FORECASTING INFLATION IN A DATA-RICH ENVIRONMENT: THE BENEFITS OF MACHINE LEARNING METHODS

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Abstract: In this paper we used several Machine Learning (ML) methods to forecast US inflation in a data-rich environments. We show that ML models are more accurate than the benchmarks for several forecasting horizons both in the 1990s and the 2000s. The ML method that deserves more attention is the Random Forest, which dominated all other models in several cases. The good performance of the Random Forest suggests a nonlinearity between past employment measures and inflation.

1. Introduction

In this paper we use Machine Learning (ML) models to forecast US inflation during more than 20 years of out-of-sample data. Inflation forecasts were deeply studied in the past by Stock & Watson (1999*a*, 2010), Groen et al. (2013) and others. However, these articles came mostly before the ML boom and they are focused on a more restrictive set of variables or even univariate models such as the Unobserved Component Stochastic Volatility model (UCSV) proposed by Stock & Watson (1999*a*).

We compared the forecasts of a vast number of ML methods covering several families such as shrinkage models, factor models, regression trees, boosting, etc. We selected the best models by comparing their errors in the out-of-sample period and using the model confidence set (MCS) proposed by Hansen et al. (2011). Our results show that most of the ML models perform better than univariate benchmarks such as autorregressive models (AR), the UCSV and the Random Walk (RW), especially if we consider the 2001-2015 period when the US inflation was more volatile if compared to the 1990s. Even though many ML methods had good results, the Random Forest (Breiman 2001) deserves a special attention because it had the smallest errors for most of the forecasting horizons for both the Consumer Price Index (CPI) and for the Personal Consumption Expenditures (PCE) inflation measures.

We made several attempts to give an economic interpretation to the results. First, we compared the variables selected by the shrinkage models with the out-of-bag importance measure of the Random Forest. We found that for small forecasting horizons (1-5 months ahead) all models select mostly employment variables. However, for longer forecasting horizons (6-12 months ahead) the shrinkage models selects mostly lags of several inflation measures and the Random Forest selects employment measures, exchange rates and interest rates. This evidence suggests that the relation between past employment measures and inflation becomes more nonlinear as we increase the forecasting horizon. Second, it is natural to assume that the ML models will have different results if we consider expansion and recession periods separately. We obtained bigger forecasting errors in recession periods and the relative performance of the models also changed. Although the Random Forest still had a good performance in recession, it was less accurate than several other models and it was out of the MCS in several forecasting horizons. Last but not least, we estimated several regression of the forecasting errors on variables such as the NBER recession dummy, the VIX volatility index and policy uncertainty measures. The results showed that the forecasting errors are bigger on periods of recession and high market volatility.

The remainder of is organized as follows. In section 2 we define the ML models that we used. The data and the main results are discussed in sections 3 and 4. We conclude in section 5. The results discussed in the paper are for the CPI inflation. The PCE results are in the appendix.

2. Definitions, Notation and Methods

Consider the direct forecasting model

$$\pi_{t+h} = T(\boldsymbol{x}_t) + u_{t+h}, \tag{1}$$

where π_{t+h} is the inflation at month $t+h$, $\boldsymbol{x}_t = (x_{1t}, \ldots, x_{n_T t})'$ is a n_T-vector of covariates, possibly containing lags of π_t, and u_t is a martingale difference process. We are interested in estimating the target function $T(\boldsymbol{x}_t)$ when n_T is large, possibly larger than the sample size T.

2.1. Benchmark Models.

We consider as benchmarks a simple random walk (RW) model, the autoregressive (AR) model of order p, determined by the Bayesian Information Criterion (BIC); and finally, the Unobserved Component Stochastic Volatility (UC-SV) model described as:

$$\begin{aligned}
\pi_t &= \tau_t + e^{h_t/2}\varepsilon_t, \\
\tau_t &= \tau_{t-1} + u_t, \\
h_t &= h_{t-1} + v_t,
\end{aligned} \tag{2}$$

where $\{\varepsilon_t\}$ is a sequence of independent and normally distributed random variables with zero mean and unit variance, $\varepsilon_t \sim \mathsf{N}(0,1)$, u_t and v_t are also normal with zero mean and variance given by inverse-gamma priors. $\tau_1 \sim \mathsf{N}(0, V_\tau)$ and $h_1 \sim \mathsf{N}(0, V_h)$, where $V_\tau = V_h = 0.12$. The model is estimated by Markov Chain Monte Carlo (MCMC) methods. The h-steps-ahead forecast is computed as $\widehat{\pi}_{t+h} = \widehat{\tau}_{t|t}$.

2.2. **Shrinkage.** In this paper we estimate several shrinkage estimators for linear models where $T(\boldsymbol{x}_t) = \boldsymbol{\beta}'\boldsymbol{x}_t$ and

$$\widehat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \left[\sum_{t=1}^{T-h} \left(y_{t+h} - \boldsymbol{\beta}'\boldsymbol{x}_t\right)^2 + \lambda \sum_{i=1}^{n} p(\beta_i;\omega_i) \right], \tag{3}$$

$p(\beta_i;\omega_i)$ is a penalty function which depends on the penalty parameter λ and on a weight $\omega_i > 0$. We consider different choices for the penalty functions as described bellow.

2.2.1. *Ridge Regression (RR):.* The Ridge regression was one of the first methods capable of dealing with a very large set of variables in a multiple regression (Hoerl & Kennard 1970*b*,*a*). It uses the quadratic or ℓ^2 penalty in the right term of equation (3).

$$\lambda \sum_{i=1}^{n} p(\beta_i;\omega_i) := \lambda \sum_{i=1}^{n} \beta_i^2; \tag{4}$$

The Ridge Regression has the advantage of having an analytic solution that is easy to compute and is also shrinks less relevant variables to zero. However, given the geometric shape of the penalty the coefficients hardly get to exactly zero for any size of λ.

2.2.2. *Least Absolute Shrinkage and Selection Operator (LASSO):.* The LASSO was originally proposed by Tibshirani (1996). It is similar to the Ridge regression but it penalizes the ℓ_1 norm of the coefficients or the sum of their absolute value.

$$\lambda \sum_{i=1}^{n} p(\beta_i;\omega_i) := \lambda \sum_{i=1}^{n} |\beta_i|; \tag{5}$$

The LASSO shrinks the irrelevant variables to zero and it has some good properties both on variable selection and goodness of fit. In order to have variable selection consistency the LASSO requires the irrepresentable condition[1] (IRC) to be satisfied (Zhao & Yu 2006). However, even if the IRC is not satisfied the LASSO still have the variable screening property, i. e. it selects the relevant variables with high-probability but it may also select some extra variables.

2.2.3. *Adaptive Least Absolute Shrinkage and Selection Operator (adaLASSO):.* The adaLASSO solves the variable selection problems of the LASSO. It was proposed by Zou (2006) who showed that the inclusion of some additional information regarding the importance of each variable could considerably improve the results. The adaLASSO does not need the IRC to have variable selection consistency and is also have oracle properties, i. e. it not only selects the correct set of variables with high-probability, but the coefficients distribution of these variables is the same as the OLS estimation using only these variables. The adaLASSO uses the same penalty as the LASSO with the inclusion of a weighting parameter that come from a first step model that can be the LASSO or even OLS.

$$\lambda \sum_{i=1}^{n} p(\beta_i; \omega_i) := \lambda \sum_{i=1}^{n} \omega_i |\beta_i|; \tag{6}$$

where $\omega_i = |\beta_i^*|^{-1}$ and β_i^* are the coefficients from the first step model. Last bu not least, the LASSO has some good properties for high-dimension. It can deal with much more variables than observation and it works well in non-Gaussian environments and under heteroskedacity (Medeiros & Mendes 2016).

2.2.4. *Elastic Net (ElNet).* The Elastic Net is a generalization that includes the LASSO and the Ridge as special cases. It is a convex combination of the ℓ_1 and the ℓ_2 norms (Zou & Hastie 2005). The Elastic Net also does regularization and it also selects the most relevant variables. Since its penalty is between that of the LASSO and the Ridge, it normally selects more variables than the LASSO, at least for the same value of λ. The ElNet penalty is define

[1]The irrepresentable condition imposes some restrictions on the correlation structure between the relevant and the irrelevant variables. In other words, the correlation between the two groups is bounded and must be small.

as:

$$\lambda \sum_{i=1}^{n} p(\beta_i; \omega_i) := \alpha\lambda \sum_{i=1}^{n} \beta_i^2 + (1-\alpha)\lambda \sum_{i=1}^{n} |\beta_i|; \tag{7}$$

where $\alpha \in [0, 1]$. We also used an adaptive version of the Elastic Net. It works in the same way as the adaptive LASSO, i. e. we estimate a first step model and use it to calculate the weights ω_i.

2.3. **Factor Models.** Factor models using principal components are a very popular approach to avoid the curse of dimensionality when the number of predictions is potentially large. The idea is to extract common components from all variables, thus reducing the model dimension.

Consider equation (1). When the number of candidate predictors q is large, potentially larger than the sample size T, ordinary least squares (OLS) is either infeasible or have a very large variance. One solution to circumvent this drawback is to use factors as predictors instead of $\boldsymbol{x}_t$. The factors can be observed as in Fama & French (1993, 1996) or unobserved as in Bernanke et al. (2005) and Han (2015). Our focus are on unobserved factors. Consider the following forecasting model:

$$\pi_{t+h} = \sum_{i=1}^{p} \boldsymbol{\gamma}_i' \boldsymbol{f}_{t-i} + u_{t+h}, \tag{8}$$

where, $\boldsymbol{f}_t$ is a vector of k of common factors extracted from $\boldsymbol{x_t}$ and k is much smaller than q. Note that $\boldsymbol{f}_t$ is not observed and must be estimated by principal components. The assumptions and the theory behind factor models and when can we treat factors as observed variables can be found in Bai & Ng (2002, 2006, 2008).

