	0.9426	StandardPoors	0.8426	M21	0.9086
DLQrnk(1)VAR2r	0.6946	DLQrnk(1)VAR1r	0.9426	DLQrnk(0)VAR1r	0.811	MHL	0.9086
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1	VAR1	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
USTrust	0.1905	VAR1c	0.9558	USTrust	0.5911	Comerica	0.5579
J.N.Woodworth	0.1905	DLQrnk(1)VAR3r	0.9558	VAR1c	0.5911	DePrince	0.5579
J.K.Thredgold	0.1905	J.K.Thredgold	0.9051	VAR1	0.5911	Nomura	0.5579
M.Levy	0.1905	VAR2c	0.9051	DLVAR3r	0.5911	USTrust	0.5579
Qrnk(0)AR2	0.1905	Qrnk(0)VAR3c	0.9051	DLQrnk(0)VAR3r	0.5911	I.L.Keller	0.5579
Qrnk(1)AR2	0.1905	Qrnk(0)VAR2rc	0.9051	DLQrnk(1)VAR1r	0.5911	J.N.Woodworth	0.5579
Qrnk(1)AR3	0.1905	Qrnk(1)VAR2c	0.9051	DLQrnk(1)VAR2r	0.5911	J.K.Thredgold	0.5579
VAR1c	0.1905	Qrnk(1)VAR2rc	0.9051	DLVAR2r	0.5439	M.Levy	0.5579
Qrnk(0)VAR3c	0.1905	VAR2	0.9051	Comerica	0.5122	M21	0.5579
Qrnk(1)VAR2c	0.1905	Qrnk(0)VAR1	0.9051	DePrince	0.5122	Qrnk(0)AR2	0.5579
VAR1	0.1905	Qrnk(1)VAR2	0.9051	Nomura	0.5122	Qrnk(0)AR3	0.5579

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 12: Root Mean Squared Forecast Errors - 1 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
Qrnk(0)AR2	0.583	VAR1	0.450	Qrnk(0)AR2	0.567	R.T.McGee	0.670
Qrnk(1)AR2	0.584	VAR1c	0.451	USTrust	0.570	Nomura	0.675
AR2	0.589	Qrnk(1)VAR1	0.452	Qrnk(1)AR2	0.571	J.K.Thredgold	0.681
Qrnk(0)VAR1	0.591	Qrnk(0)VAR1	0.455	Qrnk(0)VAR1	0.573	M21	0.685
Nomura	0.593	AR2	0.460	Qrnk(0)VAR1c	0.573	Qrnk(0)AR2	0.693
J.K.Thredgold	0.594	Qrnk(0)VAR1c	0.460	AR2	0.575	Qrnk(1)AR2	0.693
Qrnk(0)AR3	0.595	Qrnk(0)AR2	0.462	Qrnk(0)AR3	0.580	MHL	0.696
Qrnk(1)VAR1	0.595	Qrnk(1)AR2	0.464	Qrnk(1)AR3	0.581	AR2	0.703
Qrnk(1)AR3	0.595	Qrnk(1)VAR1c	0.467	Nomura	0.583	M.Levy	0.704
Qrnk(0)VAR1c	0.596	AR3	0.469	Qrnk(1)VAR1	0.586	StandardPoors	0.706
M21	0.599	DLQrnk(0)VAR1r	0.469	DLQrnk(0)VAR2	0.587	Qrnk(1)AR3	0.706
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(0)VAR1	0.888	VAR1c	0.741	Qrnk(0)VAR1	0.854	M.Levy	0.980
Qrnk(0)AR2	0.892	VAR1	0.742	Qrnk(0)VAR1c	0.868	USTrust	0.981
Qrnk(1)AR2	0.893	Qrnk(0)VAR1	0.747	Qrnk(0)AR2	0.875	J.K.Thredgold	0.983
J.K.Thredgold	0.893	Qrnk(0)VAR1c	0.763	VAR1	0.878	StandardPoors	0.990
DLQrnk(0)VAR2	0.901	DLQrnk(1)VAR3r	0.772	VAR1c	0.881	M21	0.992
Qrnk(0)VAR1c	0.907	DLQrnk(1)VAR1r	0.777	Qrnk(1)AR2	0.881	Nomura	0.992
DLQrnk(0)VAR3r	0.907	DLQrnk(1)VAR2r	0.780	J.K.Thredgold	0.881	Qrnk(1)AR2	0.992
DLQrnk(1)VAR3r	0.908	Qrnk(0)VAR2rc	0.787	StandardPoors	0.882	Qrnk(0)AR2	0.997
AR2	0.909	Qrnk(0)VAR2	0.787	DLQrnk(1)VAR2r	0.883	DLQrnk(0)VAR2	0.998
DLQrnk(1)VAR2r	0.909	DLVAR1r	0.788	DLQrnk(0)VAR1r	0.884	MHL	1.005
DLQrnk(0)VAR2r	0.910	Qrnk(1)VAR1	0.790	DLQrnk(1)VAR3r	0.885	Qrnk(1)AR3	1.014
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	1.113	VAR1	1.001	DLQrnk(1)VAR3r	1.087	USTrust	1.212
DLQrnk(1)VAR2r	1.130	DLQrnk(1)VAR3r	1.006	DLQrnk(1)VAR2r	1.103	DLQrnk(1)VAR3r	1.233
USTrust	1.147	VAR1c	1.007	DLVAR3r	1.129	DLQrnk(1)VAR2r	1.245
DLVAR3r	1.162	Qrnk(0)VAR1	1.010	DLVAR2r	1.131	DePrince	1.258
DLQrnk(0)VAR3r	1.162	DLQrnk(1)VAR2r	1.031	USTrust	1.132	Qrnk(1)AR2	1.267
DLQrnk(1)VAR1r	1.165	DLVAR3r	1.036	DLQrnk(1)VAR1r	1.139	DLQrnk(0)VAR3r	1.270
DLVAR2r	1.174	DLQrnk(1)VAR1r	1.048	DLQrnk(0)VAR3r	1.141	DLQrnk(0)VAR2	1.271
Qrnk(1)AR2	1.176	DLVAR2r	1.048	Qrnk(0)VAR1	1.142	M.Levy	1.276
Qrnk(0)AR2	1.181	Qrnk(0)VAR1c	1.052	VAR1	1.156	Qrnk(0)AR2	1.281
Qrnk(0)VAR1	1.182	Qrnk(0)VAR2rc	1.067	VAR1c	1.163	DLQrnk(0)VAR2r	1.288
DLQrnk(0)VAR2	1.182	DLQrnk(0)VAR3r	1.068	DLQrnk(0)VAR1r	1.165	M21	1.292
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1.326	DLQrnk(1)VAR3r	1.264	DLQrnk(1)VAR3r	1.313	DLQrnk(1)VAR3r	1.397
DLQrnk(1)VAR2r	1.350	VAR1	1.273	USTrust	1.324	USTrust	1.413
USTrust	1.372	VAR1c	1.284	DLQrnk(1)VAR2r	1.336	DLQrnk(1)VAR2r	1.419
DLVAR3r	1.400	Qrnk(0)VAR1	1.292	DLVAR3r	1.377	DePrince	1.463
DLQrnk(0)VAR3r	1.410	DLQrnk(1)VAR2r	1.293	DLQrnk(0)VAR3r	1.390	M.Levy	1.485
DLQrnk(1)VAR1r	1.413	DLVAR3r	1.302	DLVAR2r	1.392	DLQrnk(0)VAR3r	1.491
DePrince	1.421	DLVAR2r	1.321	I.L.Keller	1.393	Qrnk(1)VAR2	1.491
DLVAR2r	1.422	VAR2	1.331	DePrince	1.395	Qrnk(1)AR2	1.496
Qrnk(1)VAR2	1.430	Qrnk(1)VAR2	1.332	DLQrnk(1)VAR1r	1.397	DLQrnk(1)AR2	1.501
Qrnk(1)AR2	1.432	DLQrnk(1)VAR1r	1.333	Qrnk(1)AR2	1.436	DLQrnk(1)VAR1r	1.503
Qrnk(1)VAR2c	1.440	Qrnk(0)VAR2rc	1.334	Qrnk(0)VAR1	1.439	J.N.Woodworth	1.504

