Forecasting the distribution of economic variables in a data-rich environment

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Abstract

In this paper we investigate the relevance of considering a large number of macroeconomic indicators to forecast the complete distribution of a variable. The baseline time series model is a semi-parametric specification based on the Quantile Auto-Regressive (QAR) model that assumes that the quantiles depend on the lagged values of the variable. We then augment the time series model with macroeconomic information from a large dataset by including principal components or a subset of variables selected by LASSO. We forecast the distribution of the h-month growth rate for four economic variables from 1975 to 2011 and evaluate the forecast accuracy relative to a stochastic volatility model using the quantile score. The results for the output and employment measures indicate that the multivariate models outperform the time series forecasts, in particular at long horizons and in the tails of the distribution, while for the inflation variables the improved performance occurs mostly at the 6-month horizon. We also illustrate the practical relevance of predicting the distribution by considering forecasts at three dates during the last recession.

JEL Classification: C22, C53, E31, E32

Keywords: distribution forecasting, quantile regression, principal components, LASSO

Acknowledgments: We would like to thank the Associate Editor and two referees for many insightful comments as well as participants to the 21^{st} SNDE symposium, 2013 NBER-NSF Time series conference at Texas A&M University, 2013 Canadian Economic Association meeting, and seminars at UC-Riverside, Baruch College, and CUNY Graduate Center. We also thank Noelia Hernandez-Martinez for many suggestions that improved the clarity of the paper. Financial support by the PSC-CUNY Research Award Program and the Bert W. Wasserman fund is gratefully acknowledged. The usual disclaimers apply.

1 Introduction

There are several reasons to argue that forecasting the distribution of an economic variable is more interesting and useful compared to forecasting the mean. The most important one is the fact that the distribution or density forecast completely characterizes the uncertain future evolution of the variable, besides providing a gauge of its central tendency similarly to a point forecast. In addition, a distribution forecast is relevant when a decision maker faces asymmetric payoffs over the possible outcomes of the variable. For example, the loss function of a central bank might assess the risks of an increase or a decrease of future inflation differently. This has motivated an increasing number of recent papers that focus on modeling and forecasting the complete distribution of economic variables such as Jore *et al.* (2010), Ravazzolo and Vahey (2014), Clark (2011) Bache *et al.* (2011), and Geweke and Amisano (2012) among others. In particular, Jore *et al.* (2010) and Clark (2011) forecast the distribution of several economic variables and find that allowing for time variation in the conditional variance, through a time series process, is crucial to obtain accurate forecasts. They attribute this result to the decrease in macroeconomic volatility experienced by the U.S. economy after 1984, a period typically referred to as the Great Moderation. Earlier examples of models that assume a stochastic volatility component are Cogley and Sargent (2002) and Stock and Watson (2002b, 2005).

The aim of this paper is to forecast the distribution of a variable using a model that allows for both a time series component and the effect of macroeconomic indicators. The approach that we adopt follows Manzan and Zerom (2013) and assumes that the quantiles of the variable being forecast are a function of its own lags as well as macroeconomic indicators that might be relevant predictors. However, we differ with respect to this earlier paper by including in the forecasting model information about a panel of 143 macroeconomic variables, instead of limiting the analysis to a small set of predictors. The idea of using information about a large number of variables has been extensively considered in economic forecasting since the early work of Stock and Watson (2002a, 2002c) and Forni *et al.* (2000, 2005), and Rossi and Sekhposyan (2014) is a recent application to density forecasting. We consider two approaches to incorporate this vast information set in the quantile regression. The first approach consists of including, as quantile predictors, a small number of factors that are extracted from the panel of macroeconomic variables. The advantage of using this method is that the factors describe, in a parsimonious way, the information contained in the panel about the state of the economy. The flexible nature of the quantile model allows the factors to have heterogeneous effects in different parts of the distribution, such as at the left or right tail or at the center. The second approach that we consider selects a handful of predictors to be included in the quantile regression, while the remaining variables are discarded. The method that we use to select the variables is the LASSO algorithm proposed by Tibshirani (1996), and adopted in a quantile context by Koenker (2004, 2011). In this case, at each forecast date only a subset of variables are chosen as predictors which facilitates the interpretation of the relationships and allows to compare the variables selected to those typically used in the forecasting literature. In addition, we select the predictors at each quantile level which could lead to the inclusion of different sets of variables at different parts of the distribution. We also consider a combination of the two methods in which the variables selected by LASSO are then used to construct factors to be included in the quantile regression and refer to this case as targeted factors, in the sense that the factors are obtained from a set of predictors targeted to a specific variable and to a specific quantile level (see Bai and Ng, 2008, for the conditional mean case).

We forecast the h-month percentage change ($h = 3$, 6 and 12) of Industrial Production Index (INDPRO), Non-farm Payroll Employment (PAYEMS), the Consumer Price Index for all urban consumers (CPIAUCSL), and the Personal Consumption Price Index that excludes Food and Energy (PCEPILFE) starting in January 1975 until June 2011 (438 forecasts). The model that we consider is the Quantile Auto-Regressive (QAR) model proposed by Koenker and Xiao (2006), in which the conditional quantiles are only a function of past values of the variable being forecast, as well as the QAR model augmented by either the factors, the LASSO selected variables, or the targeted factors. To make our results comparable with alternative approaches, we consider an AR model and a factor-augmented AR model with stochastic volatility which allows for time-variation in the conditional variance of error term. The model forecasts are evaluated based on their accuracy relative to a benchmark, which we chose to be the AR model with stochastic volatility. The testing results indicate that augmenting the QAR model with factors and LASSO selected variables delivers distribution forecasts that are more accurate compared to the benchmark. In particular, we find that for output and employment the better performance occurs in the tails of the distribution and at the longer horizons considered. Instead, for the inflation measures we find that the macroeconomic variables matter the most at the 6-month horizon and only when considering headline CPI inflation.

A byproduct of the LASSO procedure is the selection of a subset of variables that can be considered as the most relevant predictors of a specific series at a given quantile level. For INDPRO and PAYEMS we find that among the top predictors there are several Producer Price Indices (e.g., capital goods and intermediate materials), the 3-month T-bill rate spread over the federal fund rate, housing variables (e.g., building permits and housing starts), employment variables (e.g., non-durable manufacturing employment), banking variables (e.g., saving deposits and consumer credit outstanding), as well as some of the NAPM Indices, namely New

Orders, Production, and Prices. Instead, for the inflation measures LASSO selects some Producer Prices Indices mostly related to consumer goods and commodities, the spread of the bank prime rate over the federal fund rate, several money and banking variables (e.g., saving deposits, commercial and real estate loans, and some monetary aggregates) and some housing and employment variables. In addition, also for the inflation measures several NAPM indicators are selected, in particular the Price Index, the Supplier Deliveries Index and the Employment Index.

The paper is organized as follows. Section (2) discusses the forecasting models and the approach used to evaluate the accuracy of the forecasts and their statistical significance. Section (3) discusses the results of the tests and the variables selected by LASSO. The practical use of the distribution forecasts during the latest recession is discussed in Section (4), and Section (5) draws the conclusion of the paper.

2 Methodology

In this Section, we introduce the quantile-based forecasting models and two parametric specifications that incorporate stochastic volatility to account for the possible time-variation in the conditional variance. In addition, we also discuss the criteria that we use to evaluate and compare the out-of-sample quantile and distribution forecasts.

2.1 Models

Denote by Y_t (for $t = 1, \cdots, T$) the variable we are interested to forecast h-step ahead in period T which we assume is stationary. The baseline (time series) h-step forecasting model that we consider is the Quantile Auto-Regressive (QAR) specification considered in Koenker and Xiao (2006):

$$Q_{t+h|t}^{\mathrm{QAR}}(\tau) = \alpha(\tau) + \sum_{i=1}^{p_\tau} \beta_i(\tau) Y_{t-i+1} \tag{1}$$

where $Q_{t+h|t}^{\mathrm{QAR}}(\tau)$ indicates the τ-level conditional quantile of Y_{t+h}, $\alpha(\tau)$ and $\beta_i(\tau)$ are parameters, and p_τ is the lag order used to model the τ quantile. The QAR model extends to a quantile regression setting the Auto-Regressive (AR) model used for the conditional mean. The model allows the dynamic relationship of the variable to possibly vary at different parts of its distribution. Since the parameters $\beta_i(\tau)$ (for $i = 1, \cdots, p_\tau$) could vary across quantiles τ, the model allows for heterogeneous degrees of persistence of the variable. This is for example the case in the application to interest rates in Koenker and Xiao (2006) and to inflation in Manzan and Zerom (2014). The selection of the lag order at each quantile is performed by a Schwarz-like criterion by choosing the p_τ that minimizes the following quantity:

$$SIC_\tau\left(p_\tau\right) = T \log \hat{\sigma}_\tau\left(p_\tau\right) + \frac{p_\tau}{2}\log(T)$$

where $\hat{\sigma}_\tau\left(p_\tau\right)$ is the average τ quantile loss function of the estimated model with p_τ lags.

The aim of this paper is to evaluate the relevance, from a forecasting point of view, of augmenting the time series quantile model in Equation (1) with information about a large number of macroeconomic variables rather than relying on a few, although relevant, variables. We consider three of the several approaches that have been proposed to reduce the dimensionality of the problem. The first approach has been widely used in the conditional mean forecasting literature and consists of extracting principal components from the panel of macroeconomic variables and use a subset of them as predictors. An alternative approach is to select the most relevant predictors in the panel by means of shrinkage methods. Finally, we also consider a combination of the previous methods in which the principal components are obtained from a subset of variables in the panel selected by the shrinkage method. An interesting approach that we do not pursue in this paper is the combination of forecasts from bivariate models as discussed in Huang and Lee (2010) for the conditional mean case and in Rossi and Sekhposyan (2014) for density forecasts. Furthermore, an additional refinement to the current setup is bagging the quantile predictors as proposed in Lee and Yang (2006, 2008) which represents an effective approach to account for parameter estimation uncertainty and model uncertainty and results in higher prediction accuracy. For all models, we re-arranged the quantiles to avoid their crossing as proposed in Chernozhukov *et al.* (2010).

Factor-Augmented Quantile Auto-Regression (FA-QAR)

A popular approach in forecasting is to augment a time series model with principal components obtained from a large panel of macroeconomic variables. This approach is proposed, among others, by Stock and Watson (2002a, 2002c) and Forni *et al.* (2000). Stock and Watson (2006) provide a comprehensive survey of the application of the method in macroeconomic forecasting. Denote by $f_{k,t}$ the k-th principal component obtained from the variables $X_{j,t}$ $(j = 1, \cdots, J)$ that are assumed to be stationary; the Factor-Augmented QAR (FA-QAR) is given by

$$Q^{\text{FA-QAR}}_{t+h|t}(\tau) = \alpha(\tau) + \sum_{i=1}^{p_\tau} \beta_i(\tau) Y_{t-i+1} + \sum_{k=1}^{K} \gamma_k(\tau) f_{k,t} \tag{2}$$

where K indicates the number of factors included in the regression. The advantage of this approach is that it reduces the dimensionality of the problem by concentrating the informational content of a large number of J macroeconomic variables in a small number K of factors. The FA-QAR represents a straightforward extension to the quantile framework of the FA-AR model that is often used in forecasting the conditional mean of economic indicators. In the empirical application that follows, we use the same p_τ selected for the QAR model as discussed above, while we fix the number of factors included in the quantile regression K to be equal to 3 and 5. If the macroeconomic factors are relevant predictors of the dynamics of Y_{t+h}, then we expect the predictive quantiles of the FA-QAR model to be (relatively) more accurate compared to the QAR model in a sense that will be discussed later.

LASSO Quantile Regression (LASSO-QAR)

Another way to use the information contained in the large panel of macroeconomic indicators is to select a subset of them that are relevant to forecast the variable of interest. There are several shrinkage methods proposed in the literature for the linear regression model and, prominent among them, is LASSO (Least Absolute Shrinkage and Selection Operator) proposed by Tibshirani (1996). The idea is to estimate the parameters of the model by adding a penalization term which is proportional, in the case of LASSO, to the sum of the absolute value of the parameters. In this way, the parameters of the irrelevant variables are shrunk to zero thus allowing to identify a subset of variables with non-zero coefficients. This approach has been adopted by Koenker (2004) in the context of a quantile panel data model where LASSO is used to select the fixed effects, and by Koenker (2011) for the case of additive nonparametric quantile regression. De Mol *et al.* (2008) and Inoue and Kilian (2008) consider LASSO selection in a comparison with other shrinkage and principal components methods in the case of conditional mean forecasting, while Bai and Ng (2008) adopt LASSO to select a subset of predictors that are used to calculate principal components.

In this paper, we use LASSO to select a subset of the J macroeconomic variables that are useful in forecasting the τ quantile of Y_{t+h}. The LASSO-QAR model is given by

$$Q^{\text{LASSO-QAR}}_{t+h|t}(\tau) = \alpha(\tau) + \sum_{i=1}^{p_\tau} \beta_i(\tau) Y_{t-i+1} + \sum_{j=1}^{J} \delta_j(\tau) X_{j,t} \tag{3}$$

where the parameters $\alpha(\tau)$, $\beta^{'}(\tau)$, and $\delta^{'}(\tau)$ are estimated by minimizing the following quantity:

$$\sum_{t=1}^{T} \rho_\tau \left(Y_{t+h} - \hat{\alpha}(\tau) - \sum_{i=1}^{p_\tau} \hat{\beta}_i(\tau) Y_{t-i+1} - \sum_{j=1}^{J} \hat{\delta}_j(\tau) X_{j,t} \right) + \lambda \frac{\sqrt{\tau(1-\tau)}}{T} \sum_{i=1}^{J} |\hat{\delta}_j(\tau)|$$

with $\rho_\tau(u) = u(\tau - I(u<0))$ denoting the piecewise linear quantile loss function. The non-negative parameter λ represents the shrinkage parameter that controls the amount of penalization that is applied in estimation. The two leading cases are $\lambda = 0$, which represents the case of no penalization such that the estimates are equal to the standard quantile estimates of Koenker and Bassett (1978), and $\lambda \to \infty$ in which the estimates of $\delta(\tau)$ are shrunk to zero for all macroeconomic variables. Hence, in the first case the parameter estimates are likely to be poorly estimated due to the large number (J) of variables included, while in the second case the LASSO-QAR model reduces to the pure time series QAR model.