In order to improve the forecasting performance of factor models, Bai & Ng (2008) proposed targeting the predictors. The idea is that if many variables in $\boldsymbol{x}_t$ are irrelevant predictors of π_{t+h}, factor analysis using all variables may result in noisy factors with poor forecasting ability. The target factors are regular factor models with a pre-testing procedure to select only relevant variables to be in included in the factor analysis. We show the steps of this procedure pointing out where our methodology differs from that proposed by Bai &

Ng (2008). Let $x_{i,t}$, $i = 1, \ldots, q$, be the candidate variables and $\boldsymbol{w}_t$ a set of fixed regressors that will be used as controls in the pre-testing. We follow Bai & Ng (2008) and use $\boldsymbol{w}_t$ as AR terms of π_t. The procedure is described as follows.

(1) For $i = 1, \ldots, q$, regress π_{t+h} on $\boldsymbol{w}_t$ and $x_{i,t}$ and compute the t-statistics for the coefficient corresponding to $x_{i,t}$. We include four lags of each candidate variable in the pre-testing. Bai & Ng (2008) uses only the variables in t and select the lags latter.

(2) Sort all t-statistics calculated in Step 1 in descending order.

(3) Choose a significance level α, and select all variables which are significant using the computed t-statistics.

(4) Let $\boldsymbol{x}_t(\alpha)$ be the selected variables from Steps 1–3. Estimate the factors $\boldsymbol{F}_t$ from $\boldsymbol{x}_t(\alpha)$ by principal components.

(5) Regress π_{t+h} on $\boldsymbol{w}_t$ and $\boldsymbol{f}_t \subset \boldsymbol{F}_t$. The number of factor in $\boldsymbol{f}_t$ is selected using the BIC. Bai & Ng (2008) selected also the number of lagged factors using the BIC. However, since we use lagged variables as regressors in the pre-testing, we did not use lagged factors.

The same procedure was used by Medeiros & Vasconcelos (2016). The authors showed that, in most cases, target factors slightly reduce the forecasting errors compared to factor models without targeting.

2.4. **Complete Subset Regressions.** The Complete Subset Regression (CSR) was developed by Elliott et al. (2013, 2015). The motivation is that selecting the optimal subset of $\boldsymbol{x}_t$ to predict π_{t+h} by testing all possible combinations of regressors is computationally very demanding and in most of the times even unfeasible. Suppose that we have q candidate variables, the CSR selects a number $n \leq q$ and computes all combinations of regressions using only n variables. The forecast of the model will be the average forecast of all regressions in the subset.

The CSR deals well with a small number of candidate variables. However, for large sets the number of regressions to be estimated increases very fast. For example, with $q = 25$ and

$n = 4$ we need to estimate $12,650$ regressions. As the number of candidate variables is much larger, we adopt a pre-testing procedure similar to the one used with the target factors. We start fitting a linear regression of π_{t+h} on each of the candidate variables (including lags) and saving the t-statistics of each variable[2]. The t-statistics are ranked in absolute value and we select the $\tilde{q}$ variables which are more relevant on the ranking. The CSR forecast is calculated on these variables. We used $\tilde{q} = 25$ and $n = 4$.

2.5. **Bagging.** The name Bagging comes from bootstrap aggregating, which was proposed in our context by Breiman (1996). The idea is to combine forecasts from several unstable models making use of this instability. Normally, there is much more to gain from combinations of models if they are very different. The first source of instability is generated by re-estimating the model using bootstrap samples and the second source comes from a pre-testing prior to the estimation, which for each bootstrap sample selects a subset of variables bases on significance. The Bagging steps are as follows:

- For each bootsrap sample b, run a regression with all candidate variables and select those with $|t| \geq k$,
- Estimate a new regression only with the variables selected in the previous step,
- The coefficients from the second regression are finally used to compute the forecasts **on the real sample**.
- Repeat the first three steps for B boostrap samples compute the final forecast as the average of the B forecasts.

We used $B = 100$. Note that in our case the number of observations may be smaller than the number of variables, which makes the regression in the first step infeasible. We solve the issue by introducing a new source of instability in the pre-testing. Instead of doing a single pre-testing, we randomly divided all variables in groups and did the pre-testing on each group.

[2]We did not use a fixed set of controls, $\boldsymbol{w}_t$, in the pre-testing like we did on the target factors.

2.6. **Boosting.** There are several variation of boosting algorithms. We are going to use the factor boosting proposed by Bai & Ng (2008), which has good results for time-series and it is fast to compute because we use factors instead of all variables. The authors also proposed an information criterion that corrects the degrees of freedom of the model and can also be used to know when to stop the algorithm. The algorithm is define as follows:

(1) Let $\Phi_{t,0} = \bar{y}$ for each t
(2) for $m = 1, \ldots, M$:
   - Compute $\hat{u}_t = y_t - \Phi_{t,m-1}$, defined as the current residuals,
   - for each candidate variable $i = 1, \ldots, n$ regress the current residual on $x_{i,t}$ to obtain $\hat{b}_i$ and compute $\hat{e_{t,i}} = \hat{u}_t - x_{i,t}\hat{b}_i$. Calculate $SSR_i = \hat{e}_i'\hat{e}_i$,
   - Select i^*_m as the smallest SSR and define $\hat{\phi}_{m,t} = x_{i^*_m,t}\hat{b}_{i^*_m}$,
   - Update $\hat{\Phi}_{t,m} = \hat{\Phi}_{t,m-1} + v\phi_{m,t}$, where v is the step length.
(3) Stop the algorithm when on the Mth iteration or when the information criterion starts to increase.

The above procedure is called Component-Wise boosting. There is also the Block-Wise boosting, which includes the variables in groups. For example, the candidate variables are lags of factors, the Component-Wise model will select different lags from different factors and the Block-Wise model will include a factor only if it includes all the lags. We used the step size $v = 0.2$.

2.7. **Jackknife Model Averaging.** The Jackknife Model Averaging (JMA) is a different way to combine forecasts from several small models. Instead of using the naive average of the forecasts, the JMA uses leave-one-out cross-validation to estimate optimal weights. The procedure we followed is that of Hansen & Racine (2012) with some adjustments for time-series in the cross-validation as in Zhang et al. (2013).

Suppose we have M candidate models that we want to average from and $\hat{\mu} = \{\hat{\mu}_1, \ldots, \hat{\mu}_M\}$, where $\hat{\mu}_j = E[y|X^{(j)}]$ is the expected value of y conditional to the variables in model j in a linear setup. Let $w = (w_1, \ldots, w_M)'$ be the weights of each models in the average such that $w_j \geq 0$ and $\sum_{j=1}^{M} w_j = 1$. The model average is then $\hat{\mu}(w) = \sum_{j=1}^{M} w_j \mu_j$. The JMA procedure is as follows:

(1) For each observation of (x_t, y_t):
  - estimate all the candidate models leaving the selected observation out of the estimation. Since we are in a time-series framework with lags in the model, we also removed four observation before and four observations after (x_t, y_t),
  - Compute $\hat{\mu}_t$ for the observation that was removed in the previous step.

(2) In the end of step one we will have $\tilde{\mu} = (\hat{\mu}_1, \ldots, \hat{\mu}_T)'$. Now we must compute $\tilde{e}{=}y - \tilde{\mu}$,

(3) Define the objective function as the weighted sum of the Cross-Validation squared errors $w'\tilde{e}'w\tilde{e}$ and minimize it in w.

The minimization problem above is quadratic and it has a restriction that w must be positive and sum 1. It does not have a closed solution but can be easily solved using the quadprog package (Berwin et al. 2013) in R. Given our set of candidate variables, each candidate model in the JMA has four autorregressive lags of the inflation and four lags of one candidate variable.

2.8. **Regression Trees and Random Forests.** The Random Forest (RF) methodology was initially proposed by Breiman (2001) as a solution to reduce the variance of regression trees and is based on bootstrap aggregation (Bagging) of randomly constructed regression trees.

A regression tree is a nonparametric model based on the recursive binary partitioning of the covariate space $\mathbb{X}$ where the function $T(\cdot)$ is a sum of local models (usually just a constant), each of which is determined in $K \in \mathbb{N}$ different regions (partitions) of $\mathbb{X}$. The model is usually displayed in a graph which has the format of a binary decision tree with $N \in \mathbb{N}$ parent (or split) nodes and $K \in \mathbb{N}$ terminal nodes (also called leaves), and which grows from the root node to the terminal nodes. Usually, the partitions are defined by a set of hyperplanes, each of which is orthogonal to the axis of a given predictor variable, called the *split variable*. Hence, conditionally to the knowledge of the subregions, the relationship between π_{t+h} and $\mathbf{x}_t$ in (1) is approximated by a piecewise constant model, where each leaf (or terminal node) represents a distinct regime.

To mathematically represent a complex regression-tree model, we introduce the following notation. The root node is at position 0 and a parent node at position j generates left- and right-child nodes at positions $2j+1$ and $2j+2$, respectively. Every parent node has an associated split variable $x_{s_j t} \in \mathbf{x}_t$, where $s_j \in \mathbb{S} = \{1, 2, \ldots, q\}$. Furthermore, let $\mathbb{J}$ and $\mathbb{T}$ be the sets of indexes of the parent and terminal nodes, respectively. Then, a tree architecture can be fully determined by $\mathbb{J}$ and $\mathbb{T}$.