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 13: Model Confidence Set p-values - 1 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
Qrnk(0)AR2	1	VAR1	1	Qrnk(0)AR2	1	R.T.McGee	1
Nomura	0.9916	AR2	0.9927	USTrust	0.9976	Nomura	0.9861
J.K.Thredgold	0.9916	VAR1c	0.9927	Qrnk(1)AR2	0.9976	J.K.Thredgold	0.9861
R.T.McGee	0.9916	Qrnk(0)VAR1	0.9927	Qrnk(0)VAR1c	0.9976	M21	0.9861
AR2	0.9916	Qrnk(1)VAR1	0.9927	Qrnk(0)VAR1	0.9976	MHL	0.9861
Qrnk(0)AR3	0.9916	Qrnk(0)AR2	0.9821	AR2	0.9975	Qrnk(0)AR2	0.9861
Qrnk(1)AR2	0.9916	Qrnk(0)VAR1c	0.9747	Nomura	0.9915	Qrnk(1)AR2	0.9861
Qrnk(1)AR3	0.9916	Qrnk(1)AR2	0.9692	Qrnk(1)AR3	0.9915	Qrnk(0)VAR1	0.9861
Qrnk(0)VAR1c	0.9916	Qrnk(0)VAR2	0.9648	Qrnk(0)AR3	0.9888	StandardPoors	0.983
Qrnk(0)VAR1	0.9916	DLQrnk(0)VAR1r	0.9648	VAR1	0.9888	M.Levy	0.983
Qrnk(1)VAR1	0.9916	AR3	0.952	AR3	0.9845	Qrnk(1)AR3	0.983
M21	0.9911	J.K.Thredgold	0.948	VAR1c	0.9845	AR2	0.9816
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(0)VAR1	1	VAR1c	1	Nomura	1	Nomura	1
StandardPoors	0.9995	J.K.Thredgold	0.9875	StandardPoors	1	StandardPoors	1
USTrust	0.9995	AR2	0.9875	USTrust	1	USTrust	1
J.K.Thredgold	0.9995	Qrnk(0)AR2	0.9875	J.K.Thredgold	1	J.K.Thredgold	1
AR2	0.9995	Qrnk(1)AR2	0.9875	AR2	1	M.Levy	1
Qrnk(0)AR2	0.9995	Qrnk(0)VAR1c	0.9875	Qrnk(0)AR2	1	M21	1
Qrnk(1)AR2	0.9995	Qrnk(0)VAR2c	0.9875	Qrnk(1)AR2	1	Qrnk(1)AR2	1
Qrnk(1)AR3	0.9995	Qrnk(0)VAR2rc	0.9875	Qrnk(1)AR3	1	DLQrnk(0)VAR2	1
Qrnk(0)VAR1c	0.9995	VAR1	0.9875	VAR1c	1	Qrnk(0)AR2	0.9999
DLQrnk(0)VAR2	0.9995	Qrnk(0)VAR1	0.9875	Qrnk(0)VAR1c	1	Qrnk(0)VAR1	0.9998
DLQrnk(0)VAR1r	0.9995	Qrnk(0)VAR2	0.9875	VAR1	1	MHL	0.9996
DLQrnk(0)VAR2r	0.9995	Qrnk(0)VAR3	0.9875	Qrnk(0)VAR1	1	Qrnk(1)AR3	0.9993
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR3r	1	VAR1	1	DLQrnk(1)VAR3r	1	USTrust	1
DePrince	0.796	VAR1c	0.9958	USTrust	0.9565	DePrince	0.9917
USTrust	0.796	Qrnk(0)VAR1	0.9958	VAR1c	0.9565	Nomura	0.9917
J.K.Thredgold	0.796	DLQrnk(1)VAR3r	0.9958	VAR1	0.9565	J.N.Woodworth	0.9917
Qrnk(0)AR2	0.796	DLQrnk(1)VAR2r	0.9721	Qrnk(0)VAR1	0.9565	J.K.Thredgold	0.9917
Qrnk(1)AR2	0.796	DLVAR3r	0.9446	DLVAR2r	0.9565	M.Levy	0.9917
Qrnk(1)AR3	0.796	J.K.Thredgold	0.9434	DLVAR3r	0.9565	M21	0.9917
VAR1c	0.796	VAR2c	0.9434	DLQrnk(0)VAR3r	0.9565	Qrnk(0)AR2	0.9917
Qrnk(0)VAR3c	0.796	Qrnk(0)VAR1c	0.9434	DLQrnk(1)VAR1r	0.9565	Qrnk(1)AR2	0.9917
VAR1	0.796	Qrnk(0)VAR2rc	0.9434	DLQrnk(1)VAR2r	0.9565	Qrnk(1)AR3	0.9917
Qrnk(0)VAR1	0.796	Qrnk(0)VAR2	0.9434	Qrnk(1)AR2	0.9288	Qrnk(0)VAR3c	0.9917
DLVAR2r	0.796	DLVAR2r	0.9434	Qrnk(0)AR2	0.9181	Qrnk(1)VAR2	0.9917
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1
USTrust	0.5151	VAR1c	0.9725	USTrust	0.9099	DePrince	0.8969
DLQrnk(1)VAR2r	0.5151	VAR1	0.9725	DLQrnk(1)VAR2r	0.8355	USTrust	0.8969
DePrince	0.3045	Qrnk(0)VAR1	0.9725	DePrince	0.7253	J.N.Woodworth	0.8969
I.L.Keller	0.3045	DLQrnk(1)VAR2r	0.9725	I.L.Keller	0.7253	M.Levy	0.8969
J.N.Woodworth	0.3045	VAR2	0.9707	DLVAR3r	0.7253	Qrnk(1)VAR2	0.8969
J.K.Thredgold	0.3045	DLVAR3r	0.9707	DLQrnk(0)VAR3r	0.7253	DLQrnk(1)VAR2r	0.8969
M.Levy	0.3045	Qrnk(0)VAR2rc	0.9679	DLVAR2r	0.6522	Qrnk(1)AR2	0.8739
Qrnk(0)AR2	0.3045	Qrnk(1)VAR2	0.9679	Qrnk(1)AR2	0.6506	DLQrnk(0)VAR3r	0.8704
Qrnk(1)AR2	0.3045	DLVAR2r	0.9679	VAR1c	0.6506	DLQrnk(1)AR2	0.8637
Qrnk(1)AR3	0.3045	VAR2c	0.9615	Qrnk(1)VAR2c	0.6506	Comerica	0.8327
VAR1c	0.3045	DLQrnk(1)VAR1r	0.9615	VAR1	0.6506	Cycledata	0.8327