The choice of the LASSO penalty is extremely important for the performance of the forecasting model. A small value of λ leads to the inclusion of a large number of irrelevant variables which causes more volatile forecasts, while a large value might lead to the exclusion of some relevant variables. We follow Belloni and Chernozhukov (2011) to select the value of λ. They propose to approximate the distribution of the estimation error of the quantile regression parameters by the empirical distribution of a pivotal quantity, conditional on the predictors, which is related to the sample gradient of the quantile regression objective function. The pivotal quantity delivers a choice of λ which accounts for the correlation between the predictors $X_{j,t}$ and is obtained by simulating the J-dimensional vector $S_{\tau,b} = \sum_{t=1}^{T} (\tau - I(U_{t,b} - \tau)) X_t$, where $U_{t,b}$ is a random draw from the uniform distribution in the $[0, 1]$ interval and $b = 1, \cdots, B$, with B the total number of replications. The penalty λ is then selected as c times the $(1 - \alpha)$ empirical quantile of the B simulated values of $\max_\tau ||S_{\tau,b}||_\infty$. In the application that follows, we set α equal to 0.05 and the constant c equal to 2. In an on-line Appendix that accompanies the paper we provide a comparison of the forecast accuracy of the models for values of c equal to 1, 2, and 3 in order to evaluate the sensitivity of the performance of the LASSO-QAR forecasts to the penalization parameter.

The LASSO coefficient estimates $\hat{\delta}(\tau)$ might be biased for the variables with non-zero parameters. Hence, it is common in the literature to re-estimate the quantile regression model only including the subset of variables with non-zero coefficients. For a given value of c, the selected macroeconomic variables at quantile τ are denoted by $\tilde{X}^{\tau}_{l,t}$ (for $l = 1, \cdots, L_\tau$, with $L_\tau \leq J$), and the QAR augmented by these variables (denoted as POST-LASSO-QAR) is given by

$$Q^{\text{POST-LASSO-QAR}}_{t+h|t}(\tau) = \alpha(\tau) + \sum_{i=1}^{p_\tau} \beta_i(\tau) Y_{t-i+1} + \sum_{l=1}^{L_\tau} \delta_l(\tau) \tilde{X}^{\tau}_{l,t} \tag{4}$$

Targeted Factor-Augmented QAR (TFA-QAR)

An alternative approach to construct the factors is to extract the K principal components from the subset of variables selected by LASSO. We define the subset as the 10 variables with the largest absolute coefficient while we include all the selected variables in case the number of non-zero coefficients are less than 10. The approach is similar to the proposal in Bai and Ng (2008) of constructing targeted factors, that is, factors based on a subset of the variables included in the large panel which have been selected with the specific target of forecasting the variable of interest. Furthermore, in this application the factors are also targeted to the specific quantile τ under consideration since the variable selection is quantile-specific. Denote by $tf_{k,t}(\tau)$ the targeted factor ($k = 1, \cdots, K$) at quantile τ obtained from the the first step of LASSO selection. Then, the conditional quantile model is given by:

$$Q_{t+h|t}^{\text{TFA-QAR}}(\tau) = \alpha(\tau) + \sum_{i=1}^{p_\tau} \beta_i(\tau) Y_{t-i+1} + \sum_{k=1}^{K} \gamma_k(\tau)\ tf_{k,t}(\tau) \tag{5}$$

Also in this case we fix the number of factors K to equal 3.

Stochastic Volatility Models

A specification that has gained popularity in the forecasting literature is the Stochastic Volatility (SV) model that allows for time-variation in the forecast distribution through the conditional mean and the conditional variance. Some recent applications of these models in macroeconomic forecasting are Clark (2011) and Clark and Ravazzolo (2014).

The first specification that we consider is an AR(p) model augmented by stochastic volatility, denoted AR-SV, which is given by

$$\begin{aligned} Y_{t+h} &= \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i+1} + \sigma_{t+h}\epsilon_{t+h} \qquad (6) \\ \log(\sigma_{t+h}^2) &= \mu + \phi \log(\sigma_t^2) + \eta_{t+h} \end{aligned}$$

where p denotes the order of the AR model and the error terms ϵ_{t+h} and η_{t+h} are assumed to be independent of each other and distributed as $N(0, 1)$ and $N(0, \sigma_\eta^2)$, respectively. The conditional variance at horizon h, σ_{t+h}^2, follows an AR(1) process as in Jacquier *et al.* (1994). In addition, we also consider a specification in which we augment the AR-SV with macroeconomic factors in the conditional mean of the model and denote this specification by FAR-SV:

$$\begin{aligned} Y_{t+h} &= \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i+1} + \sum_{k=1}^{K} \gamma_k f_{k,t} + \sigma_{t+h}\epsilon_t \qquad (7) \\ \log(\sigma_{t+h}^2) &= \mu + \phi \log(\sigma_t^2) + \eta_{t+h} \end{aligned}$$

where K represents the number of factors included in the regression (in the application we set $K = 5$). We estimate the models by Bayesian MCMC and assume diffuse normal prior distribution for the AR and FAR coefficients and μ, a beta distribution for $(\phi + 1)/2$ (with ϕ bounded between -1 and 1), and the volatility of volatility σ_η sampled from an inverse gamma prior.

2.2 Forecast accuracy

Methods to evaluate and compare density and distribution forecasts have rapidly expanded since Diebold *et al.* (1998) proposed to examine the properties of the Probability Integral Transform (PIT). These advances involved both the development of score (loss) functions to evaluate specific features of the distribution forecasts, in addition to appropriate statistical tools to assess their accuracy. Corradi and Swanson (2006) provides a detailed survey of the recent developments. In this paper we decided to evaluate forecasts using the *Quantile Score* (QS) which is particularly suitable for the forecasts produced by the quantile models in the previous Section since the same loss function is used in model estimation as well as in forecast evaluation (see Gneiting and Raftery, 2007, and Gneiting and Ranjan, 2011, for a discussion of the properties of score functions). The QS function represents a local evaluation of the forecasts in the sense that it concentrates on a specific quantile τ rather than providing an overall assessment of the distribution. A generalization of the QS is the Weighted Quantile Score (WQS) which weights the quantile score at each quantile based on the forecaster's interest to evaluate specific areas of the distribution, e.g., the left/right tail or the center of the distribution. More global score functions are the Interval Score (IS), that is designed to evaluate interval forecasts, and the Logarithmic Score (LS) which is extensively used as an overall measure of goodness of density forecasts. To save space, we discuss only the QS score function and refer to the on-line Appendix for the discussion of the WQS, IS, and LS functions. In addition, in the Appendix we also provide results of the evaluation of the uniformity and independence properties of the PIT as in Mitchell and Wallis (2011).

Denote by T the first monthly forecast produced based on information available up to $T-h$ and the last forecast is for month $T+F$ (total of F forecasts). We consider both a recursive and a rolling scheme to generate the forecasts. In the first case the estimation window expands as new observations are added to the sample, while for the rolling scheme the estimation window is kept constant and new observations replace the oldest ones in the sample. The QS for the quantile forecast of model i ($i = QAR$, $FA-QAR$, $LASSO-QAR$, $TFA-QAR$, $AR-SV$, $FAR-SV$), denoted by $Q^i_{t|t-h}(\tau)$ (for $t = T, \cdots, T+F$), is given by the piecewise linear asymmetric loss function

$$QS^i_{t|t-h}(\tau) = \left[Y_t - Q^i_{t|t-h}(\tau)\right] \left[\mathcal{I}(Y_t \leq Q^i_{t|t-h}(\tau)) - \tau\right]. \tag{8}$$

This loss function is asymmetric since when the realization Y_t is smaller or equal to the τ quantile forecast $Q^i_{t|t-h}$ the error is multiplied by $1-\tau$ but it is multiplied by τ when the quantile forecast under-predicts the realization ($Y_t > Q^i_{t|t-h}$). For $\tau = 0.5$ under- and over-predictions are equally weighted, but for small (large)

τ over-prediction (under-prediction) are more heavily penalized relative to the opposite. We statistically evaluate the performance of the forecasting models in relative terms, that is, by comparing the score of a model to the score of another (benchmark) model. Denote by $QS^i_{t|t-h}$ the QS of model i and $QS^j_{t|t-h}$ the score of model j. We follow Giacomini and White (2006) and Amisano and Giacomini (2007) and test the null hypothesis of equal accuracy of the quantile forecasts, $QS^i_{t|t-h} = QS^j_{t|t-h}$ (for $t = T, \cdots, T+F$), using the test statistic

$$t = \left(\overline{QS^j_h} - \overline{QS^i_h}\right) / \sigma \tag{9}$$

where $\overline{QS^i_h}$ and $\overline{QS^j_h}$ denote the sample average of the scores in the forecasting period, and σ denotes the HAC standard error of the score difference. The test statistic t is asymptotically standard normal and rejections for negative values of the statistic indicate that model j significantly outperforms model i (and vice-versa for positive values). In the next Section we present results for models estimated on a recursive and rolling window, although the recursive estimation is not consistent with the theoretical assumption of non-vanishing estimation error required by the test of Giacomini and White (2006). Hence, the results when a recursively estimated model is involved should be considered as approximate. In the on-line Appendix we also provide a fluctuation analysis of the performance of the models based on the QS test as proposed by Giacomini and Rossi (2010).

3 Application

We forecast four economic variables at the monthly frequency that represent closely watched business cycle and inflation indicators: Industrial Production Index (INDPRO), Total Non-farm Payroll Employment (PAYEMS), Consumer Price Index for all urban consumers (CPIAUCSL), and Personal Consumption Expenditure chain-type Price Index less food and energy (PCEPILFE). For all these variables we assume that they are non-stationary and forecast the annualized h-period growth rate which is defined as $Y_{t+h} = (1200/h)[\ln I_{t+h} - \ln I_t]$, where I_t indicates the level of the variable or index in month t. The sample starts in January 1960 and ends in June 2011 (618 observations) and we begin the out-of-sample exercise in January 1975 for a total of $F = 438$ monthly forecasts. We consider 3 forecast horizons h equal to 3, 6, and 12 months. In addition, we construct a dataset of 143 macroeconomic variables from the Federal Reserve Bank of Saint Louis FRED data repository that are listed in the on-line Appendix and we follow Stock and Watson (2002c) in transforming the variables to induce stationarity. Of the 143 variables included in the panel, 118 variables have observations starting in January 1960, 126 in January 1970, and all variables are available since January 1980. We estimate the forecasting models discussed in the previous Section on both a recursive (expanding) window and a rolling (fixed) window of $180 - h$ months. In the subsequent discussion and in the Tables we indicate the five forecasting models by QAR (Quantile Auto-Regressive model in Equation 1), FA-QAR (Factor Augmented- QAR in Equation 2 for $K = 3$ and 5), LASSO-QAR (Equation 3), POST-LASSO-QAR (Equation 4), and TFA-QAR (Targeted FA-QAR in Equation 5 for $K = 3$) and attach to the model's name the label REC if the model is estimated on a recursive window or ROLL if a rolling window is used. The stochastic volatility models are estimated recursively and are denoted by AR-SV (Equation 6) and FAR-SV (Equation 7). Since the panel of macroeconomic indicators is unbalanced, when estimating the models on a recursive window we only include those variables that are available since inception (118 variables). However, when we use a rolling scheme we consider all variables with no missing data in the estimation window so that the information set is expanding as new variables are included. Finally, the relative nature of the forecast evaluation requires the specification of a benchmark model. We consider the AR-SV model as the benchmark to evaluate the performance of the different forecasting models since it has proven to be an effective approach to forecast the distribution of economic variables (see Stock and Watson, 2005, Clark, 2011, and Clark and Ravazzolo, 2014). As discussed earlier, we present results for the shrinkage parameter $c = 2$ while a comparison for different values of the parameter are presented in the on-line Appendix.

3.1 Forecast accuracy tests

Table (1) and (2) report the test statistics of the Quantile Score (QS) test for the null hypothesis of equal quantile forecast accuracy of a model relative to the benchmark AR-SV model. A negative values of the test statistic indicates that the alternative model outperforms the AR-SV benchmark (in bold are reported the statistics significant at 5% against this one-sided alternative), while a positive value suggests that the AR-SV forecasts are more accurate relative to the forecasts of the alternative model (significance at 5% is denoted in italic).

The first result that emerges from Table (1) is that the QAR model (both REC and ROLL) delivers similar performance to the AR-SV benchmark at the 3 and 6-month horizon for both INDPRO and PAYEMS, but it significantly outperforms the benchmark at the 12-month horizon, in particular in the case of the recursive window. Augmenting the stochastic volatility and QAR models with factors leads to higher forecast accuracy at the 6 and 12 month horizons, in particular for τ smaller than 0.4. This suggests that macroeconomic variables contain valuable information that can improve forecast performance relative to purely time series models, although this information seems more valuable when forecasting the lower tail of the distribution.

The alternative approach of selecting the macroeconomic predictors using LASSO has a performance similar to the factor-based models, and it also outperforms the AR-SV benchmark when forecasting INDPRO at the lowest quantiles for $h = 3$ and at low and high quantiles for $h = 12$. For PAYEMS, at the one-year horizon we find that LASSO-based forecasts outperform the benchmark at all quantile levels considered. The results in Table (2) for the h-month CPIAUCSL and PCEPILFE inflation rates show that QAR REC outperforms the benchmark at the 3 and 6-month horizon for quantiles below the median. Furthermore, including macroeconomic predictors in the analysis delivers more precise forecasts of CPI inflation at the 6-month horizon using both factors or LASSO selection. At the longest horizon for CPIAUCSL and at all horizons for PCEPILFE we find that the AR-SV model provides quantile forecasts that are rarely outperformed by other methods.

Overall, these findings indicate that the AR-SV is a competitive benchmark to forecast the distribution of inflation, which is difficult to be outperformed by considering more flexible specifications or macroeconomic variables, in particular at longer horizons. However, for the real variables we find that the QAR model delivers better performance at short horizons and suggests that the quantile AR specification might be capturing possible asymmetries in the underlying process. In addition, the higher accuracy of factor and, in particular, LASSO-based models shows that macroeconomic variables are important predictors of the dynamics of the distribution of economic variables. Since we evaluate quantile forecasts, we focus the forecast comparison on specific areas of the distribution and the results show that economic indicators are particularly useful to predict the tails of the distribution, rather than its center, which indicates that they might anticipate future changes in macroeconomic uncertainty that are not captured by the time-varying volatility of the stochastic volatility model. On the other hand, we do not find evidence of a significant role of macroeconomic variables at the center of the distribution which is consistent with the earlier results in the literature of the weak predictability of economic indicators for the conditional mean.

3.2 LASSO variable selection

The overall performance of the LASSO-based models suggests that the method is able to select indicators with predictive power for the variables being forecast. It is thus interesting to examine which indicators, among the many considered, have contributed the most to the performance of LASSO. Tables (3) and (4) show the five most selected variables when $c = 2$ for the recursive and rolling POST-LASSO-QAR model for the three forecast horizons considered and at five quantile levels ($\tau = 0.1$, 0.3, 0.5, 0.7, and 0.9). In addition to the series ID (see the Appendix for the variable description and the transformation), the Tables report the frequency of selection of the variable (out of 438 forecasts), as well as the average coefficient in the months in which the indicator was selected. Since the macroeconomic variables have been standardized to have mean zero and variance one, the coefficient should be interpreted as the effect of a one standard deviation change in the indicator.