The forecasting model based on regression tree can be mathematically represented as

$$\pi_{t+h} = H_{\mathbb{J}\mathbb{T}}(\mathbf{x}_t; \boldsymbol{\psi}) + u_{t+h} = \sum_{i \in \mathbb{T}} \beta_i B_{\mathbb{J}i}\left(\mathbf{x}_t; \boldsymbol{\theta}_i\right) + u_{t+h} \tag{9}$$

where

$$B_{\mathbb{J}i}\left(\mathbf{x}_t; \boldsymbol{\theta}_i\right) = \prod_{j \in \mathbb{J}} I(x_{s_j,t}; c_j)^{\frac{n_{i,j}(1+n_{i,j})}{2}} \left[1 - I(x_{s_j,t}; c_j)\right]^{(1-n_{i,j})(1+n_{i,j})}, \tag{10}$$

$$I(x_{s_j,t}; c_j) = \begin{cases} 1 & \text{if } x_{s_j,t} \leq c_j \\ 0 & \text{otherwise,} \end{cases} \tag{11}$$

$$n_{i,j} = \begin{cases} -1 & \text{if the path to leaf } i \text{ does not include the parent node } j; \\ 0 & \text{if the path to leaf } i \text{ includes the right-child node of the parent node } j; \\ 1 & \text{if the path to leaf } i \text{ includes the left-child node of the parent node } j. \end{cases} \tag{12}$$

Let $\mathbb{J}_i$ be the subset of $\mathbb{J}$ containing the indexes of the parent nodes that form the path to leaf i. Then, $\boldsymbol{\theta}_i$ is the vector containing all the parameters c_k such that $k \in \mathbb{J}_i$, $i \in \mathbb{T}$. Note that $\sum_{j \in \mathbb{J}} B_{\mathbb{J}i}\left(\mathbf{x}_t; \boldsymbol{\theta}_j\right) = 1$, $\forall\, \mathbf{x}_t \in \mathbb{R}^{q+1}$.

A Random Forest is a collection of regression-trees each of which is specified in a bootstrapped sub-sample of the original data. Suppose there are B bootstrapped sub-samples and denote $H_{\mathbb{J}_b\mathbb{T}_b}(\cdot; \boldsymbol{\psi}_b)$ as the estimated regression-tree for each one of the sub-samples. The final prediction is defined as:

$$\widehat{\pi}_{t+h} = \frac{1}{B}\sum_{b=1}^{B} H_{\mathbb{J}_b\mathbb{T}_b}(\boldsymbol{x}_t; \boldsymbol{\psi}_b). \tag{13}$$

For each of the bootstrapped sub-samples a regression-tree is estimates by recursively repeating the following steps for each terminal node of the tree until the minimum number of observations at each node is achieved.

(1) Randomly select m out of q covariates as possible split variables.

(2) Pick the best variable/split point among the m candidates.

(3) Split the node into two children nodes.

Random Forests can deal with a very big number of explanatory variables and the predicted model is highly nonlinear. It is important to notice that since we are dealing with time-series, bootstrap samples are calculated using block bootstrap.

3. Data

Our data consists of 122 variables that describe the US economy. The sample goes from January 1960 to December 2015 (672 observations). The data is available at Michael McKraken's website at the Fed St. Louis. We only used variables with all observations in the defined sample period. All variables were differentiated and treated according to the appendix available at the same site. Price indexes were log differentiated only one time. Therefore, our inflation measures are $\pi_t = log(P_t) - log(P_{t-1}$.

We divided our analysis into two periods, i.e. 1900 to 1999 (120 out-of-sample observations) and 2001-2015 (180 out-of-sample) observations. In each case we used all the data available before the out-of-sample period for estimation in a rolling window scheme. The same procedure was repeated for all the forecasting horizons ($t+1$ to $t+12$) in a direct forecast estimation. In other words, for each model we has 300 windows to estimate times 12 forecasting horizons.

4. Results

In this section we describe our main results for the Consumer Price Index (CPI). We have the same results for the Personal Consumption Expenditures (PCE) in the appendix. The first subsection shows the results for the 1990-1900 period, the second subsection shows the results for the 2001-2015 period, the third subsection checks how the models behave in NBER expansion and recession periods, the fourth subsection deals with variable selection and variable importance for some models in order to extract some information on why some models are more accurate than others and in the last subsection we estimate some regressions on the errors using variables such as the VIX, the NBER expansion and recession dummy and the US economic policy uncertainty index[3].

4.1. **Results for 1990–1999.**

Table 1 shows the forecasting errors of the CPI for all models in the 1990-1999 period. All errors were divided by the Random Walk error. The most accurate model for each forecasting horizon is in bold and the gray cell show the models that were included in the 90% model confidence set in each horizon. The model confidence set (MCS) used the squared error loss function. The most accurate model one month ahead is the Bayesian VAR and the Random Forest dominates most of the longer horizons. The CSR also has a good performance with the smallest RMSE from $t+6$ to $t+9$. The US inflation is very stable in the 1990s compared to recent periods, and univariate models such as AR and UCSV are not far behind the ML models. The good performance of the UCSV in the 1990s was discovered by Stock & Watson (1999*b*). The forecasting mean, median and trimmed mean of all models are often included in the MCS and they are always among the most accurate models, however, these naive combinations of models were not enough to beat the best model in each forecasting horizon.

Samuels & Sekkel (2017) and Garcia et al. (2017) show that it is possible to improve the forecasting accuracy by combining the models in the MCS and Samuels & Sekkel (2017) show that the results may be even better if we use some type of weight to combine the models

[3]Available at ¡http://www.policyuncertainty.com/¿

such as a weighting the forecasts based on their inverse RMSE. Since we need to look at the forecasts to estimate the MCS, we needed to break the 120 out-of-sample observations into a training sample (1990-1994) and a test sample (1995-1999). We estimated the MCS in the training sample in a expanding window scheme and combined the models using the simple average and the inverse RMSE weighted average. The results are in 2. Unfortunately, even with the MCS combinations the combined models are behind individual models in accuracy. We justify this result in figure 1, which shows that the correlations between the forecasts is positive and high and there is not much to gain with combinations. Garcia et al. (2017) argue that they were able to significantly reduce the errors with the naive MCS combination because they had strong negative correlations among their models.

Out last result is this section is the percentage of times each model had the smallest error and the biggest error for each forecasting horizon. There results are displayed in table 3. The results are quite surprising. First, the Random Walk, which was far from the best model on average errors, is the model with smaller errors in a large proportion of the rolling windows. However, it is also often the worst model leading to a poor result on average. Something similar happened with the jackknife. The table also points out that the Random Forest is not often the best model even though it is the most accurate on the RMSE and MAE tables. Average models stable, most of them are never the best nor worst model.

4.2. **Results for 2000–2015.** The same results presented in the previous section are discussed here for the 2001-2015 out-of-sample period. There is an important detail to discuss before looking into the results. During the 2008 crisis both the CPI and the PCE had one month with a very unusual deflation (close to -2%), which contaminated all the rolling windows estimated after we observed this event. To fix this problem we included an intervention in all models once this deflation was observed that reduced the average errors by approximately 10% for some models. There is no look ahead bias in our procedure because the intervention dummy is included only after the exceptional event. Imagine a manager looking at a -2% inflation in the US. He or she would hardly expect to have anything similar on