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 14: Root Mean Squared Forecast Errors - 2 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
J.K.Thredgold	0.628	Qrnk(0)AR2	0.503	Qrnk(1)AR2	0.617	Nomura	0.729
Qrnk(1)AR2	0.630	AR2	0.503	J.K.Thredgold	0.619	J.K.Thredgold	0.733
Qrnk(0)AR2	0.633	Qrnk(0)VAR1	0.504	Qrnk(0)AR2	0.625	Qrnk(1)AR2	0.743
AR2	0.639	Qrnk(1)AR2	0.506	AR2	0.625	Qrnk(0)AR2	0.744
Qrnk(0)VAR1	0.640	J.K.Thredgold	0.510	Qrnk(1)AR3	0.631	MART	0.746
Qrnk(1)AR3	0.642	Qrnk(0)VAR1c	0.511	Qrnk(0)AR2r	0.633	Qrnk(1)AR1	0.752
MART	0.647	AR3	0.513	Qrnk(0)VAR1	0.634	Qrnk(0)AR1	0.752
Nomura	0.647	VAR1	0.514	AR3	0.639	Qrnk(1)AR3	0.754
Qrnk(0)AR2r	0.648	Qrnk(1)VAR1	0.515	Qrnk(0)VAR1c	0.641	Qrnk(0)VAR1	0.755
Qrnk(0)AR3	0.649	Qrnk(1)AR3	0.517	Qrnk(0)AR3	0.641	M21	0.758
DLQrnk(0)VAR2	0.651	DLQrnk(0)VAR2	0.517	DLQrnk(0)VAR2	0.644	AR2	0.760
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
J.K.Thredgold	0.905	Qrnk(0)VAR1	0.774	J.K.Thredgold	0.891	Nomura	0.998
Qrnk(1)AR2	0.914	Qrnk(0)VAR1c	0.793	Nomura	0.895	J.K.Thredgold	1.001
Qrnk(0)VAR1	0.915	VAR1	0.801	Qrnk(0)VAR1	0.900	DLQrnk(0)VAR2	1.012
Nomura	0.918	DLQrnk(1)VAR1r	0.803	Qrnk(1)AR2	0.902	Qrnk(1)AR2	1.015
DLQrnk(0)VAR2	0.920	DLQrnk(1)VAR2r	0.804	Qrnk(0)AR2	0.913	J.W.Coons	1.022
Qrnk(0)AR2	0.921	DLQrnk(1)VAR3r	0.807	DLQrnk(1)VAR2r	0.915	Qrnk(0)AR2	1.023
DLQrnk(1)VAR2r	0.932	VAR1c	0.811	Qrnk(0)VAR1c	0.918	MART	1.027
Qrnk(0)VAR1c	0.936	J.K.Thredgold	0.813	AR2	0.924	Qrnk(1)AR1	1.034
DLQrnk(0)VAR2r	0.937	DLQrnk(0)VAR2r	0.814	DLQrnk(0)VAR2	0.924	M21	1.035
AR2	0.937	DLQrnk(0)VAR2	0.815	DLQrnk(0)VAR1r	0.926	MHL	1.036
Qrnk(1)AR3	0.938	Qrnk(0)AR2	0.815	Qrnk(1)AR3	0.927	DLQrnk(0)AR2	1.038
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR2r	1.113	DLQrnk(1)VAR3r	0.987	DLQrnk(1)VAR2r	1.094	DLQrnk(1)VAR2r	1.234
DLQrnk(1)VAR3r	1.117	DLQrnk(1)VAR2r	1.000	DLQrnk(1)VAR3r	1.103	DLQrnk(1)VAR3r	1.245
Qrnk(1)AR2	1.159	Qrnk(0)VAR1	1.003	DLVAR2r	1.127	DLQrnk(0)VAR2	1.254
DLQrnk(1)VAR1r	1.161	DLVAR2r	1.013	DLQrnk(1)VAR1r	1.140	Nomura	1.254
DLQrnk(0)VAR2	1.161	DLVAR3r	1.016	Qrnk(1)AR2	1.150	DLQrnk(1)AR2	1.256
J.K.Thredgold	1.169	DLQrnk(1)VAR1r	1.028	I.L.Keller	1.154	Qrnk(1)AR2	1.257
DLQrnk(0)VAR2r	1.170	Qrnk(0)VAR1c	1.036	Qrnk(0)VAR1	1.154	USTrust	1.264
DLQrnk(0)VAR3r	1.171	VAR1	1.045	DLVAR3r	1.157	DePrince	1.267
DLVAR2r	1.171	DLQrnk(0)VAR2r	1.047	DLQrnk(0)VAR3r	1.157	DLQrnk(1)AR1	1.268
Nomura	1.173	J.K.Thredgold	1.048	DLQrnk(0)VAR2	1.164	DLQrnk(1)AR3	1.277
Qrnk(0)AR2	1.173	DLQrnk(0)VAR3r	1.053	Nomura	1.165	Qrnk(0)AR2	1.278
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1.299	DLQrnk(1)VAR3r	1.210	DLQrnk(1)VAR2r	1.293	DLQrnk(1)VAR2r	1.379
DLQrnk(1)VAR2r	1.300	DLQrnk(1)VAR2r	1.224	DLQrnk(1)VAR3r	1.301	DLQrnk(1)VAR3r	1.380
DLQrnk(1)AR2	1.361	DLVAR2r	1.245	I.L.Keller	1.306	DLQrnk(1)AR2	1.400
DLQrnk(1)AR3	1.369	Qrnk(0)VAR1	1.246	DLVAR2r	1.355	DLQrnk(1)AR3	1.412
DLQrnk(1)VAR1r	1.375	DLVAR3r	1.251	DLQrnk(1)VAR1r	1.365	DLQrnk(1)AR2r	1.429
DLQrnk(1)AR2r	1.381	DLQrnk(1)VAR1r	1.281	J.N.Woodworth	1.371	USTrust	1.430
DLQrnk(0)VAR3r	1.381	VAR1	1.288	DLQrnk(0)VAR3r	1.373	DLQrnk(1)AR1	1.435
Qrnk(1)AR2	1.382	DLQrnk(0)VAR2r	1.295	DLQrnk(1)AR2	1.378	DLQrnk(1)AR1r	1.436
DLVAR2r	1.384	DLQrnk(0)VAR3r	1.296	DLVAR3r	1.381	Qrnk(1)VAR2	1.446
I.L.Keller	1.386	Qrnk(0)VAR2	1.296	DLQrnk(1)AR3	1.381	DLQrnk(0)VAR2	1.448
DLQrnk(1)AR1r	1.390	VAR1c	1.298	USTrust	1.381	Qrnk(1)AR2	1.453

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 15: Model Confidence Set p-values - 2 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
J.K.Thredgold	1	Qrnk(0)AR2	1	Qrnk(1)AR2	1	Nomura	1
Qrnk(0)AR2	0.9826	AR2	0.9949	J.K.Thredgold	0.9874	J.K.Thredgold	0.9916
Qrnk(1)AR2	0.9826	Qrnk(1)AR2	0.9949	AR2	0.9874	MART	0.9916
Qrnk(0)VAR1	0.9826	Qrnk(0)VAR1	0.9949	Qrnk(0)AR2	0.9874	Qrnk(0)AR2	0.9916
AR2	0.9621	J.K.Thredgold	0.994	Qrnk(0)AR2r	0.9874	Qrnk(1)AR1	0.9916
Qrnk(1)AR3	0.9621	VAR1	0.9917	Qrnk(1)AR3	0.9874	Qrnk(1)AR2	0.9916
Nomura	0.9554	AR3	0.9886	Qrnk(0)VAR1	0.9874	Qrnk(0)VAR1	0.9916
Qrnk(0)VAR1c	0.9352	Qrnk(0)AR3	0.9886	Qrnk(0)VAR1c	0.9716	Qrnk(1)AR3	0.9911
Qrnk(0)AR2r	0.9325	Qrnk(0)AR2r	0.9886	AR3	0.9631	M21	0.9905
MART	0.9248	Qrnk(1)AR3	0.9886	Nomura	0.9568	Qrnk(0)AR1	0.9905
Qrnk(1)AR1	0.9117	VAR1c	0.9886	DLQrnk(0)VAR2	0.9507	MHL	0.9859
DLQrnk(0)VAR2	0.9117	Qrnk(0)VAR1c	0.9886	Qrnk(0)AR3	0.9391	AR2	0.9859
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
J.K.Thredgold	1	Qrnk(0)VAR1	1	J.K.Thredgold	1	Nomura	1
Nomura	0.9959	J.K.Thredgold	0.9931	Nomura	0.9959	J.W.Coons	0.9966
Qrnk(0)AR2	0.9959	AR2	0.9931	Qrnk(1)AR2	0.9959	J.K.Thredgold	0.9966
Qrnk(1)AR2	0.9959	Qrnk(0)AR2	0.9931	Qrnk(0)VAR1	0.9959	M21	0.9966
Qrnk(0)VAR1	0.9959	Qrnk(1)AR2	0.9931	AR2	0.9932	MHL	0.9966
DLQrnk(0)VAR2	0.9959	VAR1c	0.9931	Qrnk(0)AR2	0.9932	MART	0.9966
DLQrnk(1)VAR2r	0.9959	Qrnk(0)VAR1c	0.9931	Qrnk(0)AR2r	0.9932	Qrnk(0)AR1	0.9966
Qrnk(0)VAR1c	0.9921	VAR1	0.9931	Qrnk(1)AR3	0.9932	Qrnk(0)AR2	0.9966
Qrnk(1)AR3	0.9867	DLVAR1r	0.9931	Qrnk(0)VAR1c	0.9932	Qrnk(1)AR1	0.9966
DLQrnk(0)VAR2r	0.9845	DLVAR2r	0.9931	DLQrnk(0)VAR2	0.9932	Qrnk(1)AR2	0.9966
AR2	0.9785	DLQrnk(0)VAR2	0.9931	DLQrnk(0)VAR1r	0.9932	Qrnk(1)AR3	0.9966
MART	0.9784	DLQrnk(0)VAR1r	0.9931	DLQrnk(1)VAR1r	0.9932	Qrnk(0)VAR2c	0.9966
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
DLQrnk(1)VAR2r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR2r	1	Cycledata	1
Nomura	0.8438	J.K.Thredgold	0.9346	Nomura	0.9491	DePrince	1
I.L.Keller	0.8438	VAR1c	0.9346	I.L.Keller	0.9491	Nomura	1
J.K.Thredgold	0.8438	Qrnk(0)VAR1c	0.9346	J.N.Woodworth	0.9491	USTrust	1
Qrnk(0)AR2	0.8438	VAR1	0.9346	J.K.Thredgold	0.9491	I.L.Keller	1
Qrnk(0)AR2r	0.8438	Qrnk(0)VAR1	0.9346	AR2	0.9491	J.N.Woodworth	1
Qrnk(1)AR2	0.8438	Qrnk(0)VAR2	0.9346	Qrnk(0)AR2	0.9491	J.K.Thredgold	1
Qrnk(1)AR3	0.8438	DLVAR2r	0.9346	Qrnk(0)AR2r	0.9491	Qrnk(0)AR2	1
Qrnk(0)VAR1c	0.8438	DLVAR3r	0.9346	Qrnk(1)AR2	0.9491	Qrnk(1)AR2	1
Qrnk(0)VAR2c	0.8438	DLQrnk(0)VAR2r	0.9346	Qrnk(1)AR3	0.9491	Qrnk(0)VAR2c	1
Qrnk(0)VAR3c	0.8438	DLQrnk(1)VAR1r	0.9346	VAR1c	0.9491	Qrnk(0)VAR3c	1
Qrnk(0)VAR1	0.8438	DLQrnk(1)VAR2r	0.9346	Qrnk(0)VAR1c	0.9491	Qrnk(1)VAR2	1
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
DLQrnk(1)VAR3r	1	DLQrnk(1)VAR3r	1	DLQrnk(1)VAR2r	1	DLQrnk(1)VAR2r	1
DLQrnk(1)VAR2r	0.9096	Qrnk(1)AR2	0.846	I.L.Keller	0.9351	USTrust	0.9641
Cycledata	0.6208	VAR1c	0.846	DLQrnk(1)VAR3r	0.9351	J.N.Woodworth	0.9641
Nomura	0.6208	VAR2c	0.846	J.N.Woodworth	0.8362	Qrnk(1)AR2	0.9641
USTrust	0.6208	Qrnk(0)VAR1c	0.846	Nomura	0.8294	Qrnk(1)VAR2	0.9641
I.L.Keller	0.6208	Qrnk(0)VAR2rc	0.846	USTrust	0.8294	DLQrnk(1)AR1	0.9641
J.N.Woodworth	0.6208	VAR1	0.846	J.K.Thredgold	0.8294	DLQrnk(1)AR2	0.9641
J.K.Thredgold	0.6208	VAR2	0.846	M.Levy	0.8294	DLQrnk(1)AR3	0.9641
Qrnk(0)AR2	0.6208	Qrnk(0)VAR1	0.846	Qrnk(0)AR2r	0.8294	DLQrnk(1)AR1r	0.9641
Qrnk(0)AR2r	0.6208	Qrnk(0)VAR2	0.846	Qrnk(1)AR2	0.8294	DLQrnk(1)AR2r	0.9641
Qrnk(1)AR2	0.6208	Qrnk(1)VAR2	0.846	Qrnk(0)VAR3c	0.8294	DLQrnk(0)VAR2	0.9641
Qrnk(0)VAR2c	0.6208	DLQrnk(1)AR2	0.846	Qrnk(1)VAR2c	0.8294	DLQrnk(1)VAR3r	0.9641