There is significant overlap in the variables selected as predictors for INDPRO and PAYEMS and those that are selected for the inflation measures (CPIAUCSL and PCEPILFE). The main findings when forecasting INDPRO and PAYEMS are:

- *Price Indexes*: we find that several Producer Price indexes are often selected, in particular "Finished Goods, Capital Equipment" (PPICPE), "Intermediate Materials, Supplies & Components" (PPIITM), "Finished Consumer Goods Excluding Food" (PFCGEF), in addition to several Consumer Price Indexes such as "Medical Care" (CPIMEDSL) and "All items less food and energy" (CPILFESL). For both INDPRO and PAYEMS, we find that the (average) coefficients of these indicators are negative.
- *Spread*: the most selected spread is the 3-month (SPREAD3M), along with other short-term spreads (SPREAD6M). At the one-year forecast horizon, also SPREADAAA and SPREADBAA are selected.
- *Money and banking aggregates*: in several instances savings aggregates are selected, especially "Savings Deposits at Thrift Institutions" (SVGTI), "Savings and small Time Deposits" (SVSTSL), and "Savings deposits - Total" (SAVINGSL), and, in the case of PAYEMS, they are only selected at the top quantiles.
- *Employment*: at long horizons, "Average (Mean) duration of unemployment" (UEMPMEAN) is often selected, together with several sub-aggregates of "All Employees", in particular "Retail Trade" (USTRADE), "Financial Activities" (USFIRE), and "Government" (USGOVT).
- *Consumption (PCE)*: none of the aggregates are among the top five variables to predict INDPRO, but the "Services" sub-aggregate (PCES) is selected as a predictor of PAYEMS for $h = 3$ for the recursive scheme.
- *Housing*: housing-related variables are often selected - at all horizons - to predict PAYEMS, but only in few cases to predict INDPRO. The most selected indicators are "Building permits" (PERMIT), "Building permits - in structures with 1 unit" (PERMIT1), "Building permits in Midwest census region" (PERMITMW), "New one family houses sold: United States" (HSN1F; mostly selected using the rolling window), "Housing starts in Midwest census region" (HOUSTMW), and "Housing starts: 1-Unit structures" (HOUST1F).

- *NAPM indicators*: for both variables the most selected NAPM indicators are "New Orders Index" (NAPMNOI), "Production Index" (NAPMPI), and "Prices Index" (NAPMPRI; negative sign). It is interesting that, for both variables and for the rolling scheme, NAPMNOI is selected exclusively at short forecast horizons, as opposed to NAPMPRI which is selected mostly at the longest horizons.

For the inflation measures, we find the following predictors as the most relevant:

- *Price Indexes*: some Producer Price Indexes, such as "Finished consumer foods" (PPIFCF) AND "Crude materials for further processing" (PPICRM) are selected as predictors of CPIAUCSL at $h = 3$ for the recursive scheme. For PCEPILFE, several of the Producer Price Indexes and CPI sub-aggregates discussed earlier are among the top predictors, in particular at the 3- and 6-month horizons.

- *Spread*: in the case of CPIAUCSL the most relevant spread is SPREADPRIME (Bank prime loan rate minus the federal fund rate) which is selected for both estimation schemes and at all horizons. In addition, the spread between BAA and AAA corporate bond yield (CREDIT) is selected at low quantiles by the recursive LASSO for $h = 3$ and 6. Instead, for PCEPILFE we find that only the 3-year spread (SPREAD3Y) is selected at the top quantiles when $h = 12$. This contrasts with the results for INDPRO and PAYEMS for which we found that the 3-month spread was overwhelmingly selected, along with other short-term spreads. All spreads selected have an inverse relationship with the inflation measures as documented by the negative sign of the (average) coefficient.

- *Money and banking aggregates*: no variable in this group is selected to forecast PCEPILFE, whereas several are highly relevant for CPIAUCSL. For instance, the "Effective federal funds rate" (FEDFUNDS) is often selected at the short horizons, savings aggregates ("Savings and small time deposits at commercial banks", SVSTCBSL), and credit aggregates such as "Commercial and Industrial loans at all commercial banks" (BUSLOANS), "Real estate loans at all commercial banks" (REALLN), "Total nonrevolving credit outstanding" (NONREVSL). In addition, monetary aggregates like "M1 Money stock" (M1SL), "M2 Money stock" (M2SL), "Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements" (BOGAMBSL) are selected when the model is estimated recursively.

- *Employment*: variables in this group are selected when the models are estimated recursively, but in only one case for the rolling window. The most relevant indicators are "Civilians unemployed for 27 weeks and over" (UEMP27OV; negative sign) for high quantiles at $h = 3$, NDMANEMP, and some PAYEMS subaggregates, such as "Wholesale trade" (USWTRADE) and "Financial activities" (USFIRE).

- *Housing*: no housing-related variable is selected as predictor of PCEPILFE, while for CPIAUCSL the predictors are similar to the ones selected earlier for INDPRO and PAYEMS (PERMIT1, PERMITS, PERMITMW, and HSN1FW).

- *NAPM indicators*: interestingly, the NAPM indicators selected for INDPRO and PAYEMS are not useful in forecasting the inflation measures, but other NAPM indexes are often selected, such as "Supplier deliveries index" (NAPMSDI), "Employment Index" (NAPMEI), as well as the "Price Index" (NAPMPRI) for both the recursive and rolling schemes.

Another fact that emerges from the Tables is the heterogeneity in the estimated quantile coefficients when a variable is selected. This shows the models proposed offer a flexible specification to forecast the quantiles both in terms of the predictors that are included as well as in terms of the (potentially) heterogeneous effect of these predictors at different parts of the distribution.

In the on-line Appendix we provide further evidence on the LASSO variables selection in terms of the number of variables selected at different quantiles for different values of the shrinkage parameter. In addition, we also report the time series of the estimated coefficients of the five most important variables at different quantiles which allows to asses the stability (over time) of these estimates.

4 Forecasting before and during the 2008-2009 recession

An interesting exercise is to examine the forecast distributions produced by these models at a particular point in time and evaluate, in a qualitative manner, their performance and characteristics in light of the (future) realizations of the variable being forecast. We consider as forecast bases the end of January 2007, 2008, and 2009 which represent three crucial times for monetary policy-making leading to and during the recent recession that started in December 2007 and ended in June 2009 (as dated by the NBER dating committee). The aim of this exercise is to produce distribution forecasts based on the information that was available at the time the Federal Open Market Committee (FOMC) meeting took place and compare them with the outlook for the economy provided in the FOMC press releases (available at `http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm`). In particular, following the January 2007 meeting the FOMC decided to keep the federal fund rate at 5.25% since the "economy seems likely to expand at a moderate pace over coming quarters" and "inflation pressures seem likely to moderate over time", although "some inflation risks remain". In January 21, 2008 the FOMC cuts the fund rate by 75 basis points to 3.5% due to "increasing downside risks to growth" while it "expects inflation to moderate in coming quarters". This decision was followed the week after by an additional cut of the fund rate to 3% on concerns about the tightening of the credit market and the "deepening of the housing contraction". Later, the NBER Business Cycle Dating Committee declared the business cycle peaked in December 2007. The third forecast date that we consider coincides with the end of January 2009 meeting, in which the FOMC decided to maintain the federal funds rate in the interval between 0 and 0.25% due to the expectation that "economic conditions are likely to warrant exceptionally low levels of the federal funds rate for some time". In addition, "The Committee anticipates that a gradual recovery in economic activity will begin later this year, but the downside risks to that outlook are significant ... the Committee expects that inflation pressures will remain subdued in coming quarters". Furthermore, the FOMC seemed also concerned with the possibility of price deflation since "the Committee sees some risk that inflation could persist for a time below rates that best foster economic growth and price stability in the longer term."

We thus generate forecasts from the QAR, FA-QAR and LASSO-QAR models (for both recursive and rolling estimation) and we report the results for $K = 3$ (FA) and $c = 2$ (LASSO). In generating the forecasts, we use only information available up to the December ahead of the FOMC meeting since the January data is released in mid-February. For each date, we forecast the annualized growth rate of the variables from 1 up to 16 months ahead and Figures (1) to (4) show the time series of the quantile forecasts. For FA-QAR and LASSO-QAR we plot the 0.05, 0.25, 0.45, 0.55, 0.75, and 0.95 quantiles and use increasingly darker shades for the 90%, the 50%, and the 10% intervals, while the median is represented by the darkest line. In addition, in each graph we also plot the forecasts of the QAR model for the 0.05, 0.50, and 0.95 quantiles (dashed lines) estimated on the same window as the FA- and LASSO-QAR models. This allows to visually evaluate the effect on the quantile forecasts of augmenting the time series model with the macroeconomic indicators via factors or LASSO selection. For instance, we expect the FA-QAR and the LASSO-QAR quantile forecasts to be equal (or very close) to those of the QAR model in case the factors or the variables selected by LASSO are irrelevant predictors. On the other hand, if the macroeconomic indicators are relevant the two quantile forecasts might deviate significantly based on macroeconomic conditions.

Figure (1) shows the quantiles forecasts for the annualized growth rate of INDPRO for the three dates (columns) and the four models considered (rows). The forecasts generated in January 2007 show that the median, for all models, predicted moderate growth, with most differences among models occurring at the outer quantiles. A first characteristic of these forecasts is represented by the smaller interval forecasts for the QAR ROLL compared to QAR REC. In addition, the 25% quantile forecast of the recursive FA-QAR and LASSO-QAR oscillates around zero, as opposed to the case of the rolling window for which it is positive for $h \geq 6$. Augmenting the QAR model with the macroeconomic variables contributes to shift the outer quantiles in the recursive case, while in the rolling case they mostly affect the lower quantile, in particular when considering FA-QAR. In January 2008 indications of a slowing economy were emerging and this is reflected particularly well by the recursive LASSO-QAR. The median of its distribution is very close to zero, and remarkably different from the QAR REC median forecast which still predicted positive growth. In this sense, the macroeconomic variables predicted an increase of the probability of negative INDPRO growth to over 50%, in addition to significantly reducing also the top quantiles to lower values compared to the time series models. The recursive FA-QAR provides similar results, although it seems to predict a moderate recovery at the end of 2008 and beginning of 2009. On the other hand, the medians of the rolling FA- and LASSO-QAR models are quite close to the QAR ROLL median, but the lower part of the FA-QAR forecast distributions seems to shift downward with the 5% quantile becoming more negative relative to the QAR quantile. As it is clear from the realization of the (annualized) INDPRO growth, the contraction in output was significantly more severe than the models predicted, in particular in the second half of 2008. By January 2009 all major economic indicators pointed to a deterioration of the macroeconomic outlook, driven by declines in consumer demand and by a weak housing market. The distribution forecasts are all heavily shifted in negative territory at short horizons, but differ on the speed at which they predict a recovery. The median forecasts of the recursive LASSO-QAR model crosses zero in June 2009 and continues increasing afterwards in a marked difference with the median of the QAR model that becomes positive in January 2010. In addition, the 5 and 25% quantiles for the recursive LASSO-QAR predicted a recovery (in the sense of a small probability of negative INDPRO growth) in the first quarter of 2010, again a quite different forecast compared to QAR. The recursive FA-QAR displays a similar pattern, although it tracks more closely the QAR distribution and forecasts a slower recovery. Instead, both rolling models display significant downside risk in the short-run and a very slow recovery. In particular, the FA-QAR model predicts a close to 50% probability of negative output well into 2010.

The forecasts for PAYEMS in Figure (2) produced in January 2007 pointed to moderate growth in employment, with only the recursive forecasts suggesting a small probability of negative growth. Also for this variable we find that the 90% interval for the rolling estimation is smaller than the recursive at all horizons. In January 2008, the LASSO-QAR suggested a deterioration of the labor market conditions, with a shift downward of the distribution, in particular in the recursive case for which the median approaches zero starting in May 2008. The shift was particularly large (compared to the time series QAR) at the top and center of the distribution, but less pronounced at the bottom quantiles. Instead, the FA-QAR models indicated an increased risk of negative employment growth, in particular in the rolling case, although the center of the distribution was still forecasting moderate growth in PAYEMS. The decline in employment that emerged in the following months was much deeper than predicted by the models, in particular at the longest horizons. The forecasts generated in January 2009 predicted a slow recovery of PAYEMS from the recession, in particular when estimating the models on a rolling window.

Figure (3) and (4) show the forecasts for the CPIAUCSL and PCEPILFE inflation rate. When forecasting headline CPI inflation, the difference between rolling and recursive schemes are less pronounced, compared to the previous discussion, in terms of width of the 90% interval. In both cases and for both LASSO- and FA-QAR, the quantile forecasts in January 2007 predicted that inflation would be stable around 2%, with only the factors indicating some higher upside risk. The forecasts in January 2008 have similar characteristics to the 2007 forecasts, with the major difference that the distributions for both LASSO and FA-QAR estimated recursively seem to edge down toward the end of 2008 and into 2009. However, the forecasts produced in January 2009 when the contraction was underway show a quite different outlook compared to the previous dates. The recursive LASSO and FA-QAR forecast a remarkably different path for CPI inflation compared to the recursive QAR model. While the QAR quantiles predicted a high likelihood of negative inflation up to August 2009, followed by positive inflation in the first quarter of 2010, the other models' quantile forecasts departed significantly from the QAR by forecasting negative inflation in the out-of-sample period even at the top quantile level. The rolling window estimation provides a less extreme perspective on future CPI inflation, although the factors seem to have the effect of shifting the distribution (compared to QAR) downward. The interpretation of these results is that the macroeconomic conditions in January 2009 were so severe to shift the quantile forecasts (compared to QAR forecasts) in negative territory, except in the case of the rolling LASSO-QAR whose forecasts largely overlap with the time series forecasts.

When considering core PCE inflation, the main inflation indicator followed by the Federal Reserve, the recursive distribution forecasts are typically wider compared to the rolling window ones which are characterized by very narrow intervals, in particular at the longest horizons. Overall, the outlook that emerges from the forecasts produced in January 2007 and 2008 is that of a stable core PCE inflation with the median forecasts at all horizons around 2%, although the factors predicted more upside risk compared to the time series models at the beginning of 2007. For the January 2009 forecasts, only the recursive FA-QAR assigns a high likelihood of a decrease in the PCEPILFE price index, while the other models anticipated a moderation in inflation to lower, but still positive, levels. Also in this case, the severity of the downturn is evident in shifting the time series quantiles toward lower levels.