TABLE 1. Forecasting Errors for the CPI from 1990 to 2000

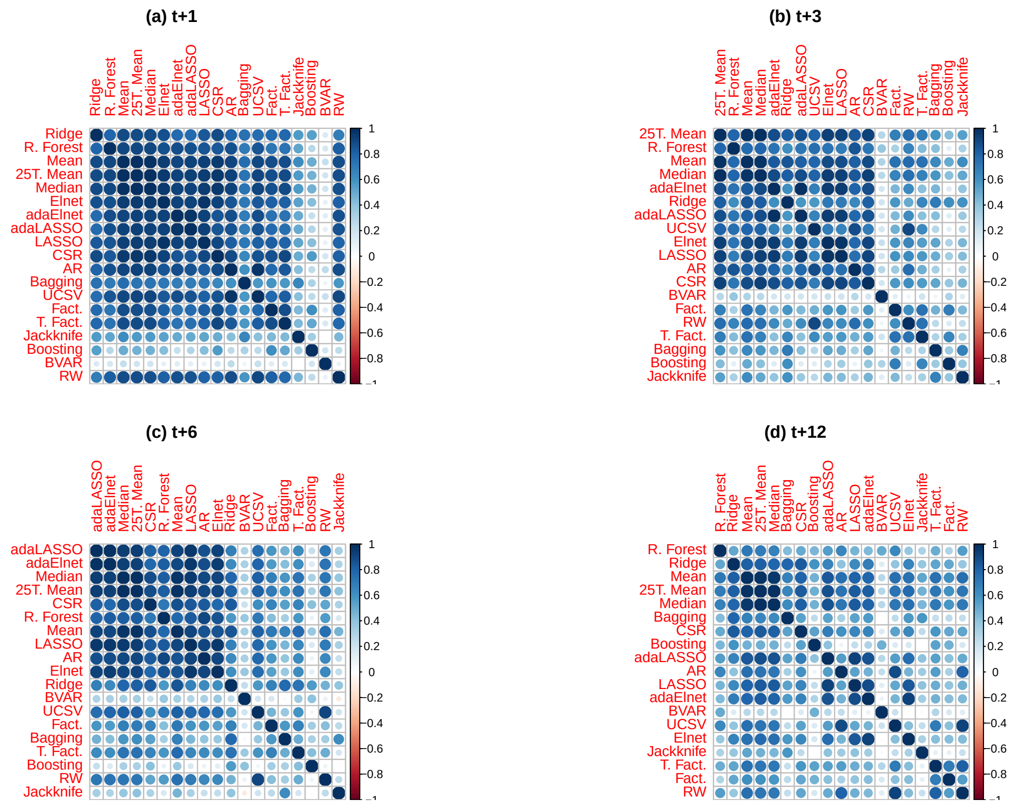
Consumer Price Index 1990-2000												
	Forecasting Horizon											
RMSE/(MAE)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.84	0.82	0.88	0.82	0.78	0.79	0.79	0.80	0.87	0.89	0.95	0.85	11
	(0.88)	(0.83)	(0.92)	(0.83)	(0.81)	(0.84)	(0.84)	(0.80)	(0.94)	(0.98)	(1.04)	(0.94)	(4)
UCSV	0.86	0.84	0.87	0.87	0.85	0.85	0.86	0.85	0.86	0.89	0.94	0.88	6
	(0.88)	(0.85)	(0.88)	(0.87)	(0.86)	(0.86)	(0.87)	(0.84)	(0.88)	(0.91)	(0.96)	(0.89)	(9)
BVAR	0.97	0.80	0.92	0.83	0.77	0.84	0.87	0.90	1.00	0.98	1.02	0.88	5
	(1.00)	**(0.77)**	(0.96)	(0.88)	(0.84)	(0.93)	(0.98)	(0.95)	(1.12)	(1.10)	(1.16)	(1.01)	(1)
LASSO	0.83	0.82	0.88	0.83	0.79	0.78	0.80	0.81	0.88	0.92	0.97	0.85	4
	(0.88)	(0.84)	(0.92)	(0.84)	(0.83)	(0.84)	(0.88)	(0.83)	(0.96)	(1.02)	(1.08)	(0.96)	(2)
Ridge	**0.79**	**0.77**	0.86	0.80	0.76	0.80	0.80	0.80	0.86	0.85	0.88	0.76	10
	(0.83)	(0.78)	(0.90)	(0.81)	(0.78)	(0.84)	(0.85)	(0.79)	(0.90)	(0.92)	(0.96)	(0.82)	(10)
Elnet	0.81	0.81	0.88	0.83	0.80	0.79	0.82	0.81	0.92	0.92	1.00	0.89	3
	(0.86)	(0.84)	(0.92)	(0.86)	(0.86)	(0.85)	(0.92)	(0.83)	(1.02)	(1.02)	(1.14)	(1.02)	(2)
adaLASSO	0.81	0.82	0.87	0.83	0.75	**0.75**	0.77	0.77	0.85	0.87	0.92	0.82	11
	(0.84)	(0.82)	(0.86)	(0.80)	(0.73)	**(0.77)**	(0.81)	(0.77)	(0.90)	(0.92)	(1.00)	(0.89)	(12)
adaElnet	0.81	0.82	0.86	0.80	0.74	0.75	0.77	0.78	0.87	0.87	0.92	0.87	11
	(0.85)	(0.83)	**(0.86)**	(0.77)	**(0.73)**	(0.78)	(0.81)	(0.78)	(0.92)	(0.93)	(1.00)	(0.95)	(11)
Fact.	0.87	0.85	0.98	0.90	0.89	0.86	0.84	0.90	1.02	0.97	1.04	0.98	0
	(0.96)	(0.92)	(1.05)	(0.97)	(0.92)	(0.90)	(0.88)	(0.91)	(1.14)	(1.09)	(1.15)	(1.14)	(0)
T. Fact.	0.87	0.91	1.01	0.98	0.92	0.94	0.86	0.91	1.04	1.02	1.02	0.95	0
	(0.93)	(0.98)	(1.13)	(1.07)	(1.02)	(1.05)	(0.94)	(0.93)	(1.16)	(1.18)	(1.15)	(1.10)	(0)
CSR	0.83	0.85	0.89	0.81	0.77	0.76	**0.76**	**0.76**	0.85	0.88	0.91	0.81	10
	(0.89)	(0.89)	(0.92)	(0.82)	(0.79)	(0.81)	(0.82)	(0.76)	(0.91)	(0.95)	(0.97)	(0.89)	(7)
Bagging	0.85	0.86	1.02	0.92	0.90	0.91	0.90	0.86	0.91	0.91	0.93	0.79	5
	(0.86)	(0.87)	(1.04)	(0.95)	(0.93)	(0.95)	(0.92)	(0.82)	(0.94)	(0.95)	(0.99)	(0.87)	(6)
Boosting	0.96	0.90	1.05	0.91	0.88	0.95	0.95	0.97	1.02	0.96	0.97	0.81	1
	(1.09)	(0.98)	(1.16)	(0.98)	(0.97)	(1.06)	(1.06)	(1.03)	(1.12)	(1.06)	(1.07)	(0.89)	(1)
Jackknife	0.94	1.01	1.17	0.99	1.03	1.01	1.06	1.03	1.21	1.13	1.13	0.93	0
	(1.00)	(1.02)	(1.19)	(1.01)	(1.07)	(1.05)	(1.06)	(1.01)	(1.29)	(1.19)	(1.20)	(0.98)	(0)
R. Forest	0.79	0.78	0.85	**0.77**	**0.73**	0.76	0.76	0.77	**0.82**	**0.82**	**0.85**	**0.72**	12
	(0.82)	(0.78)	(0.88)	**(0.77)**	(0.76)	(0.79)	**(0.78)**	**(0.75)**	**(0.86)**	**(0.86)**	**(0.89)**	**(0.76)**	(11)
Mean	0.80	0.79	0.85	0.79	0.76	0.77	0.77	0.77	0.84	0.84	0.87	0.78	9
	(0.83)	(0.81)	(0.87)	(0.80)	(0.79)	(0.81)	(0.81)	(0.76)	(0.90)	(0.91)	(0.94)	(0.85)	(8)
25T. Mean	0.80	0.80	**0.85**	0.79	0.75	0.76	0.77	0.77	0.85	0.84	0.89	0.79	7
	(0.84)	(0.82)	(0.87)	(0.79)	(0.77)	(0.80)	(0.81)	(0.78)	(0.91)	(0.91)	(0.97)	(0.87)	(10)
Median	0.80	0.80	0.85	0.79	0.75	0.76	0.77	0.77	0.85	0.85	0.89	0.79	9
	(0.84)	(0.83)	(0.88)	(0.79)	(0.78)	(0.80)	(0.82)	(0.77)	(0.91)	(0.91)	(0.97)	(0.87)	(9)
RMSE count	12	12	13	8	10	10	9	9	10	10	10	1	
MAE count	(10)	(12)	(8)	(7)	(2)	(8)	(8)	(10)	(12)	(10)	(9)	(7)	

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk. The error measures were calculated from 120 rolling windows.
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the squared error (absolute error) as loss function.

the following months and would not let that single observation contaminate his predictions of the future inflation.

Table 4 shows the forecasting errors for the entire period. All errors are divided by the Random Walk errors. The Random Forest dominated as the most accurate model for all horizons except $t + 1$, where the Bagging had the smallest RMSE (the LASSO had the smallest MAE). However, from $t + 2$ to $t + 6$ the 90% confidence MCS selected more models

Figure 1. Forecast Correlation for the CPI from 1990 to 2000



This figure shows the correlations between forecasts obtained in a 120 rolling window scheme for horizons 1, 3, 6 and 12.

than in the 1990-1999 period. Models such as bagging, factors, LASSO and Boosting are included in this group. The CSR was not selected in any forecasting horizon, even-though it had a good performance in the 1990s. The good performance of the Random Forest suggests some degree of nonlinearity in the data, we will come back to this discussion latter.

Table 5 shows the results for the MCS combinations. We used the 2001-2005 period as training sample and estimated the MCS in a expanding window scheme. The forecasting correlation for the 2001-2015 period is also highly correlated with positive correlations (see figure 2), which makes it hard to beat the best individual model with combinations. Nevertheless, in this case the MCS combinations had the smallest MAE and the 75$ confidence MCS was the best model on both measures for $t+2$. Even with MCS achieving some good results, it is not even the same MCS across the horizons, which makes it hard to select one rule of combination to use.