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 16: Root Mean Squared Forecast Errors - 5 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
Qrnk(0)AR2r	0.594	Qrnk(0)VAR1	0.487	AR2r	0.579	Qrnk(0)AR2r	0.683
Qrnk(1)AR1	0.600	Qrnk(0)AR2r	0.489	Qrnk(1)AR2r	0.586	Qrnk(1)AR1	0.687
MART	0.602	Qrnk(0)VAR1c	0.490	Qrnk(0)AR2r	0.594	MART	0.688
Qrnk(1)AR2	0.602	DLQrnk(0)AR2	0.494	Qrnk(1)AR2	0.595	Qrnk(1)AR2	0.694
DLQrnk(0)AR2	0.603	Qrnk(0)AR2	0.497	DLQrnk(0)VAR2	0.597	DLQrnk(0)AR2	0.694
AR2r	0.603	Qrnk(1)AR1	0.499	Qrnk(1)AR1	0.599	Qrnk(1)AR2r	0.697
Qrnk(1)AR2r	0.603	Qrnk(0)AR3r	0.499	Qrnk(0)AR2	0.600	DLQrnk(0)AR1r	0.697
Qrnk(0)VAR1	0.605	MART	0.500	MART	0.601	DLQrnk(0)AR1	0.698
DLQrnk(0)VAR2	0.606	AR3	0.500	DLQrnk(0)AR2	0.601	Qrnk(1)AR3	0.698
Qrnk(0)AR2	0.607	Qrnk(1)AR2	0.500	Qrnk(1)AR3	0.602	Qrnk(0)AR1	0.698
Qrnk(1)AR3	0.607	DLQrnk(0)AR1	0.501	AR2	0.604	Nomura	0.700
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(1)AR2r	0.808	Qrnk(0)VAR1	0.718	Qrnk(1)AR2r	0.804	Qrnk(1)AR2r	0.869
Qrnk(0)AR2r	0.815	Qrnk(0)VAR1c	0.723	AR2r	0.806	Qrnk(0)AR2r	0.882
AR2r	0.820	Qrnk(0)AR2r	0.732	Qrnk(0)AR2r	0.823	Nomura	0.888
Qrnk(1)AR1	0.825	DLQrnk(1)VAR1r	0.734	DLQrnk(0)VAR2	0.831	Qrnk(1)AR1	0.889
DLQrnk(0)VAR2	0.825	DLQrnk(0)VAR2r	0.738	Qrnk(1)AR1	0.832	Qrnk(0)VAR2c	0.889
DLQrnk(0)AR2	0.826	DLQrnk(1)VAR2r	0.738	Nomura	0.833	DLQrnk(0)AR2	0.892
MART	0.830	DLAR2r	0.743	DLQrnk(0)AR2	0.833	MART	0.893
Qrnk(0)VAR2c	0.831	DLAR2	0.744	MART	0.836	DLQrnk(0)VAR2	0.893
DLQrnk(1)AR1	0.833	DLQrnk(0)VAR2	0.744	Qrnk(1)AR2	0.837	DLQrnk(1)AR1	0.895
DLQrnk(0)AR1r	0.833	Qrnk(1)AR2r	0.745	J.K.Thredgold	0.837	Qrnk(0)VAR2	0.898
Qrnk(1)AR2	0.834	DLQrnk(0)AR2	0.746	Qrnk(1)AR3r	0.839	AR2r	0.899
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
Qrnk(1)AR2r	0.936	DLQrnk(1)VAR3r	0.848	Qrnk(1)AR2r	0.940	Qrnk(1)AR2r	1.003
DLQrnk(1)VAR2r	0.964	DLQrnk(1)VAR2r	0.849	DLQrnk(1)VAR2r	0.960	Qrnk(0)VAR2c	1.032
Qrnk(0)VAR2c	0.971	DLVAR2r	0.857	AR2r	0.966	FannieMae	1.034
AR2r	0.974	Qrnk(1)AR2r	0.859	Qrnk(0)VAR2c	0.983	DLQrnk(1)AR2	1.050
Qrnk(0)AR2r	0.983	DLVAR3r	0.872	DLQrnk(1)VAR3r	0.987	DLQrnk(1)AR1r	1.053
DLQrnk(1)VAR3r	0.985	AR2r	0.874	Qrnk(0)VAR2	0.993	DLQrnk(1)AR1	1.057
DLQrnk(1)AR2	0.986	Qrnk(0)AR2r	0.877	DLVAR2r	0.995	DLQrnk(1)AR2r	1.059
Qrnk(0)VAR2	0.992	Qrnk(0)VAR1c	0.878	DLQrnk(1)VAR1r	0.996	Qrnk(0)AR2r	1.064
DLQrnk(1)AR1r	0.992	Qrnk(0)VAR1	0.880	Qrnk(0)AR2r	0.998	Qrnk(1)AR3r	1.065
DLQrnk(1)AR2r	0.992	DLQrnk(1)VAR1r	0.883	Qrnk(1)AR3r	0.999	Cycledata	1.065
Qrnk(1)AR3r	0.993	DLQrnk(0)VAR2r	0.885	DLQrnk(0)VAR2	1.002	DLQrnk(1)AR3	1.066
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
Qrnk(1)AR2r	1.029	Qrnk(1)AR2r	0.977	Qrnk(1)AR2r	1.033	Qrnk(1)AR2r	1.073
DLQrnk(1)VAR2r	1.078	DLQrnk(1)VAR2r	0.989	DLQrnk(1)VAR2r	1.083	DLQrnk(1)AR2r	1.130
DLQrnk(1)AR2r	1.096	DLQrnk(1)VAR3r	0.994	AR2r	1.093	DLQrnk(1)AR2	1.137
DLQrnk(1)VAR3r	1.099	DLVAR2r	1.007	DLQrnk(1)VAR3r	1.115	DLQrnk(1)AR1r	1.141
AR2r	1.100	AR2r	1.028	DLQrnk(1)AR2r	1.116	DLQrnk(1)AR3	1.145
DLQrnk(1)AR2	1.106	DLVAR3r	1.036	Qrnk(1)AR3r	1.120	Cycledata	1.145
DLQrnk(1)AR1r	1.109	Qrnk(0)VAR2c	1.038	I.L.Keller	1.127	J.K.Thredgold	1.150
DLQrnk(1)AR3	1.112	Qrnk(0)VAR2	1.040	DLQrnk(1)AR1r	1.129	DLQrnk(1)AR3r	1.155
Qrnk(1)AR3r	1.112	DLQrnk(1)AR2r	1.040	DLQrnk(1)AR2	1.129	DLQrnk(1)VAR2r	1.155
DLQrnk(1)AR3r	1.116	Qrnk(0)AR2r	1.044	J.K.Thredgold	1.130	DLQrnk(1)AR1	1.155
Qrnk(0)AR2r	1.121	DLQrnk(1)AR2	1.050	DLQrnk(1)AR3	1.131	Qrnk(1)AR3r	1.161