5 Conclusion

In this paper we provide evidence that macroeconomic variables are indeed useful to forecast business cycle and inflation indicators. The results suggest that their predictive power occurs primarily in the tails of the distribution and at the 6-12 month horizon. These conclusions were obtained considering a large number of macroeconomic variables and comparing different approaches to isolate the relevant information in the panel. We find that augmenting a time series model using a small number of predictors selected by the LASSO method provides comparable and often more accurate forecasts compared to the alternative approach of constructing principal components. A possible reason for this result is that the LASSO selection of the predictors is specifically targeted to forecast the indicator of interest, as opposed to the factors that have no relation to the variable being forecast. We also find that, among the variables most often selected, there are several that are rarely considered in the forecasting literature such as the Producer Price Indices and the National Association of Purchasing Management (NAPM) indices. In both cases, the forecasting power of these indices relates to their inherently forward looking nature as indicators of the business cycle. We also show the practical relevance of forecasting the distribution of economic variables by producing multi-step ahead (real time) forecasts for the indicators of economic activity and inflation measures at three crucial moments before and during the last recession. The analysis suggests that the forecasts are, to a large extent, consistent with the qualitative view of the state of the economy expressed by the FOMC at the time the forecast was made. In addition, the comparison of the time series and the multivariate forecasts illustrates effectively the role of the indicators in shifting the distribution forecasts, at times asymmetrically, to reflect the changing macroeconomic outlook.

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Table 1: **INDPRO & PAYEMS - QS TEST**

Variable	h	Model	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
INDPRO	3	QAR REC	-1.15	-0.71	0.00	-0.05	0.28	-0.46	-0.43	-0.02	0.66	1.65	1.39
		QAR ROLL	-1.20	-0.66	0.53	0.42	0.46	0.44	0.47	1.05	0.96	1.83	1.72
		FAR-SV	**-2.00**	**-1.85**	-1.05	-0.56	-0.38	-0.23	-0.41	-0.72	-1.04	-0.95	-1.22
		FA-QAR REC K=3	**-1.86**	-1.47	-1.34	-1.06	-0.56	-0.02	-0.01	0.16	0.03	-0.21	-0.58
		FA-QAR REC K=5	**-1.75**	-1.50	-1.31	-0.99	-0.71	-0.65	-0.50	-0.56	-0.61	-0.51	-0.09
		FA-QAR ROLL K=3	-0.77	-0.73	-0.73	-0.53	-0.10	0.04	0.12	0.04	0.17	0.55	0.61
		FA-QAR ROLL K=5	-0.95	-0.84	-1.02	-1.05	-0.74	-0.19	0.14	0.20	0.13	1.11	1.50
		LASSO-QAR REC	**-2.04**	-1.61	-1.30	-1.38	-0.60	**-1.82**	**-2.18**	**-1.74**	-1.08	0.15	0.84
		POST-LASSO-QAR REC	**-1.89**	**-1.64**	-0.93	-0.69	-0.58	-0.47	-0.66	-1.21	-1.40	-0.24	0.74
		TFA-QAR REC	**-1.99**	**-1.77**	-1.18	-1.02	-0.72	-0.82	-1.11	-1.59	**-1.68**	-0.39	0.71
		LASSO-QAR ROLL	-1.50	-1.43	-1.00	-0.84	-0.37	-0.11	-0.01	0.19	0.58	1.27	1.66
		POST-LASSO-QAR ROLL	**-1.66**	**-1.74**	-1.09	-0.59	-0.11	-0.38	-0.21	0.26	0.67	1.14	1.47
		TFA-QAR ROLL	**-1.66**	**-1.78**	-1.15	-0.54	-0.04	-0.41	-0.34	0.22	0.52	1.11	1.51
	6	QAR REC	-1.63	**-1.85**	**-2.04**	**-2.14**	**-1.88**	-0.93	-0.30	-0.01	0.14	0.63	0.52
		QAR ROLL	-1.58	**-1.64**	-1.56	-1.18	-0.64	-0.13	0.95	1.30	1.17	0.76	0.84
		FAR-SV	**-2.14**	**-1.98**	**-1.64**	-1.44	-1.42	-1.30	-1.19	-1.09	-1.03	-0.74	-0.44
		FA-QAR REC K=3	**-2.55**	**-2.47**	**-2.08**	**-1.78**	-1.54	-1.17	-0.75	-0.53	-0.42	-0.60	-0.84
		FA-QAR REC K=5	**-2.40**	**-2.20**	**-2.03**	**-1.67**	-1.35	-1.06	-0.78	-0.77	-0.96	-1.07	-0.87
		FA-QAR ROLL K=3	-1.02	-1.05	-0.89	-0.67	-0.10	0.22	0.25	0.32	0.34	0.78	1.06
		FA-QAR ROLL K=5	-1.22	-0.98	-0.92	-0.84	-0.69	-0.50	-0.31	-0.16	-0.38	0.16	0.83
		LASSO-QAR REC	**-2.71**	**-2.95**	**-2.75**	**-2.50**	**-2.34**	**-1.70**	-1.20	-1.09	-1.23	-1.46	-0.78
		POST-LASSO-QAR REC	**-2.77**	**-2.39**	**-1.65**	-1.26	-0.81	-0.38	-0.24	-0.24	-0.86	-1.54	-1.41
		TFA-QAR REC	**-2.62**	**-2.29**	**-1.69**	-1.21	-0.88	-0.75	-0.56	-0.71	-1.16	-1.56	-1.17
		LASSO-QAR ROLL	**-2.16**	**-2.44**	**-2.08**	**-1.69**	-1.37	-0.72	-0.16	0.01	0.20	0.31	0.79
		POST-LASSO-QAR ROLL	**-2.39**	**-1.86**	-1.30	-0.96	-0.56	-0.02	0.28	0.12	-0.10	0.06	0.13
		TFA-QAR ROLL	**-2.42**	**-2.01**	-1.48	-1.08	-0.80	-0.15	0.28	0.14	-0.05	-0.04	0.18
	12	QAR REC	**-2.49**	**-2.55**	**-2.66**	**-2.60**	**-2.27**	**-2.52**	**-3.15**	**-2.12**	**-1.85**	**-1.90**	**-2.16**
		QAR ROLL	**-1.85**	-1.46	-1.59	-1.49	-1.04	-0.79	-0.89	-0.91	-1.29	-1.17	-0.51
		FAR-SV	**-2.16**	**-2.28**	**-2.29**	**-2.00**	**-1.73**	-1.55	-1.55	-1.40	-1.38	-1.34	-1.33
		FA-QAR REC K=3	**-2.43**	**-2.48**	**-2.22**	**-1.93**	**-1.65**	-1.52	-1.58	-1.51	**-1.75**	**-1.92**	**-2.25**
		FA-QAR REC K=5	**-2.73**	**-2.79**	**-2.42**	**-1.95**	**-1.71**	-1.56	**-1.66**	**-1.67**	**-1.94**	**-1.71**	-0.75
		FA-QAR ROLL K=3	**-1.80**	**-1.73**	-1.22	-0.77	-0.54	-0.38	-0.40	-0.42	-0.47	-0.24	0.13
		FA-QAR ROLL K=5	**-1.64**	**-1.74**	**-1.65**	-1.35	-1.07	-0.85	-0.94	-0.99	-1.25	-0.78	-0.33
		LASSO-QAR REC	**-3.19**	**-3.27**	**-2.75**	**-2.33**	**-2.09**	**-1.87**	**-1.82**	**-1.87**	**-2.24**	**-2.73**	**-2.67**
		POST-LASSO-QAR REC	**-2.63**	**-2.44**	**-1.82**	-1.44	-1.25	-1.17	-1.25	-1.57	**-2.07**	**-2.63**	**-2.77**
		TFA-QAR REC	**-2.84**	**-2.71**	**-2.12**	**-1.78**	-1.53	-1.34	-1.45	**-1.71**	**-2.16**	**-2.73**	**-2.88**
		LASSO-QAR ROLL	**-2.04**	**-2.26**	**-2.23**	**-2.04**	**-1.86**	-1.57	-1.54	-1.47	-1.62	-1.47	-0.82
		POST-LASSO-QAR ROLL	**-2.24**	**-2.00**	**-1.78**	-1.60	-1.50	-1.43	-1.51	-1.42	**-1.81**	**-2.07**	**-1.65**
		TFA-QAR ROLL	**-2.35**	**-2.12**	**-1.86**	**-1.71**	-1.56	-1.41	-1.39	-1.37	**-1.80**	**-2.17**	**-1.64**
PAYEMS	3	QAR REC	0.23	0.16	0.44	0.82	0.82	0.47	0.95	1.55	*3.55*	*4.38*	*3.66*
		QAR ROLL	0.49	0.61	0.91	1.12	0.90	0.72	0.93	0.83	0.69	0.95	1.13
		FAR-SV	**-2.60**	**-2.67**	**-2.56**	**-2.28**	**-1.82**	-1.33	-0.98	-0.75	-0.54	-0.76	-0.85
		FA-QAR REC K=3	-0.90	-0.86	-1.24	-1.30	-1.03	-0.51	0.04	0.51	1.14	1.69	1.73
		FA-QAR REC K=5	-1.02	-0.90	-1.31	-1.51	-1.33	-0.98	-0.50	-0.17	-0.11	0.16	0.66
		FA-QAR ROLL K=3	-1.04	-1.04	-0.95	-0.84	-0.43	-0.32	-0.19	-0.02	0.21	0.52	1.00
		FA-QAR ROLL K=5	-1.05	-1.03	-1.22	-1.03	-0.68	-0.60	-0.19	-0.01	0.17	0.50	0.83
		LASSO-QAR REC	-0.51	-0.61	-0.74	-0.66	-0.60	-0.43	0.10	0.27	1.42	*2.19*	*2.47*
		POST-LASSO-QAR REC	-0.75	-0.80	-1.25	-1.41	-1.19	-0.57	-0.17	-0.13	0.51	0.96	1.77
		TFA-QAR REC	-0.69	-0.82	-1.28	-1.56	-1.32	-0.66	-0.17	-0.20	0.61	1.14	1.68
		LASSO-QAR ROLL	0.18	0.11	-0.17	-0.17	-0.04	0.06	0.03	-0.09	0.02	0.44	0.97
		POST-LASSO-QAR ROLL	-0.30	-0.49	-0.50	-0.49	-0.39	-0.25	-0.35	-0.52	-0.23	0.22	0.95
		TFA-QAR ROLL	-0.30	-0.48	-0.66	-0.62	-0.42	-0.24	-0.42	-0.68	-0.40	0.05	0.87
	6	QAR REC	**-1.69**	-1.44	-1.40	-1.40	**-1.70**	**-2.01**	-1.40	-0.19	0.95	*2.18*	*2.40*
		QAR ROLL	-0.61	-0.53	-0.38	0.12	0.13	-0.25	-0.22	-0.34	-0.41	-0.25	0.18
		FAR-SV	**-3.41**	**-3.35**	**-2.95**	**-2.45**	**-2.02**	-1.58	-1.25	-1.10	-1.06	-1.11	-1.03
		FA-QAR REC K=3	**-2.71**	**-2.66**	**-2.51**	**-2.31**	**-2.04**	**-1.68**	-1.05	-0.44	0.07	0.67	1.08
		FA-QAR REC K=5	**-2.51**	**-2.58**	**-2.42**	**-2.28**	**-2.15**	**-1.97**	-1.53	-0.91	-0.47	-0.02	0.26
		FA-QAR ROLL K=3	**-2.39**	**-2.11**	**-1.70**	-1.40	-1.10	-0.85	-0.58	-0.44	-0.62	-0.47	0.30
		FA-QAR ROLL K=5	**-2.19**	**-2.11**	**-1.73**	-1.33	-1.06	-0.73	-0.40	-0.24	-0.12	0.10	0.46
		LASSO-QAR REC	**-2.51**	**-2.63**	**-2.56**	**-2.29**	**-2.08**	**-1.72**	-1.32	-0.98	-0.58	-0.15	1.03
		POST-LASSO-QAR REC	**-2.70**	**-2.51**	**-2.17**	**-1.87**	**-1.60**	-1.17	-0.81	-0.79	-0.51	-0.38	0.42
		TFA-QAR REC	**-2.65**	**-2.43**	**-2.18**	**-1.89**	-1.62	-1.25	-0.96	-0.90	-0.80	-0.40	0.59
		LASSO-QAR ROLL	-0.84	-1.14	-1.36	-1.17	-1.05	-0.91	-0.81	-0.84	-0.75	-0.51	0.16
		POST-LASSO-QAR ROLL	-1.18	-1.44	-1.08	-0.76	-0.64	-0.72	-0.72	-0.98	-1.10	-0.76	-0.08
		TFA-QAR ROLL	-1.30	-1.55	-1.35	-1.05	-0.91	-1.04	-1.03	-1.23	-1.22	-0.87	-0.02
	12	QAR REC	**-2.49**	**-2.39**	**-2.30**	**-2.71**	**-3.16**	**-3.32**	**-3.87**	**-2.95**	**-1.91**	-1.40	-1.40
		QAR ROLL	-1.34	-1.43	-1.27	-1.30	**-1.78**	**-1.97**	**-2.45**	**-3.03**	**-3.10**	**-2.64**	**-1.88**
		FAR-SV	**-2.56**	**-2.69**	**-2.52**	**-2.15**	**-1.71**	-1.49	-1.51	-1.55	-1.56	-1.59	-1.51
		FA-QAR REC K=3	**-3.15**	**-2.88**	**-2.39**	**-2.13**	**-1.94**	**-1.82**	**-1.82**	**-1.77**	-1.62	-1.53	-1.54
		FA-QAR REC K=5	**-2.98**	**-2.96**	**-2.73**	**-2.70**	**-2.56**	**-2.42**	**-2.36**	**-2.34**	**-2.09**	-1.57	-1.02
		FA-QAR ROLL K=3	**-2.27**	**-2.43**	**-2.11**	**-1.86**	**-1.61**	-1.39	-1.40	-1.44	-1.29	-0.62	-0.10
		FA-QAR ROLL K=5	**-2.22**	**-2.35**	**-2.24**	**-2.15**	**-1.91**	-1.58	-1.52	-1.45	-1.25	-0.63	-0.15
		LASSO-QAR REC	**-3.23**	**-3.12**	**-2.67**	**-2.56**	**-2.46**	**-2.43**	**-2.65**	**-2.83**	**-2.71**	**-2.24**	**-1.68**
		POST-LASSO-QAR REC	**-2.98**	**-2.78**	**-2.38**	**-2.26**	**-2.09**	**-2.03**	**-1.98**	**-2.12**	**-2.49**	**-2.46**	**-1.91**
		TFA-QAR REC	**-3.01**	**-2.58**	**-2.25**	**-2.27**	**-2.28**	**-2.25**	**-2.19**	**-2.28**	**-2.50**	**-2.37**	**-1.84**
		LASSO-QAR ROLL	**-1.82**	**-2.47**	**-2.61**	**-2.50**	**-2.32**	**-2.08**	**-2.28**	**-2.77**	**-3.13**	**-2.85**	**-1.94**
		POST-LASSO-QAR ROLL	**-2.44**	**-2.56**	**-2.42**	**-2.23**	**-1.98**	**-1.72**	**-1.84**	**-2.25**	**-2.72**	**-2.67**	**-1.94**
		TFA-QAR ROLL	**-2.41**	**-2.85**	**-2.77**	**-2.59**	**-2.25**	**-1.92**	**-2.01**	**-2.35**	**-2.79**	**-2.77**	**-1.96**

The values in the Table represent the t statistic for the null hypothesis of equal accuracy of the quantile forecasts from the models indicated relative to the AR-SV benchmark. The values of τ that we consider for the QS test are indicated at the top row of the Table, while h denotes the forecasting horizon. The value of c is equal to 2. A negative value of the test statistic indicates that the alternative model outperforms the benchmark (AR-SV) and in bold are denoted the rejections of equal accuracy at 5% against the one-sided alternative that the benchmark is outperformed.