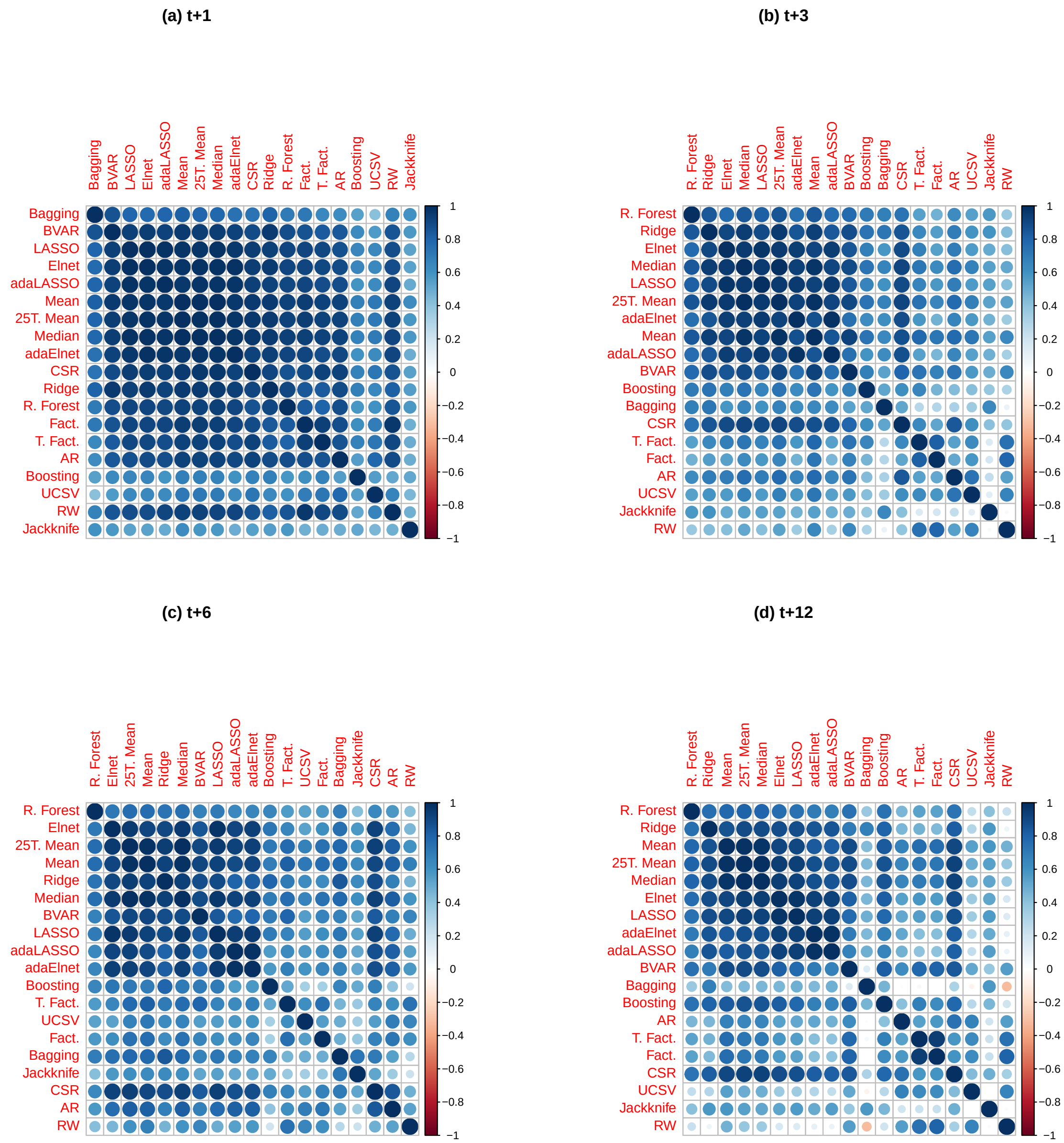
Finally, table 6 shows the percentage of times each model had the smallest (biggest) errors over the 180 windows. The same thing happened with the Random Walk as in the 1990-1999 period. It is the best model very often but it is the worst model even more often, which leads to a poor performance on average.

4.3. **NBER expansion recession.** In this section we used the NBER recession dummy[4] to check if the models behave differently during the economic cycle. By combining the two out-of-sample windows we have 300 forecasts for each horizon. We simply calculated the error measures in recession periods and expansion periods separately. The RMSE is reported in table 7 and the MAE is reported in table 8. The Random Forest is clearly the most accurate model in expansion periods, however we have different results during recession. In the RMSE table the bagging and the CSR perform very well for smaller horizons and the boosting is the best model is the best model for longer horizons. The Random Forest dominates only the forecasts for $t+11$ and $t+12$. The results are slightly different if we look at the MAE. First, the Random Forest is the most accurate model from $t+3$ to $t+6$ even on recession periods. But in recession we have the LASSO, the BVAR and the ridge in some cases. Although the Random Forest lost its dominance in recession periods, its performance was not far behind the most accurate models.

4.4. **Variable Selection.** Many ML methods have some output regarding the most important variables selected to predict the inflation. We are going to focus on the LASSO, where the importance of the variables come straight to the amount of times they were selected across the rolling windows and on the Random Forest to try to explain its good performance. We used the mean decrease in accuracy (MSE) on the out-of-bag observations each variable contributed when selected in a node as the variable importance measure. The total importance of each variable is the sum of the importance measure across all the 300

[4]Available at the Fed St. Louis website

FIGURE 2. Forecast Correlation for the CPI from 2001 to 2015



This figure shows the correlations between forecasts obtained in a 180 rolling window scheme for horizons 1, 3, 6 and 12.

models estimated to generate the forecasts. In order to have an easier interpretation of the results, grouped the variables according to the data appendix[5]. The groups are output and income, employment, housing, consumption, money, interest and exchange rates, prices and

[5]Available at ¡https://research.stlouisfed.org/econ/mccracken/fred-databases/¿

stocks. There is a last group of factors, which were available as candidate variables for all ML models.

The results for the LASSO, adaLASSO and Random Forest are in figures 3 4 and 5. The importance measures were adjusted to sum one on each forecasting horizon. The LASSO and the adaLASSO selected many variables based on employment (some times exchange and interest rates) for horizons 1 to 4. However, variables related to prices are the most dominant for all late horizons starting in $t + 4$ and employment lost a lot of its importance. The Random Forest is much more stable on the relative importance of each group and employment variables dominate all forecasting horizons, followed by interest and exchange and prices, which accounted for approximately 10% of the relative importance.

The results discussed here show that the LASSO (adaLASSO) fails to obtain the employment-inflation relation for longer forecasting horizons and instead it selects mostly price variables like the past CPI and the past of other inflation measures. The Random Forest was able to find importance on the employment variables for all horizons, which may be seen as evidence that for longer horizons the employment-inflation relation may become more nonlinear. The Random Forest is also much more stable on the groups relative importance.

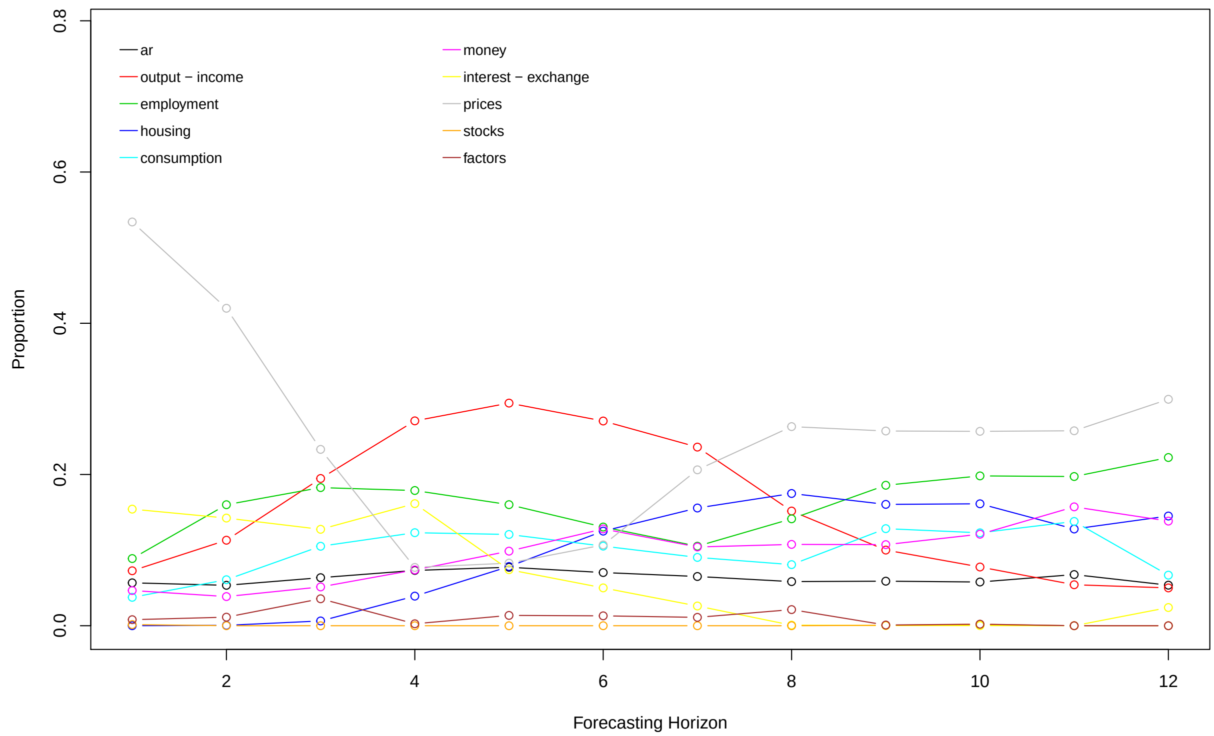
4.5. **Conditional Giacomini & White test.**

5. Conclusion

We showed that with recent advances in ML methods it is possible to improve inflation forecasts in a data-rich environment where the set of potential variables is big. Models such as LASSO, Bagging, Random Forest and others produced more accurate forecasts than the standard benchmarks. The Random Forest deserves a special attention because it had the smallest errors for most forecasting horizons in the two out-of-sample periods (1990-1999 and 2001-2015).

We tried to give an economic interpretation to the good performance of the Random Forest by looking at variable importance measures. The results showed that the RF variable importance is very stable across the forecasting horizon and we found evidence that there is a

FIGURE 3. Proportion each variable group was selected by the LASSO in the CPI forecasts



This figure shows the relative importance of each variable group for the LASSO for all the 12 forecasting horizons. The relative importance was calculated using the number of times each variable was selected across the rolling windows. The values were rescaled to sum one.