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 17: Model Confidence Set p-values - 5 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
Qrnk(0)AR2r	1	Qrnk(0)VAR1	1	AR2r	1	Qrnk(0)AR2r	1
MART	0.9836	MART	0.9944	J.K.Thredgold	0.9934	Nomura	0.9962
AR2r	0.9836	AR2	0.9944	MART	0.9934	MART	0.9962
Qrnk(0)AR2	0.9836	AR3	0.9944	AR2	0.9934	AR2r	0.9962
Qrnk(1)AR1	0.9836	AR2r	0.9944	AR3r	0.9934	Qrnk(0)AR1	0.9962
Qrnk(1)AR2	0.9836	Qrnk(0)AR1	0.9944	Qrnk(0)AR2	0.9934	Qrnk(0)AR2	0.9962
Qrnk(1)AR3	0.9836	Qrnk(0)AR2	0.9944	Qrnk(0)AR2r	0.9934	Qrnk(1)AR1	0.9962
Qrnk(1)AR2r	0.9836	Qrnk(0)AR3	0.9944	Qrnk(1)AR1	0.9934	Qrnk(1)AR2	0.9962
Qrnk(0)VAR1c	0.9836	Qrnk(0)AR2r	0.9944	Qrnk(1)AR2	0.9934	Qrnk(1)AR3	0.9962
Qrnk(0)VAR1	0.9836	Qrnk(0)AR3r	0.9944	Qrnk(1)AR3	0.9934	Qrnk(1)AR2r	0.9962
DLQrnk(0)AR2	0.9836	Qrnk(1)AR1	0.9944	Qrnk(1)AR2r	0.9934	Qrnk(0)VAR1c	0.9962
DLQrnk(0)AR1r	0.9836	Qrnk(1)AR2	0.9944	Qrnk(1)AR3r	0.9934	Qrnk(0)VAR2c	0.9962
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(1)AR2r	1	Qrnk(0)VAR1	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
Nomura	0.9934	AR2r	0.9998	Nomura	0.9996	Nomura	0.9999
J.K.Thredgold	0.9934	Qrnk(0)AR2r	0.9998	J.K.Thredgold	0.9996	MART	0.9999
MART	0.9934	Qrnk(1)AR1	0.9998	MART	0.9996	AR2r	0.9999
AR2r	0.9934	Qrnk(1)AR2	0.9998	AR2r	0.9996	Qrnk(0)AR2r	0.9999
Qrnk(0)AR2r	0.9934	Qrnk(1)AR2r	0.9998	Qrnk(0)AR2r	0.9996	Qrnk(1)AR1	0.9999
Qrnk(1)AR1	0.9934	Qrnk(0)VAR1c	0.9998	Qrnk(1)AR1	0.9996	Qrnk(1)AR2	0.9999
Qrnk(1)AR2	0.9934	Qrnk(0)VAR2c	0.9998	Qrnk(1)AR2	0.9996	Qrnk(1)AR1r	0.9999
Qrnk(1)AR1r	0.9934	Qrnk(1)VAR1	0.9998	Qrnk(1)AR3	0.9996	Qrnk(0)VAR2c	0.9999
Qrnk(0)VAR1c	0.9934	DLAR2	0.9998	Qrnk(1)AR1r	0.9996	Qrnk(0)VAR2	0.9999
Qrnk(0)VAR2c	0.9934	DLAR3	0.9998	Qrnk(1)AR3r	0.9996	DLQrnk(0)AR2	0.9999
Qrnk(0)VAR1	0.9934	DLAR2r	0.9998	Qrnk(0)VAR1c	0.9996	DLQrnk(0)AR1r	0.9999
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
Qrnk(1)AR2r	1	DLQrnk(1)VAR3r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
J.K.Thredgold	0.9439	Qrnk(1)AR2r	0.9734	J.N.Woodworth	0.9939	Cycledata	0.997
AR2r	0.9439	DLVAR2r	0.9734	J.K.Thredgold	0.9939	FannieMae	0.997
Qrnk(0)AR2r	0.9439	DLQrnk(1)VAR2r	0.9734	M.Levy	0.9939	J.K.Thredgold	0.997
Qrnk(1)AR2	0.9439	AR2r	0.9727	AR2r	0.9939	AR2r	0.997
Qrnk(1)AR1r	0.9439	Qrnk(0)AR2r	0.9727	Qrnk(0)AR2r	0.9939	Qrnk(0)AR2r	0.997
Qrnk(1)AR3r	0.9439	Qrnk(0)VAR1c	0.9727	Qrnk(1)AR2	0.9939	Qrnk(1)AR3r	0.997
Qrnk(0)VAR2c	0.9439	Qrnk(0)VAR2c	0.9727	Qrnk(1)AR1r	0.9939	Qrnk(0)VAR2c	0.997
Qrnk(0)VAR3c	0.9439	Qrnk(0)VAR1	0.9727	Qrnk(1)AR3r	0.9939	Qrnk(0)VAR2	0.997
Qrnk(0)VAR1	0.9439	Qrnk(0)VAR2	0.9727	Qrnk(0)VAR2c	0.9939	DLQrnk(1)AR1	0.997
Qrnk(0)VAR2	0.9439	DLVAR3r	0.9727	Qrnk(0)VAR3c	0.9939	DLQrnk(1)AR2	0.997
DLAR2r	0.9439	DLQrnk(0)VAR2r	0.9727	Qrnk(0)VAR2	0.9939	DLQrnk(1)AR3	0.997
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
Cycledata	0.7816	Qrnk(0)VAR2	0.915	Cycledata	0.9687	Cycledata	0.9782
J.K.Thredgold	0.7816	DLVAR2r	0.915	I.L.Keller	0.9687	J.K.Thredgold	0.9782
AR2r	0.7816	DLQrnk(1)VAR2r	0.915	J.N.Woodworth	0.9687	Qrnk(0)VAR2c	0.9782
Qrnk(0)AR2r	0.7816	DLQrnk(1)VAR3r	0.915	J.K.Thredgold	0.9687	DLQrnk(1)AR2	0.9782
Qrnk(1)AR3r	0.7816	AR2r	0.8563	M.Levy	0.9687	DLQrnk(1)AR3	0.9782
Qrnk(0)VAR2c	0.7816	Qrnk(0)VAR2c	0.8468	AR2r	0.9687	DLQrnk(1)AR1r	0.9782
Qrnk(0)VAR2	0.7816	DLQrnk(1)AR2r	0.8114	Qrnk(0)AR2r	0.9687	DLQrnk(1)AR2r	0.9782
DLAR2r	0.7816	Qrnk(0)VAR1	0.7922	Qrnk(1)AR1r	0.9687	DLQrnk(1)VAR2r	0.9782
DLQrnk(1)AR1	0.7816	DLVAR3r	0.7693	Qrnk(1)AR3r	0.9687	Qrnk(1)AR3r	0.9715
DLQrnk(1)AR2	0.7816	Qrnk(0)AR2r	0.7631	Qrnk(0)VAR2c	0.9687	DLQrnk(1)AR1	0.9712
DLQrnk(1)AR3	0.7816	Qrnk(1)AR2	0.7631	Qrnk(0)VAR3c	0.9687	DLQrnk(1)AR3r	0.9711