Table 2: **CPIAUCSL & PCEPILFE - QS TEST**

Variable	h	Model	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
CPIAUCSL	3	QAR REC	0.82	0.32	-0.53	-0.92	-0.98	-1.00	-0.98	-0.96	-0.23	0.40	0.61
		QAR ROLL	0.58	-0.04	-0.46	-0.84	-0.95	-1.28	-1.64	-1.92	-0.71	1.16	2.01
		FAR-SV	0.68	0.62	-0.11	-0.63	-0.82	-0.84	-0.89	-1.09	-0.41	0.14	0.44
		FA-QAR REC K=3	-0.50	-1.29	**-1.85**	**-1.65**	-1.43	-1.16	-0.92	-0.77	-0.18	0.33	0.84
		FA-QAR REC K=5	-0.11	-0.60	-1.43	-1.48	-1.45	-1.38	-1.26	-1.12	-0.33	0.39	0.94
		FA-QAR ROLL K=3	-0.67	-1.54	-1.60	**-1.74**	-1.09	-0.67	-0.51	-0.27	0.79	*1.66*	*1.96*
		FA-QAR ROLL K=5	-0.18	-0.89	-1.52	**-2.00**	**-2.00**	**-1.87**	**-1.90**	**-1.81**	-0.51	0.75	1.56
		LASSO-QAR REC	0.61	-0.23	-1.27	-1.52	-1.38	-1.24	-1.05	-0.90	-0.20	0.45	0.62
		POST-LASSO-QAR REC	0.51	-0.38	-1.23	-1.51	-1.28	-1.04	-0.90	-0.60	-0.03	0.35	0.76
		TFA-QAR REC	0.62	-0.43	-1.29	-1.48	-1.26	-1.07	-0.98	-0.72	-0.14	0.37	0.81
		LASSO-QAR ROLL	0.41	-0.46	-1.31	**-1.83**	**-1.71**	-1.60	**-1.88**	**-2.08**	-0.78	1.09	*2.11*
		POST-LASSO-QAR ROLL	0.40	-0.71	**-1.98**	**-2.46**	**-2.46**	**-2.30**	**-2.10**	**-2.07**	-0.72	0.76	1.91
		TFA-QAR ROLL	0.42	-0.69	**-1.93**	**-2.41**	**-2.44**	**-2.25**	**-2.01**	**-2.08**	-0.69	0.76	1.93
	6	QAR REC	**-2.74**	**-2.56**	**-2.77**	**-2.95**	**-2.40**	-0.93	0.23	1.18	2.05	1.41	0.92
		QAR ROLL	**-2.19**	**-2.28**	**-1.94**	-1.05	-0.39	-0.14	0.24	0.42	0.79	1.14	0.96
		FAR-SV	**-2.21**	**-2.07**	**-1.71**	**-1.67**	-1.54	-1.19	-0.58	-0.52	-0.24	-0.47	-0.82
		FA-QAR REC K=3	**-3.27**	**-3.26**	**-2.69**	**-2.29**	-1.59	-0.59	0.48	1.02	1.27	1.11	0.91
		FA-QAR REC K=5	**-2.95**	**-3.00**	**-2.53**	**-2.12**	-1.56	-0.75	0.27	0.84	1.32	1.22	1.03
		FA-QAR ROLL K=3	**-3.50**	**-3.41**	**-2.91**	**-2.28**	-1.39	-0.44	0.48	1.14	*1.78*	*1.71*	1.48
		FA-QAR ROLL K=5	**-3.46**	**-3.38**	**-2.93**	**-2.78**	**-2.14**	-1.32	-0.38	0.10	0.81	1.37	1.23
		LASSO-QAR REC	**-3.23**	**-3.19**	**-2.97**	**-2.65**	**-1.95**	-0.99	0.60	1.33	*1.77*	1.24	0.96
		POST-LASSO-QAR REC	**-3.34**	**-3.27**	**-2.80**	**-2.33**	-1.46	-0.35	0.86	1.47	*1.67*	1.25	0.95
		TFA-QAR REC	**-3.28**	**-3.27**	**-2.84**	**-2.43**	-1.46	-0.44	0.80	1.37	*1.66*	1.15	0.87
		LASSO-QAR ROLL	**-2.56**	**-2.71**	**-2.37**	**-1.93**	-1.44	-1.14	-0.37	0.01	0.51	0.76	0.70
		POST-LASSO-QAR ROLL	**-3.03**	**-3.08**	**-2.41**	**-2.14**	**-1.68**	-1.20	-0.70	-0.32	0.28	0.44	0.25
		TFA-QAR ROLL	**-3.08**	**-3.12**	**-2.51**	**-2.27**	**-1.73**	-1.24	-0.75	-0.32	0.34	0.47	0.24
	12	QAR REC	-0.29	-1.39	**-1.97**	**-1.92**	-1.44	-0.74	-0.00	0.54	0.47	0.52	0.31
		QAR ROLL	0.47	-0.08	-0.21	-0.20	-0.17	-0.07	0.25	0.37	0.32	0.23	0.11
		FAR-SV	-1.55	**-1.80**	**-1.73**	**-1.67**	**-1.67**	-1.63	-1.59	**-1.72**	**-1.79**	**-1.77**	-1.13
		FA-QAR REC K=3	-1.39	-1.64	-1.63	-1.52	-1.23	-0.90	-0.63	-0.44	-0.31	-0.03	0.13
		FA-QAR REC K=5	-1.05	-1.35	-1.30	-1.08	-0.77	-0.50	-0.20	0.06	0.31	0.62	0.82
		FA-QAR ROLL K=3	-1.18	-1.40	-1.14	-0.83	-0.68	-0.72	-0.82	-0.94	-0.98	-0.85	-0.66
		FA-QAR ROLL K=5	0.13	-0.34	-0.53	-0.43	-0.40	-0.43	-0.43	-0.35	-0.23	-0.06	0.28
		LASSO-QAR REC	-1.29	**-1.78**	**-1.71**	-1.45	-1.17	-0.83	-0.47	-0.18	0.01	0.24	0.13
		POST-LASSO-QAR REC	**-1.70**	-1.60	-1.19	-0.93	-0.77	-0.46	-0.22	-0.06	0.09	0.32	0.36
		TFA-QAR REC	-1.58	**-1.81**	-1.67	-1.44	-1.12	-0.82	-0.56	-0.34	-0.15	0.15	0.28
		LASSO-QAR ROLL	-0.03	-0.50	-0.79	-0.86	-0.84	-0.82	-0.71	-0.59	-0.57	-0.39	-0.26
		POST-LASSO-QAR ROLL	-0.73	-1.11	-1.27	-1.14	-1.00	-0.93	-0.90	-0.90	-0.86	-0.80	-0.68
		TFA-QAR ROLL	-0.67	-1.08	-1.29	-1.18	-1.06	-1.01	-0.89	-0.90	-0.85	-0.79	-0.64
PCEPILFE	3	QAR REC	-1.38	**-2.63**	**-2.22**	**-2.41**	**-2.93**	**-3.00**	**-2.66**	**-2.14**	-0.96	1.17	*2.54*
		QAR ROLL	-0.18	-1.03	-0.92	-1.49	**-1.94**	**-2.15**	-1.37	-0.41	0.78	2.08	2.15
		FAR-SV	1.80	0.93	0.40	-0.20	-0.64	-0.91	-1.18	-1.02	-0.36	-0.14	-0.73
		FA-QAR REC K=3	-0.62	-0.99	-1.01	-1.46	**-1.83**	**-1.86**	**-1.69**	-1.00	0.06	0.89	1.08
		FA-QAR REC K=5	0.48	-0.39	-0.53	-1.05	-1.52	-1.61	-1.26	-0.87	-0.20	0.77	0.99
		FA-QAR ROLL K=3	1.48	0.92	0.49	0.04	-0.12	-0.18	-0.13	0.09	0.76	1.44	1.34
		FA-QAR ROLL K=5	1.38	0.74	0.26	-0.14	-0.35	-0.53	-0.46	-0.24	0.16	0.47	0.14
		LASSO-QAR REC	-1.29	**-2.24**	**-2.10**	**-2.26**	**-2.75**	**-2.88**	**-2.58**	**-2.19**	-1.19	0.44	1.16
		POST-LASSO-QAR REC	-0.71	-1.01	-1.11	-0.96	-1.12	-1.25	-1.16	-1.13	-0.38	0.47	0.52
		TFA-QAR REC	-0.74	-1.04	-1.06	-0.96	-1.15	-1.22	-1.19	-1.12	-0.32	0.56	0.62
		LASSO-QAR ROLL	0.01	-0.88	-0.98	-1.52	**-1.95**	**-2.27**	**-1.79**	-1.05	-0.15	1.26	1.93
		POST-LASSO-QAR ROLL	-0.28	-0.86	-0.87	-1.40	-1.53	-1.47	-1.17	-0.95	-0.46	0.46	1.20
		TFA-QAR ROLL	-0.29	-0.88	-0.87	-1.39	-1.56	-1.48	-1.22	-0.99	-0.48	0.46	1.22
	6	QAR REC	-0.47	0.20	0.95	0.95	1.26	*1.81*	1.54	0.75	*3.18*	*4.29*	*3.71*
		QAR ROLL	0.60	1.10	1.38	1.37	1.21	1.37	1.28	1.25	*2.05*	*1.83*	*1.66*
		FAR-SV	-0.31	-0.40	-0.83	-0.92	-0.89	-0.72	-0.69	-0.69	-0.13	0.34	0.46
		FA-QAR REC K=3	-0.05	0.47	0.38	0.22	0.28	0.62	0.94	1.23	*2.12*	*2.45*	*2.29*
		FA-QAR REC K=5	0.01	0.87	0.79	0.90	1.07	1.13	1.19	1.49	*1.93*	*1.93*	*2.18*
		FA-QAR ROLL K=3	1.58	*1.97*	*2.38*	*2.32*	*2.20*	*2.06*	*1.75*	1.44	*1.91*	1.60	1.36
		FA-QAR ROLL K=5	0.97	1.61	*1.73*	*1.75*	1.63	1.64	1.41	1.28	1.16	1.11	0.96
		LASSO-QAR REC	-0.40	0.22	0.90	0.85	1.21	1.26	0.76	0.48	*1.71*	*1.75*	*2.36*
		POST-LASSO-QAR REC	0.21	0.83	1.08	1.15	1.43	*1.82*	*1.88*	1.47	1.23	1.24	*1.76*
		TFA-QAR REC	0.18	0.76	0.98	1.00	1.28	1.54	*1.67*	1.28	1.22	1.43	*1.76*
		LASSO-QAR ROLL	0.73	1.10	1.42	1.41	1.10	1.10	0.57	0.31	1.26	0.68	0.99
		POST-LASSO-QAR ROLL	0.68	1.06	1.39	1.43	1.25	1.25	0.65	-0.04	0.05	0.37	0.86
		TFA-QAR ROLL	0.65	1.05	1.38	1.43	1.23	1.30	0.76	0.09	0.02	0.47	0.89
	12	QAR REC	-1.05	-0.60	0.69	1.04	0.89	0.72	0.28	0.03	0.43	1.24	1.36
		QAR ROLL	-0.89	-0.40	0.63	1.23	1.17	1.22	1.19	0.98	0.58	0.43	0.44
		FAR-SV	0.33	0.44	0.40	-0.57	-0.69	-0.56	-0.49	-0.66	-0.60	-0.29	-0.18
		FA-QAR REC K=3	-0.85	-0.29	0.61	0.62	0.27	0.25	0.28	0.38	0.69	0.95	1.03
		FA-QAR REC K=5	-0.00	1.09	1.35	0.98	0.55	0.66	0.68	0.77	0.97	1.13	1.12
		FA-QAR ROLL K=3	0.86	1.54	*1.89*	1.49	0.93	0.56	0.34	0.21	0.31	0.53	0.70
		FA-QAR ROLL K=5	0.20	1.04	*1.74*	1.55	0.91	0.67	0.50	0.43	0.52	0.72	0.84
		LASSO-QAR REC	-1.00	-0.59	0.11	0.20	0.01	-0.26	-0.49	-0.80	-0.62	-0.18	0.31
		POST-LASSO-QAR REC	-0.68	-0.22	0.53	0.48	0.22	0.24	0.13	-0.02	0.15	0.09	0.25
		TFA-QAR REC	-0.70	-0.25	0.36	0.18	-0.10	-0.05	-0.11	-0.17	-0.02	-0.08	0.13
		LASSO-QAR ROLL	-0.84	-0.44	0.43	0.69	0.71	0.73	0.58	0.25	-0.10	0.19	0.38
		POST-LASSO-QAR ROLL	-0.55	-0.04	0.74	0.83	0.64	0.55	0.40	0.15	0.34	0.37	0.44
		TFA-QAR ROLL	-0.60	-0.14	0.62	0.75	0.54	0.46	0.28	-0.02	0.19	0.15	0.32

The values represent the t statistic for the null hypothesis of equal accuracy of the quantile forecasts from the models indicated relative to the AR-SV benchmark. The values of τ that we consider for the QS test are indicated at the top row of the Table, while h denotes the forecasting horizon. A negative value of the test statistic indicates that the alternative model outperforms the benchmark (AR-SV) and in bold are denoted the rejections of equal accuracy at 5% against the one-sided alternative that the benchmark is outperformed.