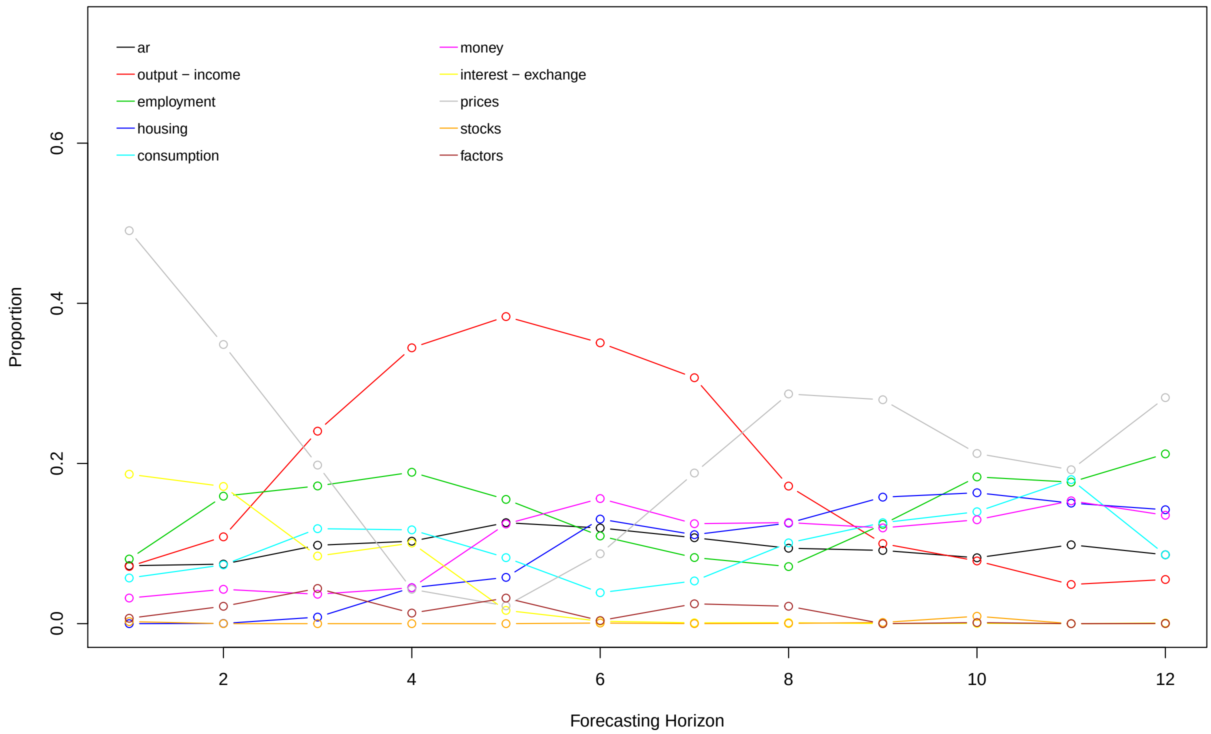
nonlinear relationship between past employment measures and inflation that can be explored to improve the forecasting accuracy. Even though the Random Forest was the most accurate model overall, its superiority was not that clear if we consider only recession periods.

Overall the forecasting accuracy of all ML models decreases in recession periods, especially when we have high market volatility. We showed that the forecasting errors can be partially explained by high volatility during recession and policy uncertainty.

REFERENCES

Bai, J. & Ng, S. (2002), 'Determine the number of factors in approximate factor model', *Econometrica* **70**, 191–221.

FIGURE 4. Proportion each variable group was selected by the adaLASSO in the CPI forecasts



This figure shows the relative importance of each variable group for the adaLASSO for all the 12 forecasting horizons. The relative importance was calculated using the number of times each variable was selected across the rolling windows. The values were rescaled to sum one.

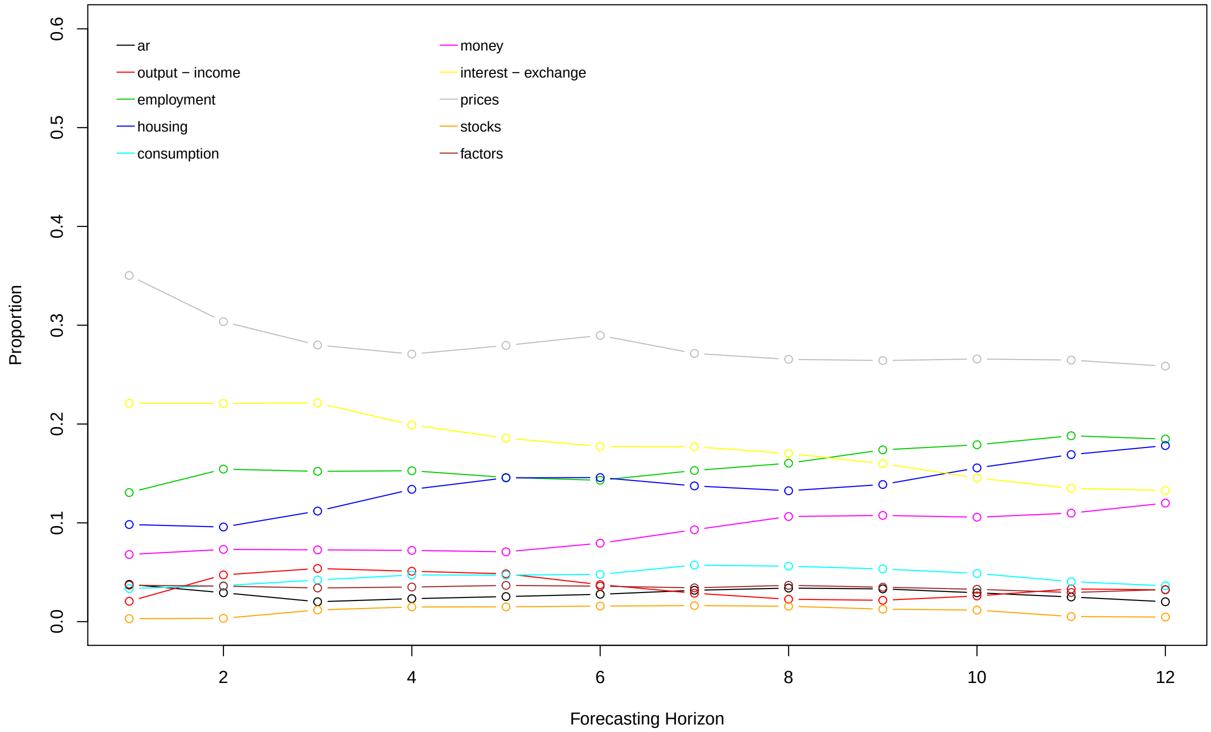
Bai, J. & Ng, S. (2006), 'Confidence intervals for diffusion index forecasts and inference for factor augmented regressions', *Econometrica* **74**, 1133–1155.

Bai, J. & Ng, S. (2008), 'Forecasting economic time series using targeted predictors', *Journal of Econometrics* **146**, 304–317.

Bernanke, B., Boivin, J. & Eliasz, P. (2005), 'easuring the effects of monetary policy: A factor-augmented vector autoregressive (favar) approach', *Quarterly Journal of Economics* **120**, 387–422.

Berwin, A., Turlach, R. & Weingessel, A. (2013), *quadprog: Functions to solve Quadratic Programming Problems*. R package version 1.5-5.

FIGURE 5. Proportion each variable had on the Random Forest out-of-bag importance measure in the CPI forecast



This figure shows the relative importance of each variable group for the Random Forest for all the 12 forecasting horizons. The relative importance was calculated using the mean decrease in accuracy each variable had in the out-of-bag observations in each regression tree. The total importance is the sum of the importance on all rolling windows. The values were rescaled to sum one.

URL: *https://CRAN.R-project.org/package=quadprog*

Breiman, L. (1996), 'Bagging predictors', *Machine learning* **24**(2), 123–140.

Breiman, L. (2001), 'Random forests', *Machine Learning* **45**, 5–32.

Elliott, G., Gargano, A. & Timmermann, A. (2013), 'Complete subset regressions', *Journal of Econometrics* **177**(2), 357–373.

Elliott, G., Gargano, A. & Timmermann, A. (2015), 'Complete subset regressions with large-dimensional sets of predictors', *Journal of Economic Dynamics and Control* **54**, 86–110.

Fama, E. F. & French, K. R. (1993), 'Common risk factors in the returns of stocks and bonds', *Journal of Financial Economics* **33**, 3–53.

Fama, E. F. & French, K. R. (1996), 'Multifactor explanation of asset pricing anomalies', *Journal of Finance* **51**, 55–84.

Garcia, M. G., Medeiros, M. C. & Vasconcelos, G. F. (2017), 'Real-time inflation forecasting with high-dimensional models: The case of brazil', *International Journal of Forecasting* **33**(3), 679–693.

Groen, J. J., Paap, R. & Ravazzolo, F. (2013), 'Real-time inflation forecasting in a changing world', *Journal of Business & Economic Statistics* **31**(1), 29–44.

Han, X. (2015), 'Tests for overidentifying restrictions in factor-augmented var models', *Journal of Econometrics* **184**, 394–419.

Hansen, B. E. & Racine, J. S. (2012), 'Jackknife model averaging', *Journal of Econometrics* **167**(1), 38–46.

Hansen, P. R., Lunde, A. & Nason, J. M. (2011), 'The model confidence set', *Econometrica* **79**(2), 453–497.

Hoerl, A. E. & Kennard, R. W. (1970*a*), 'Ridge regression: applications to nonorthogonal problems', *Technometrics* **12**(1), 69–82.

Hoerl, A. E. & Kennard, R. W. (1970*b*), 'Ridge regression: Biased estimation for nonorthogonal problems', *Technometrics* **12**(1), 55–67.

Medeiros, M. C. & Mendes, E. F. (2016), 'l1-regularization of high-dimensional time-series models with non-gaussian and heteroskedastic errors', *Journal of Econometrics* **191**(1), 255–271.

Medeiros, M. & Vasconcelos, G. (2016), 'Forecasting macroeconomic variables in data-rich environments', *Economics Letters* **138**, 50–52.

Samuels, J. D. & Sekkel, R. M. (2017), 'Model confidence sets and forecast combination', *International Journal of Forecasting* **33**(1), 48–60.

Stock, J. H. & Watson, M. W. (1999*a*), 'Forecasting inflation', *Journal of Monetary Economics* **44**(2), 293–335.