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 18: Root Mean Squared Forecast Errors - 10 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
Qrnk(1)AR2r	0.508	Qrnk(0)VAR1	0.426	Qrnk(1)AR2r	0.509	Qrnk(1)AR2r	0.570
AR2r	0.514	Qrnk(0)AR2r	0.428	AR2r	0.511	AR2r	0.582
MART	0.514	Qrnk(0)VAR1c	0.429	MART	0.514	Qrnk(1)AR1r	0.584
Qrnk(1)AR1r	0.515	MART	0.432	Qrnk(1)AR1r	0.515	MART	0.584
Qrnk(0)AR2r	0.518	Qrnk(1)AR1	0.433	Qrnk(1)AR1	0.519	Qrnk(0)AR2r	0.588
Qrnk(1)AR1	0.518	Qrnk(1)AR1r	0.434	Qrnk(0)AR2	0.520	Qrnk(1)AR1	0.589
Qrnk(0)AR2	0.522	Qrnk(1)AR2r	0.436	Qrnk(0)AR1	0.522	Qrnk(1)AR2	0.592
Qrnk(1)AR2	0.523	Qrnk(0)AR1	0.436	Qrnk(0)VAR1c	0.522	Qrnk(0)AR2	0.596
Qrnk(0)AR1	0.523	Qrnk(0)AR2	0.436	Qrnk(1)AR2	0.523	Qrnk(0)AR1	0.597
Qrnk(0)VAR1c	0.527	AR1	0.438	Qrnk(0)AR2r	0.523	Qrnk(0)AR1r	0.599
Qrnk(0)AR1r	0.527	AR3	0.438	Qrnk(0)AR1r	0.528	Qrnk(1)AR3r	0.602
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(1)AR2r	0.683	Qrnk(1)AR2r	0.626	Qrnk(1)AR2r	0.697	Qrnk(1)AR2r	0.723
Qrnk(1)AR1r	0.703	AR2r	0.633	J.K.Thredgold	0.714	Qrnk(1)AR1r	0.748
AR2r	0.707	Qrnk(0)VAR1c	0.635	Qrnk(1)AR1r	0.717	J.K.Thredgold	0.754
MART	0.709	Qrnk(0)VAR1	0.636	MART	0.720	MART	0.756
Qrnk(1)AR1	0.716	Qrnk(1)AR1r	0.638	AR2r	0.722	AR2r	0.760
Qrnk(0)AR2r	0.719	Qrnk(0)AR2r	0.638	Qrnk(1)AR1	0.731	Qrnk(1)AR1	0.768
J.K.Thredgold	0.720	Qrnk(1)AR1	0.644	Qrnk(1)AR3r	0.733	Qrnk(1)AR3r	0.773
Qrnk(1)AR3r	0.722	MART	0.646	Qrnk(0)AR2r	0.737	Qrnk(0)AR2r	0.776
Qrnk(1)AR2	0.727	Qrnk(1)AR2	0.652	Qrnk(0)AR1	0.739	Qrnk(0)AR1	0.781
Qrnk(0)AR1	0.728	Qrnk(0)AR2	0.653	Qrnk(0)AR2	0.742	Qrnk(1)AR2	0.781
Qrnk(0)AR2	0.729	Qrnk(1)AR3	0.654	Qrnk(1)AR2	0.743	DLQrnk(0)AR2	0.782
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
Qrnk(1)AR2r	0.781	Qrnk(1)AR2r	0.719	Qrnk(1)AR2r	0.798	Qrnk(1)AR2r	0.822
J.K.Thredgold	0.832	AR2r	0.746	J.K.Thredgold	0.838	J.K.Thredgold	0.878
Qrnk(1)AR1r	0.834	DLQrnk(1)VAR2r	0.755	Qrnk(1)AR1r	0.851	Qrnk(1)AR1r	0.887
AR2r	0.834	Qrnk(1)AR1r	0.759	Qrnk(1)AR3r	0.851	Qrnk(1)AR3r	0.888
Qrnk(1)AR3r	0.838	DLQrnk(1)VAR3r	0.760	AR2r	0.853	FannieMae	0.890
MART	0.857	DLVAR2r	0.761	DLQrnk(1)VAR2r	0.869	AR2r	0.896
DLQrnk(1)VAR2r	0.860	Qrnk(0)AR2r	0.768	MART	0.874	MART	0.910
DLQrnk(1)AR1r	0.864	Qrnk(1)AR3r	0.770	M.Levy	0.879	DLQrnk(1)AR1r	0.913
DLQrnk(1)AR2r	0.865	J.K.Thredgold	0.777	DLQrnk(0)VAR2	0.883	DLQrnk(1)AR2r	0.917
Qrnk(1)AR1	0.866	DLQrnk(0)VAR2r	0.780	Qrnk(0)VAR2c	0.883	Qrnk(0)VAR2c	0.918
Qrnk(0)VAR2c	0.867	Qrnk(1)AR1	0.781	Qrnk(0)VAR3c	0.885	DLQrnk(1)AR2	0.922
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
Qrnk(1)AR2r	0.836	Qrnk(1)AR2r	0.791	Qrnk(1)AR2r	0.853	Qrnk(1)AR2r	0.863
J.K.Thredgold	0.881	DLQrnk(1)VAR2r	0.846	J.K.Thredgold	0.893	J.K.Thredgold	0.898
Qrnk(1)AR3r	0.909	AR2r	0.846	DePrince	0.922	FannieMae	0.934
AR2r	0.916	J.K.Thredgold	0.851	Qrnk(1)AR3r	0.922	Qrnk(1)AR3r	0.946
Qrnk(1)AR1r	0.922	Qrnk(1)AR3r	0.857	AR2r	0.934	Cycledata	0.950
DLQrnk(1)VAR2r	0.930	DLQrnk(1)VAR3r	0.857	Qrnk(1)AR1r	0.941	DLQrnk(1)AR2r	0.959
DLQrnk(1)AR2r	0.932	DLVAR2r	0.859	DLQrnk(1)VAR2r	0.945	Qrnk(1)AR1r	0.959
DLQrnk(1)AR1r	0.940	Qrnk(1)AR1r	0.864	DLQrnk(1)AR2r	0.956	I.L.Keller	0.959
DLQrnk(1)AR3r	0.948	DLQrnk(1)AR2r	0.878	FannieMae	0.960	M.Levy	0.962
DePrince	0.949	DLAR2r	0.890	M.Levy	0.961	AR2r	0.963
FannieMae	0.949	DLQrnk(1)AR1r	0.891	DLQrnk(1)AR1r	0.963	DLQrnk(1)AR1r	0.964

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 19: Model Confidence Set p-values - 10 Year Yield