Table 3: **INDPRO & PAYEMS - LASSO Variable Selection**

h	τ	1^{st}			2^{nd}			3^{rd}			4^{th}			5^{th}		
INDPRO								*Recursive*								
3	0.1	SPREAD3M	0.993	1.757	PPICPE	0.897	-1.876	PFCGEF	0.518	-0.388	PERMIT1	0.349	0.349	SPREAD10Y	0.297	0.135
	0.3	SPREAD3M	0.995	1.505	PPICPE	0.801	-0.747	NAPMNOI	0.575	1.177	SVGTI	0.466	0.307	CPIAPPSL	0.333	-0.123
	0.5	SPREAD3M	0.993	1.67	NAPMNOI	0.731	1.669	CPIMEDSL	0.553	-0.562	SVGTI	0.548	0.337	SAVINGSL	0.429	0.266
	0.7	SPREAD3M	1	1.36	NAPMNOI	0.767	1.939	SVGTI	0.676	0.638	SVSTSL	0.6	0.36	CPIMEDSL	0.509	-0.294
	0.9	SPREAD3M	0.733	1.268	SVSTSL	0.674	0.492	NAPMNOI	0.493	1.135	CPIMEDSL	0.409	-0.393	SVGTI	0.315	0.335
6	0.1	SPREAD3M	0.995	1.766	PPICPE	0.982	-1.28	PERMITMW	0.662	0.576	PPIITM	0.541	-0.526	NAPMNOI	0.527	0.595
	0.3	SPREAD3M	0.961	1.914	CPIMEDSL	0.788	-0.581	SVGTI	0.785	0.536	NAPMNOI	0.598	1.182	HOUST1F	0.358	0.142
	0.5	SPREAD3M	0.991	1.47	CPIMEDSL	0.852	-0.753	NAPMNOI	0.642	1.2	SVGTI	0.61	0.585	SPREAD6M	0.523	0.253
	0.7	SVSTSL	0.936	0.715	SPREAD3M	0.836	0.885	CPIMEDSL	0.79	-0.596	NAPMNOI	0.733	1.057	SVGTI	0.594	0.447
	0.9	SVSTSL	0.861	0.816	CPIMEDSL	0.685	-0.432	NAPMNOI	0.642	1.042	SVGTI	0.587	0.54	PPICPE	0.534	-0.37
12	0.1	SPREADAAA	0.724	1.078	CPIMEDSL	0.715	-0.331	PPIITM	0.655	-0.376	SPREAD3M	0.55	0.655	SPREAD6M	0.466	0.545
	0.3	SPREAD3M	0.934	0.91	CPIMEDSL	0.918	-0.466	SPREAD6M	0.749	0.526	PFCGEF	0.737	-0.473	SPREADAAA	0.712	0.835
	0.5	CPIMEDSL	0.804	-0.336	CPILFESL	0.795	-0.275	SPREAD6M	0.735	0.92	SVSTSL	0.733	0.521	PPIITM	0.664	-0.287
	0.7	CPILFESL	0.824	-0.329	SVSTSL	0.801	0.617	CPIMEDSL	0.744	-0.448	PCEPILFE	0.658	-0.453	SPREADAAA	0.648	0.612
	0.9	SVGTI	0.66	0.574	SVSTSL	0.632	0.402	PCEPILFE	0.621	-0.527	CPILFESL	0.584	-0.236	CPIAUCSL	0.541	-0.194
								Rolling								
3	0.1	SPREAD3M	0.345	0.868	PPICPE	0.317	-0.849	HSN1FW	0.16	0.273	SAVINGSL	0.13	0.223	PPIITM	0.096	-0.037
	0.3	SPREAD3M	0.365	0.909	SVGTI	0.249	0.312	HSN1FW	0.203	0.272	SVGCBSL	0.176	0.187	PPICPE	0.153	-0.226
	0.5	SVGTI	0.45	0.534	SPREAD3M	0.313	0.759	HSN1FW	0.112	0.134	SVSTCBSL	0.094	0.085	NAPMPRI	0.089	-0.062
	0.7	SVGTI	0.358	0.45	SPREAD3M	0.308	0.438	SVSTSL	0.274	0.227	NAPMPRI	0.139	-0.112	CPIMEDSL	0.123	-0.121
	0.9	CPIMEDSL	0.155	-0.142	SVGTI	0.144	0.211	SPREADAAA	0.128	0.162	SVSTSL	0.082	0.076	SPREAD3M	0.068	0.167
6	0.1	SPREAD3M	0.377	0.896	PPICPE	0.363	-0.796	CPIMEDSL	0.356	-0.368	UEMPMEAN	0.221	0.268	SPREADBAA	0.21	0.232
	0.3	SPREAD3M	0.402	0.869	SVGTI	0.333	0.299	SAVINGSL	0.272	0.316	CPIMEDSL	0.265	-0.215	NAPMPRI	0.237	-0.239
	0.5	SVGTI	0.573	0.684	CPIMEDSL	0.393	-0.423	SPREAD3M	0.37	0.638	NAPMPRI	0.34	-0.289	UEMPMEAN	0.258	0.236
	0.7	CPIMEDSL	0.432	-0.399	SVGTI	0.358	0.34	SVSTSL	0.304	0.247	NAPMPRI	0.272	-0.304	SPREAD3M	0.235	0.383
	0.9	CPIAPPSL	0.292	-0.152	SVSTSL	0.249	0.289	PPICPE	0.21	-0.188	SVGTI	0.167	0.195	SVGCBSL	0.128	0.128
12	0.1	UEMPMEAN	0.299	0.363	SPREADAAA	0.247	0.407	NAPMPRI	0.217	-0.443	PFCGEF	0.217	-0.182	SPREADBAA	0.217	0.363
	0.3	NAPMPRI	0.447	-0.637	SPREADAAA	0.37	0.623	CPIMEDSL	0.354	-0.249	PFCGEF	0.292	-0.237	UEMPMEAN	0.263	0.245
	0.5	SPREADAAA	0.422	0.705	NAPMPRI	0.384	-0.555	CPILFESL	0.304	-0.123	CPIMEDSL	0.269	-0.222	UEMPMEAN	0.242	0.23
	0.7	NAPMPRI	0.386	-0.426	SPREADAAA	0.349	0.574	CPIMEDSL	0.281	-0.184	SVGTI	0.26	0.185	UEMPMEAN	0.258	0.22
	0.9	SVGTI	0.324	0.337	NAPMPRI	0.148	-0.128	UEMPMEAN	0.114	0.064	HSN1FMW	0.112	0.112	CPIAPPSL	0.098	-0.034
PAYEMS								*Recursive*								
3	0.1	PPICPE	0.696	-0.259	SPREAD3M	0.696	0.249	PCEDG	0.603	0.174	CPILFESL	0.518	-0.17	PERMIT1	0.413	0.164
	0.3	SPREAD3M	1	0.393	NAPMNOI	0.427	0.153	SVGTI	0.384	0.085	SAVINGSL	0.354	0.067	PERMIT1	0.283	0.073
	0.5	SPREAD3M	0.998	0.487	NAPMNOI	0.678	0.286	SAVINGSL	0.461	0.093	M2SL	0.29	0.058	PCES	0.276	0.049
	0.7	SPREAD3M	0.838	0.416	PCES	0.543	0.135	SVGTI	0.418	0.106	PERMITMW	0.402	0.084	SVSTSL	0.393	0.098
	0.9	SVGTI	0.527	0.131	SVSTSL	0.486	0.137	SPREAD6M	0.276	0.067	SPREAD1Y	0.276	0.105	PERMIT24	0.249	0.041
6	0.1	PPICPE	0.92	-0.387	SPREAD3M	0.518	0.284	CPIMEDSL	0.489	-0.105	NAPMNOI	0.374	0.144	SVGTI	0.372	0.081
	0.3	SPREAD3M	0.991	0.337	NAPMNOI	0.776	0.277	PPICPE	0.539	-0.113	SVGTI	0.473	0.112	SPREAD6M	0.406	0.087
	0.5	SPREAD6M	0.781	0.271	NAPMNOI	0.66	0.239	SAVINGSL	0.47	0.133	SPREAD3M	0.443	0.218	PERMIT1	0.363	0.101
	0.7	SPREAD6M	0.637	0.31	SVSTSL	0.457	0.131	PERMITMW	0.447	0.126	SAVINGSL	0.434	0.136	NAPMNOI	0.384	0.091
	0.9	SVSTSL	0.591	0.167	SPREAD6M	0.582	0.203	SVGTI	0.578	0.199	IPDCONGD	0.4	0.065	SAVINGSL	0.297	0.106
12	0.1	SPREAD6M	0.628	0.258	NAPMPI	0.623	0.279	PERMITMW	0.584	0.239	SPREADAAA	0.539	0.219	SPREAD3M	0.486	0.261
	0.3	PERMITMW	0.811	0.279	SPREAD6M	0.74	0.24	NAPMNOI	0.726	0.328	SPREAD3M	0.653	0.231	PPIITM	0.562	-0.119
	0.5	SPREAD6M	0.813	0.333	PERMITMW	0.655	0.179	PPIITM	0.591	-0.12	SPREADAAA	0.518	0.241	SVSTSL	0.441	0.145
	0.7	SPREAD6M	0.696	0.322	SVSTSL	0.443	0.133	SAVINGSL	0.416	0.127	SPREAD10Y	0.416	0.2	HOUSTMW	0.386	0.066
	0.9	SVGTI	0.674	0.238	SVSTSL	0.587	0.136	CONSUMER	0.55	0.1	SPREAD6M	0.491	0.212	USGOVT	0.235	0.043
								Rolling								
3	0.1	PPICPE	0.322	-0.139	SPREAD3M	0.279	0.151	CPILFESL	0.196	-0.05	CPIMEDSL	0.196	-0.063	UEMPMEAN	0.139	0.031
	0.3	SPREAD3M	0.381	0.232	HSN1F	0.308	0.136	SVGTI	0.178	0.049	CPIMEDSL	0.16	-0.051	SPREADBAA	0.114	0.027
	0.5	SPREAD3M	0.397	0.25	SVGTI	0.267	0.088	SVSTCBSL	0.123	0.037	NAPMPRI	0.103	-0.016	HSN1F	0.094	0.066
	0.7	SPREAD3M	0.308	0.162	SVGTI	0.228	0.083	HSN1F	0.221	0.11	AWOTMAN	0.18	0.048	SAVINGSL	0.139	0.037
	0.9	AWOTMAN	0.205	0.053	SVGTI	0.155	0.052	SPREAD3M	0.146	0.069	HSN1F	0.116	0.033	CPIMEDSL	0.11	-0.025
6	0.1	CPIMEDSL	0.388	-0.149	PPICPE	0.326	-0.153	SPREAD3M	0.301	0.258	SPREADBAA	0.155	0.058	HSN1F	0.1	0.044
	0.3	CPIMEDSL	0.4	-0.148	SVGTI	0.381	0.096	HSN1F	0.342	0.203	SPREAD3M	0.324	0.172	NAPMPRI	0.203	-0.072
	0.5	HSN1F	0.452	0.275	SVGTI	0.349	0.101	NAPMPRI	0.285	-0.105	SPREAD3M	0.285	0.123	SPREAD6M	0.217	0.102
	0.7	HSN1F	0.267	0.151	SVGCBSL	0.178	0.046	SVSTSL	0.171	0.043	NAPMPRI	0.169	-0.072	SVGTI	0.167	0.054
	0.9	SVSTSL	0.288	0.061	SVGTI	0.158	0.055	SAVINGSL	0.151	0.046	SPREAD6M	0.126	0.061	NAPMPRI	0.11	-0.04
12	0.1	SPREADBAA	0.247	0.132	SPREAD6M	0.231	0.109	CPIMEDSL	0.228	-0.08	PERMIT1	0.18	0.164	SPREADAAA	0.18	0.134
	0.3	NAPMPRI	0.39	-0.209	SPREADAAA	0.363	0.278	HSN1F	0.317	0.135	CPIMEDSL	0.279	-0.075	SPREAD3M	0.187	0.051
	0.5	NAPMPRI	0.411	-0.186	SPREADAAA	0.324	0.274	HSN1F	0.251	0.13	SPREAD6M	0.201	0.1	HOUST1F	0.192	0.072
	0.7	NAPMPRI	0.406	-0.136	SPREADAAA	0.192	0.151	USFIRE	0.189	0.054	SPREAD10Y	0.171	0.13	SAVINGSL	0.151	0.049
	0.9	SPREAD10Y	0.171	0.161	SVGTI	0.153	0.046	UEMPMEAN	0.114	0.033	HSN1FMW	0.096	0.08	USFIRE	0.096	0.018

Top 5 variables selected by LASSO at quantiles $\tau = 0.1, 0.3, 0.5, 0.7$, and 0.9 and for each forecast horizon h considered. The indicators are denoted by their FRED series ID and more details can be found in the Appendix and on the FRED website. The columns next to the variable ID report the frequency of selection in the out-of-sample period (438 months) and the average value of the parameter in the months in which the variable was selected (in interpreting the coefficients notice that the RHS variables have been standardize to have mean zero and variance one). The value of c is set to 2.