Stock, J. H. & Watson, M. W. (1999*b*), 'Forecasting inflation', *Journal of Monetary Economics* **44**(2), 293–335.

Stock, J. H. & Watson, M. W. (2010), Modeling inflation after the crisis, Technical report, National Bureau of Economic Research.

Tibshirani, R. (1996), 'Regression shrinkage and selection via the LASSO', *Journal of the Royal Statistical Society. Series B (Methodological)* **58**, 267–288.

Zhang, X., Wan, A. T. & Zou, G. (2013), 'Model averaging by jackknife criterion in models with dependent data', *Journal of Econometrics* **174**(2), 82–94.

Zhao, P. & Yu, B. (2006), 'On model selection consistency of lasso', *Journal of Machine learning research* **7**(Nov), 2541–2563.

Zou, H. (2006), 'The adaptive lasso and its oracle properties', *Journal of the American statistical association* **101**(476), 1418–1429.

Zou, H. & Hastie, T. (2005), 'Regularization and variable selection via the elastic net', *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **67**(2), 301–320.

Table 2. Forecasting errors for the CPI from 1995 to 2000 with MCS combinations

	Consumer Price Index 1995-2000 - MCS											
	Forecasting Horizon											
$RMSE/(MAE)$	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
AR	0.82	0.79	0.89	0.83	0.81	0.84	0.78	**0.79**	0.87	0.90	1.07	0.92
	(0.92)	(0.87)	(0.91)	(0.83)	(0.87)	(0.89)	(0.83)	(0.84)	(0.99)	(0.96)	(1.21)	(1.06)
UCSV	0.83	0.79	**0.86**	0.86	0.85	0.88	0.87	0.86	0.86	0.90	0.98	0.90
	(0.87)	**(0.84)**	(0.86)	(0.86)	(0.86)	(0.88)	(0.87)	(0.86)	**(0.90)**	(0.89)	**(1.00)**	(0.94)
BVAR	0.89	**0.74**	1.05	0.90	0.85	1.00	0.95	1.04	1.17	1.15	1.36	1.06
	(1.03)	(0.85)	(1.06)	(0.90)	(0.96)	(1.11)	(1.10)	(1.19)	(1.40)	(1.26)	(1.60)	(1.31)
LASSO	0.85	0.81	0.97	0.93	0.85	0.87	0.85	0.90	1.00	1.10	1.27	1.04
	(0.99)	(0.95)	(0.99)	(0.93)	(0.93)	(0.93)	(0.96)	(1.01)	(1.15)	(1.22)	(1.49)	(1.27)
Ridge	**0.78**	0.75	0.92	0.86	0.83	0.89	0.80	0.83	0.89	0.91	1.06	0.85
	(0.90)	(0.87)	(0.94)	(0.85)	(0.89)	(0.95)	(0.88)	(0.89)	(1.00)	(0.96)	(1.21)	(0.98)
Elnet	0.83	0.79	0.97	0.92	0.88	0.89	0.88	0.91	1.02	1.06	1.29	1.08
	(0.97)	(0.93)	(0.98)	(0.93)	(0.98)	(0.96)	(1.00)	(1.02)	(1.19)	(1.15)	(1.54)	(1.33)
adaLASSO	0.80	0.78	0.90	0.92	0.77	0.79	0.79	0.82	0.91	0.98	1.16	1.00
	(0.90)	(0.88)	**(0.84)**	(0.84)	(0.77)	**(0.78)**	(0.83)	(0.88)	(1.02)	(1.01)	(1.30)	(1.15)
adaElnet	0.80	0.79	0.89	0.87	**0.76**	**0.79**	0.80	0.82	0.92	0.99	1.19	1.04
	(0.90)	(0.89)	(0.84)	(0.80)	**(0.75)**	(0.79)	(0.86)	(0.88)	(1.04)	(1.05)	(1.35)	(1.23)
Fact.	0.92	0.91	1.17	1.02	1.03	1.03	0.91	1.03	1.19	1.15	1.40	1.22
	(1.09)	(1.10)	(1.25)	(1.08)	(1.13)	(1.06)	(0.98)	(1.13)	(1.41)	(1.28)	(1.65)	(1.50)
T. Fact.	0.90	1.01	1.26	1.16	1.10	1.19	0.94	1.04	1.22	1.21	1.30	1.13
	(1.04)	(1.23)	(1.37)	(1.25)	(1.29)	(1.34)	(1.05)	(1.17)	(1.46)	(1.37)	(1.55)	(1.41)
CSR	0.85	0.84	0.93	0.86	0.83	0.86	0.79	0.80	0.91	0.96	1.10	0.93
	(1.00)	(0.99)	(0.94)	(0.85)	(0.89)	(0.89)	(0.86)	(0.86)	(1.03)	(1.02)	(1.25)	(1.10)
Bagging	0.87	0.88	1.16	1.04	0.93	0.97	0.85	0.80	**0.85**	0.87	1.06	0.90
	(0.94)	(0.96)	(1.09)	(0.99)	(1.00)	(0.96)	(0.83)	(0.85)	(0.94)	(0.87)	(1.13)	(1.02)
Boosting	1.08	1.00	1.33	1.12	1.12	1.28	1.13	1.23	1.28	1.20	1.34	1.01
	(1.39)	(1.28)	(1.46)	(1.17)	(1.29)	(1.43)	(1.33)	(1.43)	(1.52)	(1.31)	(1.55)	(1.18)
Jackknife	0.95	0.97	1.40	1.15	1.15	1.04	0.99	1.04	1.18	1.07	1.21	1.04
	(1.07)	(1.08)	(1.32)	(1.08)	(1.22)	(1.06)	(0.98)	(1.09)	(1.28)	(1.06)	(1.30)	(1.11)
R. Forest	0.79	0.77	0.91	**0.81**	0.77	0.83	**0.74**	0.79	0.86	**0.85**	**0.97**	**0.77**
	(0.88)	(0.88)	(0.90)	**(0.78)**	(0.81)	(0.85)	**(0.78)**	**(0.81)**	(0.93)	**(0.86)**	(1.06)	**(0.87)**
Mean	0.80	0.78	0.93	0.86	0.83	0.86	0.80	0.82	0.91	0.92	1.06	0.89
	(0.91)	(0.90)	(0.93)	(0.86)	(0.88)	(0.91)	(0.86)	(0.89)	(1.04)	(0.99)	(1.22)	(1.04)
25T. Mean	0.81	0.78	0.93	0.86	0.81	0.85	0.80	0.83	0.92	0.94	1.10	0.91
	(0.91)	(0.90)	(0.93)	(0.84)	(0.87)	(0.90)	(0.87)	(0.91)	(1.05)	(1.00)	(1.27)	(1.08)
Median	0.80	0.78	0.93	0.85	0.81	0.84	0.80	0.83	0.92	0.94	1.11	0.91
	(0.91)	(0.90)	(0.93)	(0.83)	(0.88)	(0.89)	(0.87)	(0.90)	(1.05)	(1.01)	(1.28)	(1.09)
MCS50	0.80	0.78	0.92	0.86	0.81	0.86	0.81	0.84	0.89	0.93	1.06	0.89
	(0.90)	(0.90)	(0.92)	(0.84)	(0.87)	(0.91)	(0.88)	(0.90)	(1.01)	(0.98)	(1.20)	(1.04)
MCS75	0.80	0.78	0.92	0.86	0.82	0.86	0.81	0.84	0.90	0.93	1.07	0.88
	(0.90)	(0.90)	(0.92)	(0.85)	(0.88)	(0.91)	(0.88)	(0.91)	(1.02)	(1.00)	(1.23)	(1.04)
MCS90	0.81	0.79	0.93	0.86	0.82	0.86	0.80	0.83	0.91	0.93	1.07	0.89
	(0.91)	(0.91)	(0.93)	(0.85)	(0.88)	(0.91)	(0.87)	(0.89)	(1.03)	(0.99)	(1.23)	(1.04)
MCS50-IRMSE	0.80	0.78	0.92	0.86	0.81	0.86	0.80	0.83	0.89	0.93	1.06	0.88
	(0.90)	(0.90)	(0.92)	(0.84)	(0.87)	(0.91)	(0.88)	(0.90)	(1.01)	(0.99)	(1.20)	(1.04)
MCS75-IRMSE	0.80	0.78	0.92	0.86	0.82	0.86	0.81	0.83	0.90	0.94	1.08	0.88
	(0.90)	(0.90)	(0.92)	(0.85)	(0.88)	(0.91)	(0.88)	(0.91)	(1.02)	(1.00)	(1.24)	(1.03)
MCS90-IRMSE	0.80	0.78	0.92	0.86	0.82	0.86	0.80	0.83	0.91	0.93	1.08	0.89
	(0.91)	(0.91)	(0.93)	(0.84)	(0.88)	(0.91)	(0.87)	(0.90)	(1.03)	(1.00)	(1.24)	(1.04)

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk.
[b] The 120 rolling window forecasts were divided into a training sample (1990-1994) and test sample (1995-2000) and the error measures were calculated in the test sample.
[c] The MCS used for the combinations were calculated in a expanding window starting with the training sample to avoid look ahead bias.