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
Qrnk(1)AR2r	1	Qrnk(0)VAR1	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
MART	0.9879	MART	0.9894	MART	0.9911	MART	0.9663
AR2r	0.9879	Qrnk(0)AR2r	0.9894	AR2r	0.9911	AR2r	0.9663
Qrnk(0)AR2r	0.9879	Qrnk(1)AR1	0.9894	Qrnk(1)AR1r	0.9911	Qrnk(0)AR1	0.9663
Qrnk(1)AR1	0.9879	Qrnk(1)AR1r	0.9894	Qrnk(0)VAR1c	0.9911	Qrnk(0)AR2	0.9663
Qrnk(1)AR1r	0.9879	Qrnk(1)AR2r	0.9894	Qrnk(0)AR2	0.9888	Qrnk(0)AR2r	0.9663
Qrnk(0)VAR1c	0.9879	Qrnk(0)VAR1c	0.9894	Qrnk(1)AR1	0.9888	Qrnk(1)AR1	0.9663
Qrnk(0)AR1	0.9748	AR1	0.9798	Qrnk(0)AR1	0.9837	Qrnk(1)AR2	0.9663
Qrnk(1)AR2	0.9748	AR3	0.9798	Qrnk(0)AR2r	0.9837	Qrnk(1)AR1r	0.9663
Qrnk(0)AR2	0.9723	AR2r	0.9798	Qrnk(1)AR2	0.9837	Qrnk(1)AR3r	0.9663
Qrnk(0)VAR1	0.966	AR3r	0.9798	Qrnk(0)VAR1	0.9837	Qrnk(0)VAR1	0.9663
Qrnk(1)AR3r	0.9498	Qrnk(0)AR1	0.9798	Qrnk(1)AR3r	0.9817	Qrnk(0)VAR1c	0.9535
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
J.K.Thredgold	0.8278	AR2r	0.9964	J.K.Thredgold	0.9679	J.K.Thredgold	0.9164
MART	0.8278	Qrnk(0)AR2r	0.9964	MART	0.9679	MART	0.9164
AR2r	0.8278	Qrnk(1)AR1r	0.9964	AR2r	0.9679	AR2r	0.9164
Qrnk(0)AR2r	0.8278	Qrnk(0)VAR1c	0.9964	Qrnk(1)AR1r	0.9679	Qrnk(1)AR1r	0.9164
Qrnk(1)AR1	0.8278	Qrnk(0)VAR1	0.9964	Qrnk(1)AR1	0.9434	M.Levy	0.9152
Qrnk(1)AR1r	0.8278	Qrnk(1)AR1	0.9944	Qrnk(1)AR3r	0.9434	Qrnk(0)AR1	0.9152
Qrnk(1)AR3r	0.8278	MART	0.9922	AR3r	0.9418	Qrnk(0)AR2	0.9152
Qrnk(0)VAR1c	0.8278	Qrnk(1)AR3r	0.9873	Qrnk(0)AR1	0.9418	Qrnk(0)AR1r	0.9152
Qrnk(0)AR1	0.8196	Qrnk(1)AR2	0.9849	Qrnk(0)AR2	0.9418	Qrnk(0)AR2r	0.9152
Qrnk(1)AR2	0.8196	M.Levy	0.9836	Qrnk(0)AR1r	0.9418	Qrnk(1)AR1	0.9152
Qrnk(0)VAR2c	0.8196	AR3r	0.9836	Qrnk(0)AR2r	0.9418	Qrnk(1)AR2	0.9152
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
J.K.Thredgold	0.6292	J.K.Thredgold	0.9873	DePrince	0.9508	Cycledata	0.8588
M.Levy	0.6292	MART	0.9873	J.K.Thredgold	0.9508	DePrince	0.8588
MART	0.6292	AR2r	0.9873	M.Levy	0.9508	FannieMae	0.8588
AR2r	0.6292	AR3r	0.9873	MART	0.9508	I.L.Keller	0.8588
Qrnk(0)AR1	0.6292	Qrnk(0)AR2	0.9873	AR2r	0.9508	J.W.Coons	0.8588
Qrnk(0)AR2	0.6292	Qrnk(0)AR2r	0.9873	Qrnk(0)AR2	0.9508	J.K.Thredgold	0.8588
Qrnk(0)AR2r	0.6292	Qrnk(1)AR1	0.9873	Qrnk(0)AR2r	0.9508	M.Levy	0.8588
Qrnk(1)AR1	0.6292	Qrnk(1)AR2	0.9873	Qrnk(1)AR1	0.9508	MART	0.8588
Qrnk(1)AR2	0.6292	Qrnk(1)AR1r	0.9873	Qrnk(1)AR2	0.9508	AR2r	0.8588
Qrnk(1)AR1r	0.6292	Qrnk(1)AR3r	0.9873	Qrnk(1)AR3	0.9508	Qrnk(1)AR1	0.8588
Qrnk(1)AR3r	0.6292	Qrnk(0)VAR1c	0.9873	Qrnk(1)AR1r	0.9508	Qrnk(1)AR2	0.8588
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1	Qrnk(1)AR2r	1
J.K.Thredgold	0.4028	J.K.Thredgold	0.8083	Cycledata	0.7432	Cycledata	0.7335
Cycledata	0.2803	AR2r	0.8083	DePrince	0.7432	DePrince	0.7335
DePrince	0.2803	Qrnk(1)AR1r	0.8083	FannieMae	0.7432	FannieMae	0.7335
FannieMae	0.2803	Qrnk(1)AR3r	0.8083	I.L.Keller	0.7432	I.L.Keller	0.7335
I.L.Keller	0.2803	Qrnk(0)VAR2c	0.8083	J.K.Thredgold	0.7432	J.K.Thredgold	0.7335
M.Levy	0.2803	DLVAR2r	0.8083	M.Levy	0.7432	M.Levy	0.7335
MART	0.2803	DLQrnk(1)VAR2r	0.8083	MART	0.7432	Qrnk(1)AR1r	0.7335
AR2r	0.2803	DLQrnk(1)VAR3r	0.8083	AR2r	0.7432	Qrnk(1)AR3r	0.7335
Qrnk(1)AR1	0.2803	Qrnk(0)VAR2	0.7744	AR3r	0.7432	AR2r	0.7216
Qrnk(1)AR1r	0.2803	DLQrnk(1)AR2r	0.7744	Qrnk(0)AR2r	0.7432	Qrnk(0)VAR2c	0.7216
Qrnk(1)AR3r	0.2803	DLQrnk(1)AR1r	0.7549	Qrnk(1)AR1	0.7432	DLQrnk(1)AR1r	0.7216

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.

Table 20: Root Mean Squared Forecast Errors - CPI

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
J.L.Naroff	1.194	Qrnk(1)AR1r	1.200	Nomura	1.096	J.N.Woodworth	1.141
J.N.Woodworth	1.197	Qrnk(0)AR2r	1.237	J.N.Woodworth	1.099	I.L.Keller	1.160
I.L.Keller	1.227	Qrnk(1)AR3r	1.239	J.L.Naroff	1.117	J.W.Coons	1.182
J.W.Coons	1.231	AR3r	1.245	M21	1.151	J.L.Naroff	1.185
Qrnk(1)AR1r	1.240	Qrnk(1)AR3	1.249	MHL	1.156	MHL	1.215
MHL	1.241	Qrnk(1)AR1	1.250	I.L.Keller	1.161	M21	1.223
M21	1.243	Qrnk(1)VAR1c	1.253	J.W.Coons	1.170	J.K.Thredgold	1.231
J.K.Thredgold	1.255	Qrnk(0)VAR3c	1.262	J.K.Thredgold	1.178	J.M.Griffin	1.251
Nomura	1.262	Qrnk(0)AR3r	1.267	WayneHummer	1.186	DePrince	1.254
AR3r	1.270	Qrnk(1)AR2r	1.270	FannieMae	1.191	WayneHummer	1.262
J.M.Griffin	1.272	J.L.Naroff	1.277	ScotiaBank	1.208	WellsFargo	1.265
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
J.N.Woodworth	1.197	J.N.Woodworth	1.161	J.L.Naroff	1.189	J.N.Woodworth	1.229
J.L.Naroff	1.225	J.W.Coons	1.217	J.N.Woodworth	1.199	J.W.Coons	1.234
J.W.Coons	1.225	J.L.Naroff	1.246	J.W.Coons	1.224	J.L.Naroff	1.238
MHL	1.249	Qrnk(1)AR1r	1.247	MHL	1.230	Qrnk(1)AR1	1.244
Qrnk(1)AR1r	1.258	MHL	1.253	M21	1.254	M.Levy	1.256
Qrnk(1)AR1	1.258	Nomura	1.254	J.K.Thredgold	1.254	Qrnk(1)AR1r	1.261
J.K.Thredgold	1.260	J.K.Thredgold	1.258	M.Levy	1.256	MHL	1.263
M21	1.270	Qrnk(1)AR1	1.259	Comerica	1.257	Qrnk(1)AR3r	1.265
Qrnk(1)AR3r	1.272	Qrnk(1)VAR1c	1.273	Qrnk(1)AR1r	1.266	J.K.Thredgold	1.267
M.Levy	1.277	M21	1.275	DePrince	1.266	AR1r	1.270
AR1r	1.283	AR1r	1.276	Qrnk(1)AR3r	1.270	WellsFargo	1.281
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
J.L.Naroff	1.223	J.L.Naroff	1.219	M.Levy	1.200	M.Levy	1.229
M.Levy	1.225	J.W.Coons	1.239	J.L.Naroff	1.208	J.L.Naroff	1.241
J.W.Coons	1.252	Qrnk(1)AR1	1.240	J.N.Woodworth	1.239	J.W.Coons	1.258
J.N.Woodworth	1.253	J.N.Woodworth	1.244	AR3r	1.253	MHL	1.269
AR3r	1.264	AR1r	1.245	J.W.Coons	1.259	AR2r	1.272
MHL	1.264	M.Levy	1.246	MHL	1.263	J.N.Woodworth	1.275
Qrnk(1)AR3r	1.268	Qrnk(1)AR1r	1.252	Qrnk(1)AR3r	1.263	M21	1.279
Qrnk(1)AR1	1.274	J.K.Thredgold	1.253	M21	1.270	Qrnk(1)AR2r	1.280
M21	1.276	AR3r	1.254	Qrnk(1)AR2r	1.277	Qrnk(1)AR3r	1.281
Qrnk(1)AR2r	1.279	Qrnk(1)AR3r	1.259	J.K.Thredgold	1.280	AR3r	1.285
J.K.Thredgold	1.279	MHL	1.261	WellsFargo	1.281	Qrnk(1)AR1	1.300
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
J.L.Naroff	1.238	J.L.Naroff	1.239	J.L.Naroff	1.241	J.L.Naroff	1.235
M.Levy	1.263	J.W.Coons	1.258	J.W.Coons	1.265	M.Levy	1.238
J.W.Coons	1.264	M.Levy	1.274	M.Levy	1.276	MHL	1.264
MHL	1.290	AR2r	1.280	AR2r	1.292	J.W.Coons	1.270
M21	1.294	DePrince	1.290	I.L.Keller	1.301	M21	1.271
AR2r	1.295	Qrnk(1)AR2r	1.296	MHL	1.301	BearStearns	1.274
DePrince	1.302	MHL	1.304	M21	1.303	WayneHummer	1.283
Qrnk(1)AR2r	1.305	M21	1.306	Qrnk(1)AR2r	1.304	Nomura	1.287
BearStearns	1.315	Qrnk(1)AR1	1.319	WayneHummer	1.310	DePrince	1.301
Comerica	1.317	WellsFargo	1.322	BearStearns	1.313	I.L.Keller	1.306
WayneHummer	1.320	Qrnk(1)AR3r	1.322	DePrince	1.316	Comerica	1.308