Table 4: **CPIAUCSL & PCEPILFE - LASSO Variable Selection**

h	τ	1^{st}			2^{nd}			3^{rd}			4^{th}			5^{th}		
CPIAUCSL								*Recursive*								
3	0.1	NAPMEI	0.767	0.344	FEDFUNDS	0.66	0.127	SPREADPRIME	0.457	-0.18	PERMIT1	0.452	0.154	CREDIT	0.269	-0.119
	0.3	NAPMEI	1	0.446	SPREADPRIME	0.699	-0.187	USFIRE	0.482	0.148	PPIITM	0.436	0.186	PPICRM	0.418	0.131
	0.5	NAPMEI	0.979	0.541	SPREADPRIME	0.571	-0.141	PPIITM	0.559	0.289	USFIRE	0.393	0.093	PERMIT1	0.283	0.107
	0.7	NAPMEI	0.603	0.269	NAPMSDI	0.425	0.13	SPREADPRIME	0.393	-0.094	SPREAD5Y	0.331	-0.11	NONREVSL	0.249	0.059
	0.9	PPIFCF	0.502	0.112	PERMITW	0.5	0.129	PPICRM	0.322	0.072	CPIUFDSL	0.208	0.054	M1SL	0.205	0.04
6	0.1	NAPMEI	0.767	0.252	SPREADPRIME	0.438	-0.154	PERMIT1	0.427	0.172	PERMITMW	0.416	0.088	FEDFUNDS	0.397	0.078
	0.3	FEDFUNDS	0.966	0.188	NAPMEI	0.838	0.212	SPREADPRIME	0.758	-0.23	M1SL	0.687	0.15	NAPMSDI	0.575	0.112
	0.5	NAPMEI	0.811	0.2	SPREADPRIME	0.779	-0.271	FEDFUNDS	0.614	0.127	PERMIT1	0.573	0.305	BOGAMBSL	0.55	0.109
	0.7	M1SL	0.669	0.163	HOUSTMW	0.642	0.134	NAPMEI	0.635	0.166	SPREADPRIME	0.482	-0.137	PERMIT1	0.47	0.205
	0.9	PERMIT	0.667	0.386	SPREAD5Y	0.39	-0.139	SPREADPRIME	0.331	-0.134	PERMITS	0.299	0.145	REALLN	0.203	0.047
12	0.1	NAPMEI	0.918	0.315	HOUSTMW	0.539	0.12	PERMITMW	0.395	0.083	PERMIT1	0.377	0.111	NAPM	0.301	0.09
	0.3	NAPMSDI	0.813	0.216	NAPMEI	0.808	0.245	PERMITMW	0.655	0.195	PERMIT1	0.582	0.372	SPREADPRIME	0.562	-0.149
	0.5	NAPMEI	0.792	0.29	PERMITMW	0.751	0.244	M1SL	0.658	0.148	USFIRE	0.648	0.142	PERMIT1	0.637	0.461
	0.7	NAPMEI	0.975	0.336	NAPMSDI	0.756	0.258	M1SL	0.724	0.172	PERMIT1	0.628	0.432	PERMITMW	0.596	0.187
	0.9	NAPMSDI	0.61	0.286	PERMITS	0.564	0.336	USFIRE	0.432	0.127	PERMITMW	0.422	0.147	PERMIT1	0.413	0.22
								Rolling								
3	0.1	USWTRADE	0.265	0.113	FEDFUNDS	0.185	0.071	SPREADPRIME	0.185	-0.131	NAPMEI	0.164	0.086	MANEMP	0.155	0.047
	0.3	NAPMEI	0.379	0.234	SPREADPRIME	0.301	-0.144	USFIRE	0.196	0.026	OILPRICE	0.155	0.054	PPICRM	0.126	0.051
	0.5	SPREADPRIME	0.354	-0.266	OILPRICE	0.263	0.085	NAPMEI	0.167	0.188	USFIRE	0.084	-0.013	MANEMP	0.043	0.02
	0.7	SPREADPRIME	0.242	-0.155	NAPMEI	0.155	0.121	NAPMSDI	0.068	0.038	SPREADBAA	0.066	-0.073	RMFSL	0.05	0.069
	0.9	SPREADPRIME	0.148	-0.091	NAPMSDI	0.068	0.017	BUSLOANS	0.05	0.025	PERMITW	0.041	0.018	NAPMEI	0.037	0.015
6	0.1	NAPMEI	0.324	0.176	SPREADPRIME	0.135	-0.084	PERMITMW	0.128	0.035	FEDFUNDS	0.123	0.032	USTRADE	0.098	0.022
	0.3	SPREADPRIME	0.395	-0.184	NAPMEI	0.393	0.175	FEDFUNDS	0.26	0.085	NAPMSDI	0.18	0.11	HSN1FW	0.155	0.141
	0.5	NAPMEI	0.363	0.192	SPREADPRIME	0.345	-0.183	FEDFUNDS	0.281	0.081	HOUSTMW	0.128	0.035	HSN1FW	0.121	0.101
	0.7	SPREADPRIME	0.279	-0.16	NAPMEI	0.272	0.156	HOUSTMW	0.146	0.036	M1SL	0.11	0.032	PERMIT1	0.094	0.043
	0.9	PERMITS	0.174	0.086	SPREADPRIME	0.126	-0.071	BUSLOANS	0.112	0.033	RMFSL	0.084	0.066	HSN1F	0.062	0.045
12	0.1	NAPMEI	0.281	0.155	OTHSEC	0.146	-0.029	NAPMNOI	0.098	0.036	NAPM	0.091	0.031	HSN1FS	0.078	-0.015
	0.3	NAPMEI	0.402	0.207	PERMIT1	0.295	0.204	SPREADPRIME	0.269	-0.099	USFIRE	0.24	-0.013	NAPMPRI	0.212	0.092
	0.5	PERMIT1	0.39	0.324	NAPMEI	0.34	0.199	SPREADPRIME	0.283	-0.112	USFIRE	0.187	-0.027	HSN1FW	0.169	0.134
	0.7	PERMIT1	0.425	0.349	NAPMEI	0.347	0.219	SPREADPRIME	0.242	-0.108	PERMITS	0.196	0.114	HSN1FW	0.116	0.049
	0.9	PERMIT1	0.192	0.116	PERMITS	0.171	0.111	HSN1FW	0.137	0.144	SPREADPRIME	0.121	-0.05	HSN1F	0.105	0.066
PCEPILFE								*Recursive*								
3	0.1	NAPMPRI	0.372	0.072	UEMPMEAN	0.205	-0.052	SPREADBAA	0.066	-0.018	USWTRADE	0.057	0.013	PPIFCG	0.025	0.004
	0.3	USFIRE	0.701	0.109	NAPMPRI	0.491	0.12	SPREADPRIME	0.425	-0.06	SVGTI	0.046	-0.009	CPIUFDSL	0.03	0.004
	0.5	NAPMPRI	0.644	0.138	CPIUFDSL	0.47	0.063	PPIITM	0.313	0.072	SPREADPRIME	0.046	-0.012	PFCGEF	0.043	0.012
	0.7	PPIITM	0.847	0.219	CPIUFDSL	0.648	0.098	NAPMSDI	0.311	0.037	NAPMPRI	0.256	0.058	PFCGEF	0.066	0.023
	0.9	NAPMSDI	0.872	0.196	PPIITM	0.678	0.144	PFCGEF	0.639	0.193	CPIAUCSL	0.619	0.126	CPIUFDSL	0.514	0.074
6	0.1	NAPMSDI	0.217	0.046	USINFO	0.203	0.029	SPREADBAA	0.144	-0.026	NAPMPRI	0.137	0.022	BOGAMBSL	0.046	0.006
	0.3	USFIRE	0.897	0.161	NAPMPRI	0.621	0.163	NAPMSDI	0.502	0.087	PERMITMW	0.064	0.016	M1SL	0.062	0.01
	0.5	NAPMPRI	0.911	0.232	USFIRE	0.55	0.084	PPIITM	0.285	0.074	CPIUFDSL	0.194	0.028	M1SL	0.053	0.007
	0.7	NAPMSDI	0.993	0.184	PPIITM	0.938	0.218	CPIUFDSL	0.482	0.075	UEMPMEAN	0.324	-0.051	NAPMPRI	0.281	0.063
	0.9	NAPMSDI	0.902	0.232	PPIITM	0.822	0.164	UEMPMEAN	0.553	-0.148	SPREAD10Y	0.445	-0.101	NAPMPRI	0.436	0.144
12	0.1	NAPMSDI	0.452	0.081	NAPMPRI	0.269	0.048	SVGTI	0.121	-0.032	SVSTSL	0.096	-0.028	SPREADBAA	0.084	-0.025
	0.3	NAPMSDI	0.774	0.185	USFIRE	0.651	0.128	UEMPMEAN	0.578	-0.092	REALLN	0.338	0.072	NAPMPRI	0.308	0.09
	0.5	NAPMSDI	0.829	0.266	USFIRE	0.594	0.085	UEMPMEAN	0.527	-0.103	NAPMPRI	0.45	0.175	REALLN	0.427	0.085
	0.7	NAPMSDI	0.984	0.396	PPIITM	0.605	0.127	UEMPMEAN	0.53	-0.134	NAPMPRI	0.45	0.162	USFIRE	0.361	0.056
	0.9	NAPMSDI	0.925	0.379	NAPMPRI	0.884	0.273	UEMPMEAN	0.626	-0.179	SPREAD3Y	0.571	-0.138	SPREAD5Y	0.32	-0.075
								Rolling								
3	0.1	SPREADBAA	0.023	-0.006	PFCGEF	0.021	0.009	HSN1FS	0.018	0.005	CPIENGSL	0.014	0.005	UEMP27OV	0.014	-0.002
	0.3	SVGTI	0.105	-0.017	SPREADBAA	0.103	-0.035	PERMITNE	0.078	0.012	USFIRE	0.046	0.01	HOUSTNE	0.041	0.008
	0.5	CPIUFDSL	0.135	0.031	SPREADBAA	0.098	-0.028	PPIITM	0.078	0.028	NAPMPRI	0.073	0.015	SVGTI	0.064	-0.011
	0.7	PFCGEF	0.244	0.095	PPIITM	0.233	0.066	NAPMPRI	0.137	0.036	NAPMNOI	0.112	0.019	CPIAUCSL	0.068	0.02
	0.9	PFCGEF	0.315	0.147	PPIITM	0.274	0.077	NAPMPRI	0.103	0.034	TWEXOMTH	0.08	0.034	CPIUFDSL	0.075	0.019
6	0.1	SVSTSL	0.05	-0.007	NAPMPRI	0.034	0.01	UEMP15OV	0.032	-0.007	PERMIT5	0.025	0.006	USFIRE	0.025	0.007
	0.3	USFIRE	0.155	0.026	SPREADBAA	0.13	-0.028	PERMITNE	0.114	0.022	NAPMPRI	0.094	0.034	CPIUFDSL	0.084	0.019
	0.5	NAPMPRI	0.167	0.048	HOUSTNE	0.13	0.023	UEMPMEAN	0.11	-0.021	PPIITM	0.096	0.026	NAPMSDI	0.094	0.026
	0.7	PPIITM	0.221	0.061	NAPMPRI	0.212	0.058	PFCGEF	0.189	0.079	NAPMSDI	0.174	0.056	PERMITNE	0.148	0.026
	0.9	PFCGEF	0.306	0.147	PPIITM	0.263	0.067	NAPMPRI	0.199	0.065	UEMP5TO14	0.187	-0.054	NAPMSDI	0.155	0.048
12	0.1	UEMP15OV	0.153	-0.038	SVGTI	0.105	-0.028	SVSTSL	0.098	-0.007	SPREADBAA	0.059	-0.018	NAPMPRI	0.048	0.011
	0.3	NAPMPRI	0.249	0.102	PERMITNE	0.169	0.022	UEMP15OV	0.148	-0.036	UEMPMEAN	0.128	-0.048	HSN1F	0.114	0.027
	0.5	NAPMPRI	0.322	0.135	UEMPMEAN	0.189	-0.053	NAPMSDI	0.148	0.076	PERMITNE	0.132	0.025	UEMP15OV	0.11	-0.029
	0.7	NAPMPRI	0.4	0.155	NAPMSDI	0.21	0.109	CPIENGSL	0.208	0.063	UEMP5TO14	0.176	-0.042	PFCGEF	0.174	0.036
	0.9	NAPMPRI	0.308	0.134	NAPMSDI	0.208	0.094	UEMP5TO14	0.203	-0.056	SPREAD3M	0.1	-0.04	SPREAD5Y	0.1	-0.03

Top 5 variables selected by LASSO at quantiles $\tau = 0.1, 0.3, 0.5, 0.7$, and 0.9 and for each forecast horizon h considered. The indicators are denoted by their FRED series ID and more details can be found in the Appendix and on the FRED website. The columns next to the variable ID report the frequency of selection in the out-of-sample period (438 months) and the average value of the parameter in the months in which the variable was selected (in interpreting the coefficients notice that the RHS variables have been standardize to have mean zero and variance one). The value of c is set to 2.

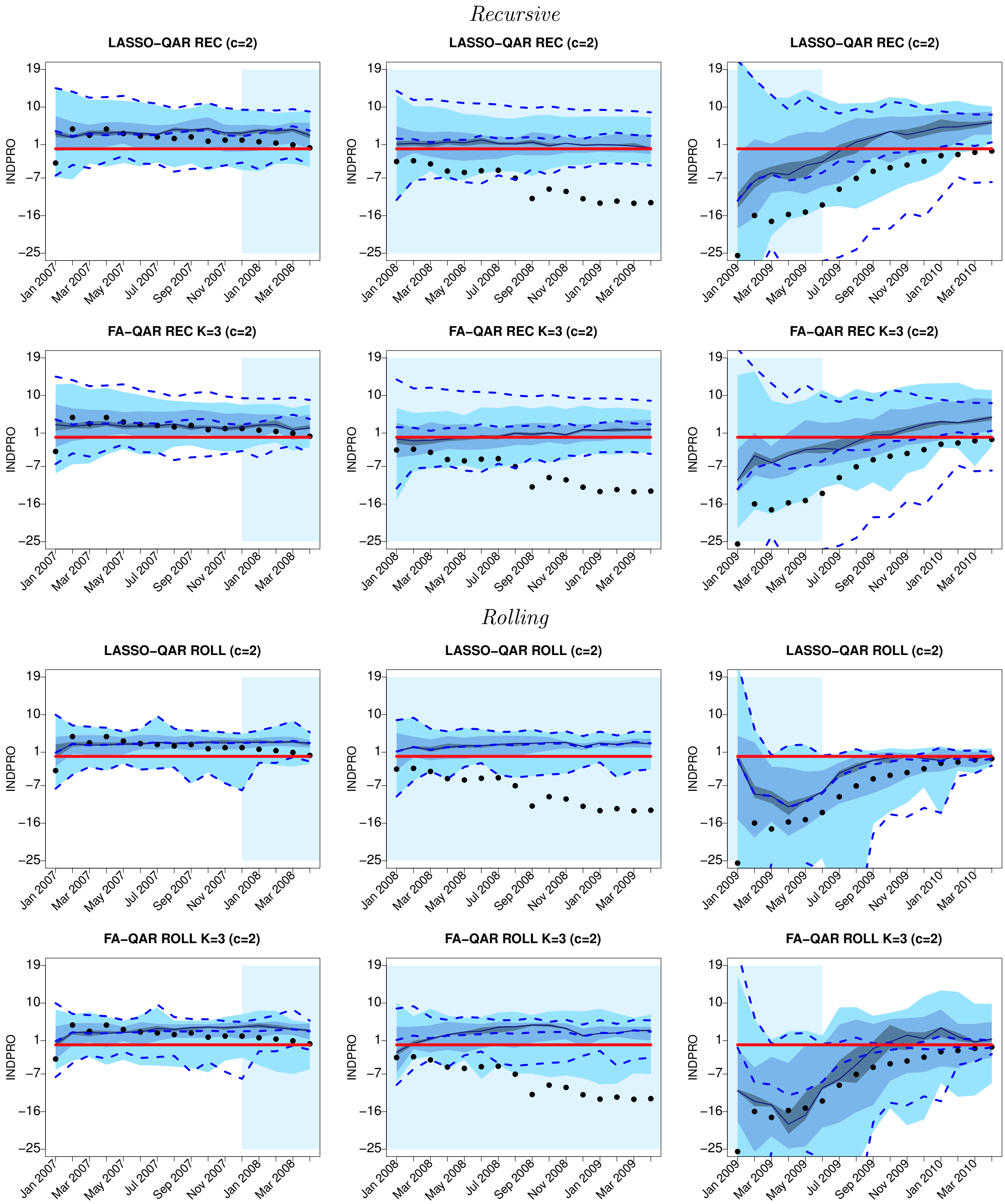

Figure 1: Quantile forecasts for the h-month ($h = 1, \cdots, 16$) growth of INDPRO made at the end of January 2007 (left column), January 2008 (center column), and January 2009 (right column). To save space, we report the quantile forecasts for only four models: LASSO-QAR REC (first row), LASSO-QAR ROLL (second row), FA-QAR REC (third row), and FA-QAR ROLL (last row) where for both factor models we used $K = 3$. The predictive quantiles reported are for $\tau = 0.05, 0.25, 0.45, 0.55, 0.75, 0.95$. The dashed lines denote the forecasts of the QAR model estimated recursively or rolling based on the model they are compared to, and the dots denote the realization of the variable. The shaded area starting in December 2007 denotes the start of the recession as determined by the NBER Business Cycle Dating Committee.