For each forecast horizon, the 12 models with the lowest root mean squared forecast errors (RMSFE) are given. Recall that the k-quarter ahead forecast horizon is time-varying and comprises 3 separate h-month ahead horizons.

Table 21: Model Confidence Set p-values - CPI

1 − quarter		**1 − month**		**2 − month**		**3 − month**	
J.L.Naroff	1	Qrnk(1)AR1r	1	Nomura	1	J.N.Woodworth	1
J.N.Woodworth	0.9511	J.L.Naroff	0.9409	J.N.Woodworth	0.9688	I.L.Keller	0.8985
I.L.Keller	0.8315	AR3	0.9409	J.L.Naroff	0.9118	J.W.Coons	0.8985
J.W.Coons	0.8315	AR1r	0.9409	I.L.Keller	0.7784	J.L.Naroff	0.8985
Qrnk(1)AR1r	0.8315	AR2r	0.9409	J.W.Coons	0.7784	MHL	0.7242
M21	0.7984	AR3r	0.9409	M21	0.7784	J.M.Griffin	0.547
MHL	0.7984	Qrnk(0)AR2r	0.9409	MHL	0.748	ScotiaBank	0.547
AR3r	0.7984	Qrnk(0)AR3r	0.9409	WayneHummer	0.7451	DePrince	0.547
Qrnk(1)AR3	0.7867	Qrnk(1)AR1	0.9409	FannieMae	0.7444	J.K.Thredgold	0.547
Nomura	0.782	Qrnk(1)AR3	0.9409	Cycledata	0.6984	M21	0.547
J.K.Thredgold	0.782	Qrnk(1)AR2r	0.9409	Comerica	0.6854	Cycledata	0.5169
Qrnk(1)AR3r	0.782	Qrnk(1)AR3r	0.9409	J.K.Thredgold	0.6803	Comerica	0.5096
2 − quarter		**4 − month**		**5 − month**		**6 − month**	
J.N.Woodworth	1	J.N.Woodworth	1	J.L.Naroff	1	J.N.Woodworth	1
J.W.Coons	0.7921	DePrince	0.9199	Comerica	0.8902	J.W.Coons	0.9972
J.L.Naroff	0.7921	Nomura	0.9199	DePrince	0.8902	J.K.Thredgold	0.9972
Qrnk(1)AR1	0.7609	J.W.Coons	0.9199	Nomura	0.8902	J.L.Naroff	0.9972
MHL	0.7425	J.K.Thredgold	0.9199	I.L.Keller	0.8902	M.Levy	0.9972
Qrnk(1)AR1r	0.7351	J.L.Naroff	0.9199	J.W.Coons	0.8902	MHL	0.9972
J.K.Thredgold	0.7252	M21	0.9199	J.N.Woodworth	0.8902	AR1r	0.9972
M.Levy	0.7252	MHL	0.9199	J.K.Thredgold	0.8902	Qrnk(1)AR1	0.9972
AR1r	0.7252	AR1r	0.9199	M.Levy	0.8902	Qrnk(1)AR1r	0.9972
Qrnk(1)AR3r	0.7252	AR3r	0.9199	M21	0.8902	Qrnk(1)AR3r	0.9972
Nomura	0.7197	Qrnk(1)AR1	0.9199	MHL	0.8902	AR1	0.9963
M21	0.7197	Qrnk(1)AR1r	0.9199	AR1r	0.8902	WellsFargo	0.996
3 − quarter		**7 − month**		**8 − month**		**9 − month**	
J.L.Naroff	1	J.L.Naroff	1	M.Levy	1	M.Levy	1
M.Levy	0.9535	J.W.Coons	0.9992	WayneHummer	0.9178	DePrince	0.9786
J.W.Coons	0.863	J.N.Woodworth	0.9992	WellsFargo	0.9178	WellsFargo	0.9786
J.N.Woodworth	0.863	J.K.Thredgold	0.9992	J.W.Coons	0.9178	J.W.Coons	0.9786
WellsFargo	0.8616	M.Levy	0.9992	J.N.Woodworth	0.9178	J.N.Woodworth	0.9786
MHL	0.8616	MHL	0.9992	J.K.Thredgold	0.9178	J.L.Naroff	0.9786
AR3r	0.8616	AR1r	0.9992	J.L.Naroff	0.9178	M21	0.9786
Qrnk(1)AR1	0.8616	AR3r	0.9992	MHL	0.9178	MHL	0.9786
Qrnk(1)AR3r	0.8616	Qrnk(0)AR1r	0.9992	AR3r	0.9178	AR2r	0.9786
J.K.Thredgold	0.8549	Qrnk(1)AR1	0.9992	Qrnk(1)AR1	0.9178	AR3r	0.9786
Qrnk(1)AR2r	0.8217	Qrnk(1)AR1r	0.9992	Qrnk(1)AR2r	0.9178	Qrnk(1)AR1	0.9786
Qrnk(1)AR1r	0.8119	Qrnk(1)AR3r	0.9992	Qrnk(1)AR3r	0.9178	Qrnk(1)AR2r	0.9786
4 − quarter		**10 − month**		**11 − month**		**12 − month**	
J.L.Naroff	1	J.L.Naroff	1	J.L.Naroff	1	J.L.Naroff	1
J.W.Coons	0.797	Comerica	0.9079	BearStearns	0.9738	BearStearns	0.9738
M.Levy	0.797	Cycledata	0.9079	Comerica	0.9738	Nomura	0.9738
DePrince	0.6084	DePrince	0.9079	Cycledata	0.9738	WayneHummer	0.9738
BearStearns	0.5912	WellsFargo	0.9079	DePrince	0.9738	J.W.Coons	0.9738
Comerica	0.5912	J.W.Coons	0.9079	WayneHummer	0.9738	M.Levy	0.9738
Cycledata	0.5912	J.N.Woodworth	0.9079	I.L.Keller	0.9738	M21	0.9738
WayneHummer	0.5912	J.K.Thredgold	0.9079	J.W.Coons	0.9738	MHL	0.9738
I.L.Keller	0.5912	M.Levy	0.9079	M.Levy	0.9738	I.L.Keller	0.9603
M21	0.5912	M21	0.9079	M21	0.9738	DePrince	0.9532
MHL	0.5912	MHL	0.9079	MHL	0.9738	Comerica	0.9331
AR2r	0.5912	AR2r	0.9079	AR2r	0.9738	Cycledata	0.9042

For each forecast horizon, the 12 models with the highest Model Confidence Set (MCS) p-values are given. Higher MCS p-values correpond to models that lie within the set of best perfoming models with a higher level of probability. The best model will therefore have a MCS p-value equal to 1. Recall that the k-quarter ahead forecast horizon is time varying and comprises 3 separate h-month ahead horizons.