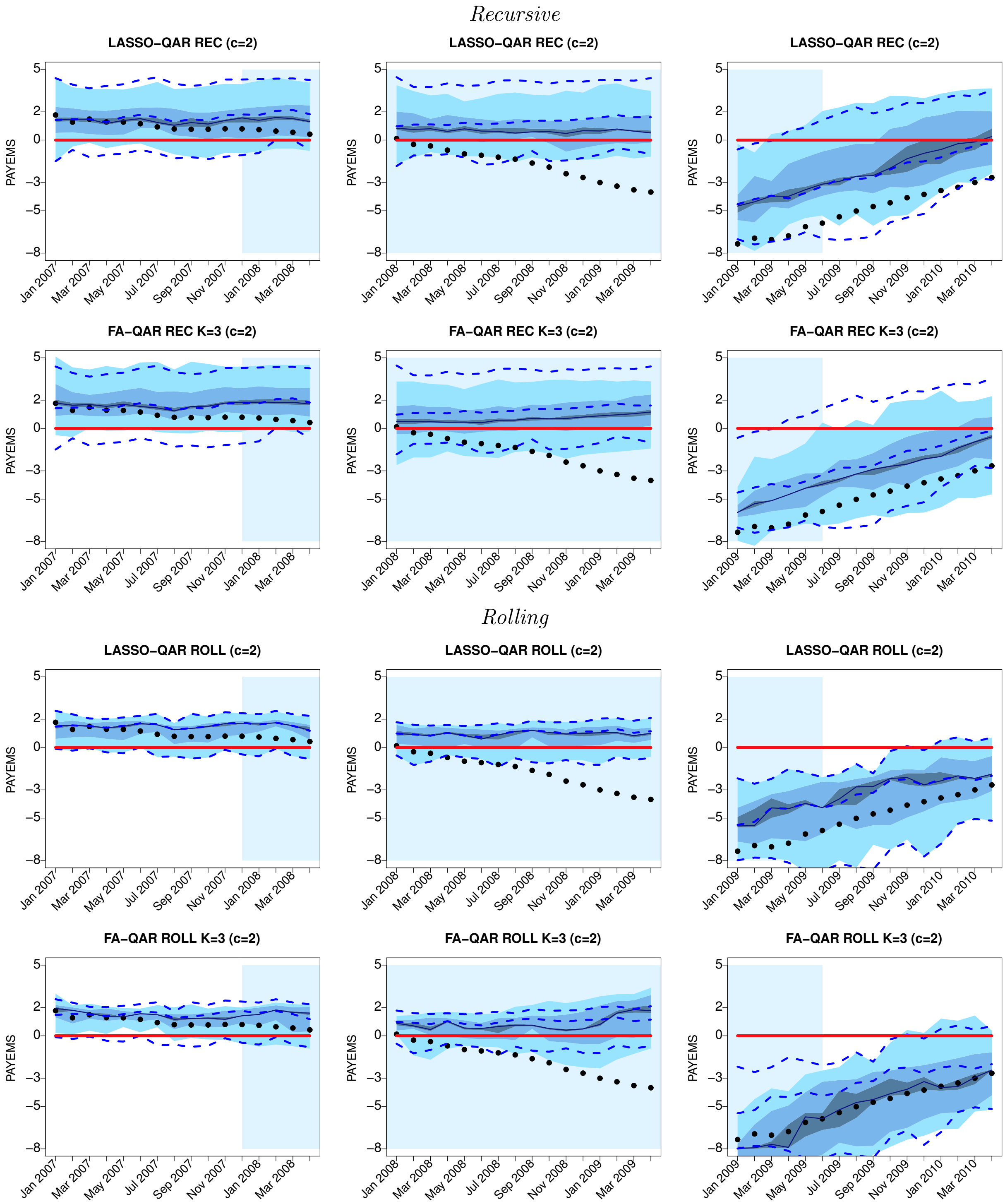

Figure 2: Quantile forecasts for the h-month ($h = 1, \cdots, 16$) growth of PAYEMS made at the end of January 2007 (left column), January 2008 (center column), and January 2009 (right column). To save space, we report the quantile forecasts for only four models: LASSO-QAR REC (first row), LASSO-QAR ROLL (second row), FA-QAR REC (third row), and FA-QAR ROLL (last row) where for both factor models we used $K = 3$. The predictive quantiles reported are for $\tau = 0.05, 0.25, 0.45, 0.55, 0.75, 0.95$. The dashed lines denote the forecasts of the QAR model estimated recursively or rolling based on the model they are compared to, and the dots denote the realization of the variable. The shaded area starting in December 2007 denotes the start of the recession as determined by the NBER Business Cycle Dating Committee.

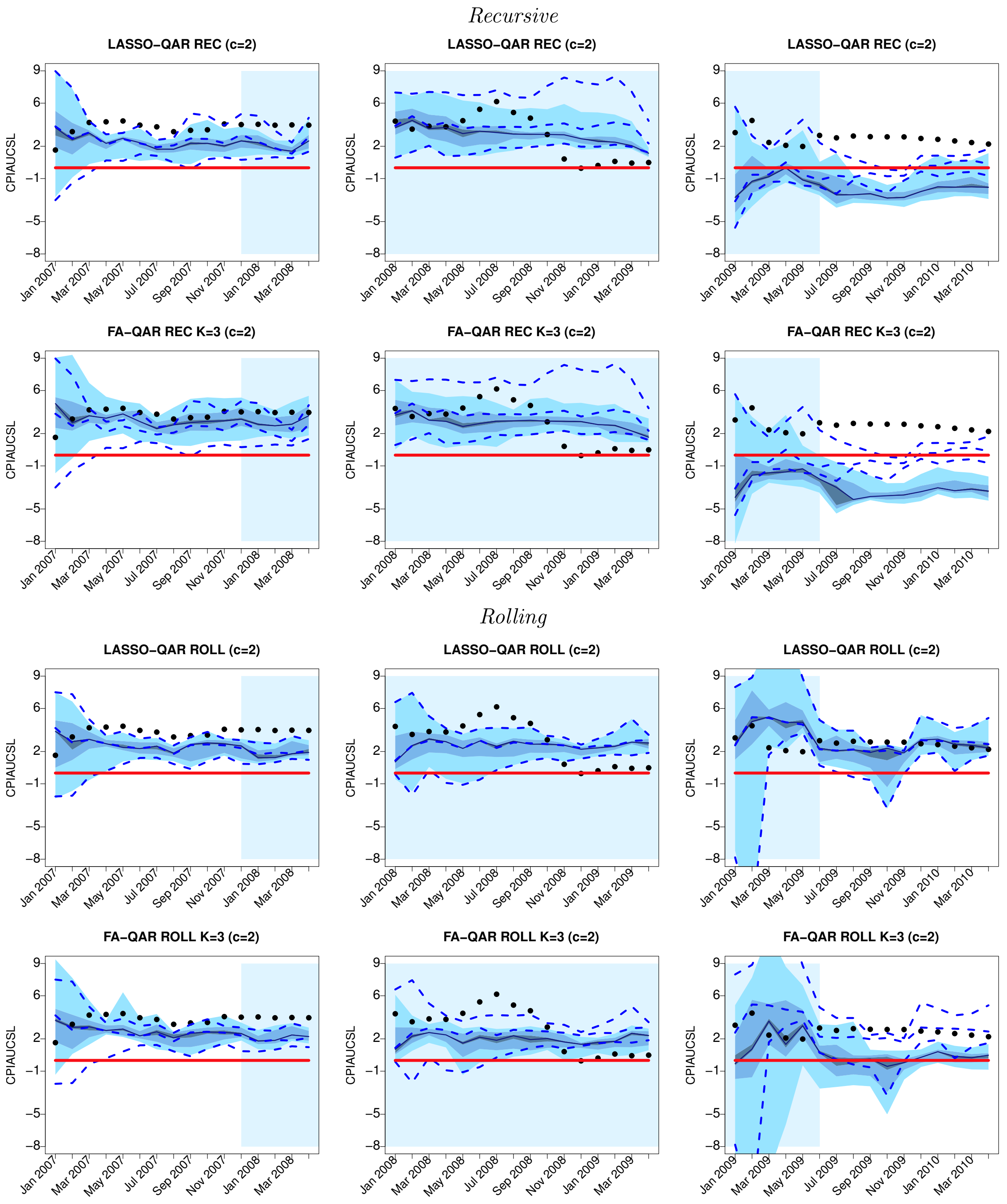

Figure 3: Quantile forecasts for the h-month ($h = 1, \cdots, 16$) growth of CPIAUCSL made at the end of January 2007 (left column), January 2008 (center column), and January 2009 (right column). To save space, we report the quantile forecasts for only four models: LASSO-QAR REC (first row), LASSO-QAR ROLL (second row), FA-QAR REC (third row), and FA-QAR ROLL (last row) where for both factor models we used $K = 3$. The predictive quantiles reported are for $\tau = 0.05, 0.25, 0.45, 0.55, 0.75, 0.95$. The dashed lines denote the forecasts of the QAR model estimated recursively or rolling based on the model they are compared to, and the dots denote the realization of the variable. The shaded area starting in December 2007 denotes the start of the recession as determined by the NBER Business Cycle Dating Committee.

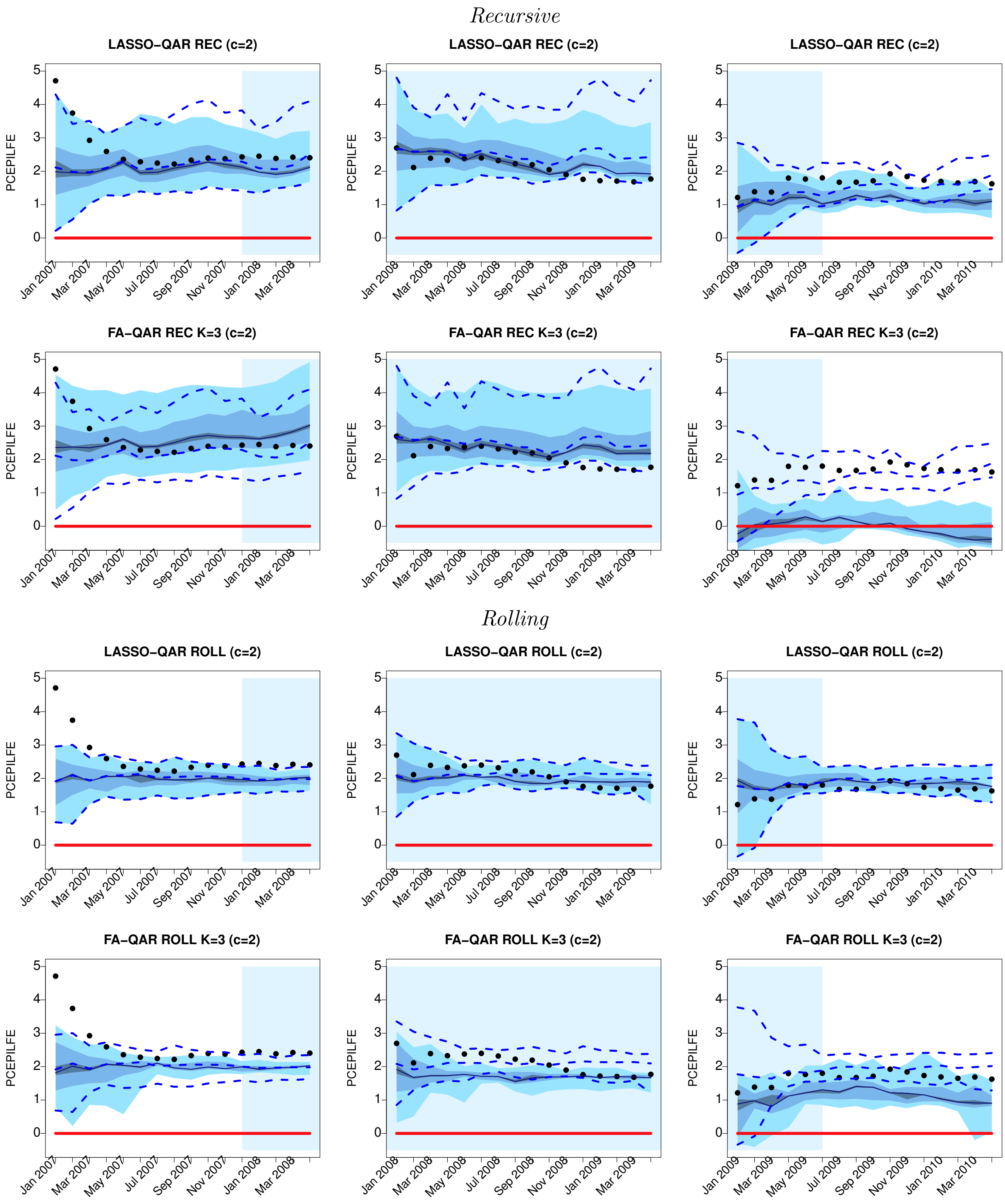

Figure 4: Quantile forecasts for the h-month ($h = 1, \cdots, 16$) growth of PCEPILFE made at the end of January 2007 (left column), January 2008 (center column), and January 2009 (right column). To save space, we report the quantile forecasts for only four models: LASSO-QAR REC (first row), LASSO-QAR ROLL (second row), FA-QAR REC (third row), and FA-QAR ROLL (last row) where for both factor models we used $K = 3$. The predictive quantiles reported are for $\tau = 0.05, 0.25, 0.45, 0.55, 0.75, 0.95$. The dashed lines denote the forecasts of the QAR model estimated recursively or rolling based on the model they are compared to, and the dots denote the realization of the variable. The shaded area starting in December 2007 denotes the start of the recession as determined by the NBER Business Cycle Dating Committee.