Table 3. Percentage of times each model had the smallest (biggest) error for the CPI from 1990 to 2000

	Consumer Price Index - Ranking - 1990-2000											
	Forecasting Horizon											
%best/(%worst)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
RW	**21.37**	**16.79**	**19.85**	**15.91**	**14.39**	**17.56**	14.62	10.69	**18.60**	**15.38**	12.88	11.36
	(20.61)	**(20.93)**	(15.62)	(18.46)	(19.53)	(16.67)	(18.32)	**(24.24)**	(14.62)	(17.19)	(11.36)	(16.15)
AR	1.53	4.58	4.58	6.82	2.27	6.11	2.31	3.05	4.65	3.85	1.52	6.82
	(2.29)	(3.88)	(3.12)	(2.31)	(0.78)	(0.76)	(3.05)	(2.27)	(3.08)	(3.91)	(5.30)	(5.38)
UCSV	4.58	0.76	7.63	6.06	6.82	5.34	6.92	5.34	5.43	10.00	7.58	3.79
	(1.53)	(0.00)	(0.78)	(0.77)	(1.56)	(3.03)	(1.53)	(2.27)	(0.00)	(0.78)	(5.30)	(3.08)
BVAR	11.45	14.50	7.63	6.06	6.82	7.63	4.62	3.05	3.88	3.08	5.30	3.03
	(9.16)	(7.75)	(6.25)	(3.85)	(3.91)	(9.09)	(9.16)	(6.82)	(6.15)	(10.94)	(7.58)	(6.92)
LASSO	3.82	5.34	2.29	2.27	6.06	2.29	0.77	1.53	2.33	1.54	1.52	2.27
	(0.76)	(0.78)	(0.00)	(0.77)	(1.56)	(0.76)	(0.00)	(1.52)	(0.77)	(1.56)	(1.52)	(0.00)
Ridge	6.11	5.34	3.05	2.27	4.55	4.58	3.08	3.05	6.98	3.08	5.30	6.06
	(1.53)	(0.00)	(0.78)	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.00)	(0.00)	(1.52)	(0.77)
Elnet	2.29	1.53	0.76	3.79	4.55	3.05	2.31	3.82	3.88	0.77	1.52	2.27
	(1.53)	(3.10)	(0.00)	(3.08)	(2.34)	(1.52)	(5.34)	(0.00)	(0.00)	(0.78)	(5.30)	(5.38)
adaLASSO	3.82	3.05	6.11	3.03	4.55	3.05	2.31	6.87	4.65	6.15	3.79	4.55
	(0.76)	(0.78)	(2.34)	(3.08)	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.78)	(0.76)	(0.00)
adaElnet	2.29	5.34	2.29	3.03	5.30	4.58	2.31	2.29	0.78	0.77	0.76	1.52
	(0.00)	(0.78)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(4.62)
Fact.	1.53	1.53	5.34	3.79	5.30	4.58	4.62	4.58	6.98	6.15	7.58	2.27
	(1.53)	(0.78)	(6.25)	(6.15)	(5.47)	(6.06)	(5.34)	(8.33)	(14.62)	(12.50)	(16.67)	(15.38)
T. Fact.	2.29	6.11	0.00	6.82	3.79	3.82	3.08	8.40	3.10	2.31	3.79	1.52
	(3.05)	(8.53)	(14.06)	(13.08)	(9.38)	(9.85)	(3.82)	(3.79)	(6.15)	(6.25)	(3.79)	(6.15)
CSR	2.29	1.53	1.53	2.27	3.03	1.53	5.38	3.05	1.55	3.08	2.27	5.30
	(0.76)	(0.00)	(0.78)	(1.54)	(0.78)	(1.52)	(0.00)	(0.76)	(1.54)	(0.78)	(0.00)	(2.31)
Bagging	16.03	9.92	11.45	8.33	9.09	8.40	8.46	9.92	8.53	13.08	9.85	9.85
	(12.98)	(13.95)	(11.72)	(11.54)	(9.38)	(6.06)	(9.16)	(4.55)	(6.92)	(9.38)	(6.82)	(8.46)
Boosting	9.16	9.16	4.58	11.36	7.58	11.45	9.23	9.16	11.63	9.23	**15.15**	14.39
	(24.43)	(18.60)	(14.84)	(15.38)	(18.75)	**(21.97)**	**(23.66)**	(23.48)	(19.23)	(11.72)	(9.85)	(5.38)
Jackknife	5.34	8.40	9.92	9.85	10.61	9.16	**15.38**	**12.21**	8.53	11.54	11.36	**16.67**
	(19.08)	(19.38)	**(23.44)**	**(19.23)**	**(26.56)**	(21.21)	(19.08)	(20.45)	**(25.38)**	**(22.66)**	**(21.97)**	**(19.23)**
R. Forest	2.29	3.82	6.87	4.55	3.03	4.58	10.00	9.16	2.33	5.38	6.06	3.79
	(0.00)	(0.78)	(0.00)	(0.77)	(0.00)	(1.52)	(0.76)	(0.76)	(1.54)	(0.78)	(2.27)	(0.77)
Mean	2.29	2.29	3.05	2.27	1.52	1.53	3.08	1.53	2.33	3.08	1.52	3.79
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
25T. Mean	0.76	0.00	0.76	0.76	0.76	0.76	1.54	0.76	3.10	0.77	0.76	0.76
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median	0.76	0.00	2.29	0.76	0.00	0.00	0.00	1.53	0.78	0.77	1.52	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

[a] This table show the percentage of times each model had the smallest (bigger) errors in the 120 rolling windows.
[b] The biggest values are in bold.

Table 4. Forecasting Errors for the CPI from 2001 to 2015

	Consumer Price Index 2000-2015												
	Forecasting Horizon												
RMSE/(MAE)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.92	0.81	0.78	0.80	0.79	0.79	0.78	0.76	0.77	0.81	0.82	0.73	6
	(0.87)	(0.78)	(0.74)	(0.79)	(0.80)	(0.80)	(0.75)	(0.75)	(0.76)	(0.80)	(0.79)	(0.70)	(1)
UCSV	0.98	0.81	0.79	0.80	0.77	0.77	0.77	0.76	0.76	0.79	0.81	0.76	8
	(0.93)	(0.81)	(0.76)	(0.77)	(0.78)	(0.77)	(0.77)	(0.77)	(0.75)	(0.76)	(0.81)	(0.73)	(4)
BVAR	0.83	0.75	0.72	0.75	0.74	0.74	0.75	0.74	0.74	0.79	0.79	0.72	12
	(0.81)	(0.72)	(0.68)	(0.75)	(0.75)	(0.73)	(0.69)	(0.69)	(0.70)	(0.73)	(0.74)	(0.67)	(12)
LASSO	0.84	0.74	0.71	0.75	0.74	0.74	0.75	0.72	0.74	0.78	0.79	0.70	11
	(0.79)	(0.71)	(0.67)	(0.75)	(0.74)	(0.72)	(0.69)	(0.67)	(0.69)	(0.73)	(0.75)	(0.65)	(10)
Ridge	0.86	0.72	0.70	0.75	0.73	0.74	0.74	0.72	0.72	0.76	0.77	0.69	8
	(0.83)	(0.70)	(0.67)	(0.75)	(0.75)	(0.74)	(0.69)	(0.68)	(0.69)	(0.71)	(0.73)	(0.67)	(11)
Elnet	0.84	0.74	0.71	0.74	0.73	0.74	0.74	0.73	0.73	0.79	0.79	0.70	9
	(0.80)	(0.70)	(0.67)	(0.74)	(0.74)	(0.72)	(0.69)	(0.67)	(0.69)	(0.73)	(0.74)	(0.64)	(10)
adaLASSO	0.84	0.75	0.72	0.76	0.75	0.75	0.76	0.74	0.75	0.79	0.81	0.70	12
	(0.80)	(0.72)	(0.68)	(0.76)	(0.76)	(0.73)	(0.71)	(0.69)	(0.71)	(0.75)	(0.78)	(0.67)	(7)
adaElnet	0.85	0.74	0.72	0.76	0.75	0.75	0.75	0.74	0.74	0.79	0.80	0.70	12
	(0.81)	(0.71)	(0.68)	(0.76)	(0.76)	(0.73)	(0.70)	(0.68)	(0.70)	(0.74)	(0.76)	(0.67)	(9)
Fact.	0.87	0.77	0.75	0.77	0.76	0.77	0.79	0.80	0.79	0.81	0.81	0.74	7
	(0.84)	(0.76)	(0.72)	(0.77)	(0.78)	(0.76)	(0.74)	(0.76)	(0.78)	(0.79)	(0.77)	(0.69)	(3)
T. Fact.	0.88	0.76	0.74	0.76	0.74	0.76	0.78	0.78	0.76	0.78	0.80	0.74	8
	(0.85)	(0.75)	(0.71)	(0.74)	(0.75)	(0.76)	(0.75)	(0.75)	(0.74)	(0.76)	(0.76)	(0.69)	(4)
CSR	0.86	0.75	0.74	0.78	0.78	0.79	0.80	0.77	0.78	0.82	0.83	0.75	9
	(0.82)	(0.71)	(0.69)	(0.78)	(0.79)	(0.78)	(0.74)	(0.73)	(0.75)	(0.78)	(0.80)	(0.73)	(4)
Bagging	**0.82**	0.74	0.72	0.78	0.76	0.77	0.81	0.80	0.76	0.80	0.81	0.73	10
	(0.84)	(0.74)	(0.71)	(0.83)	(0.84)	(0.82)	(0.80)	(0.79)	(0.76)	(0.80)	(0.82)	(0.74)	(3)
Boosting	0.95	0.75	0.72	0.76	0.74	0.76	0.77	0.75	0.76	0.81	0.81	0.73	10
	(0.91)	(0.72)	(0.70)	(0.79)	(0.78)	(0.79)	(0.76)	(0.75)	(0.76)	(0.79)	(0.79)	(0.69)	(4)
Jackknife	1.00	0.78	0.79	0.83	0.80	0.77	0.89	0.83	0.79	0.91	0.88	0.77	5
	(0.99)	(0.78)	(0.79)	(0.92)	(0.91)	(0.84)	(0.85)	(0.82)	(0.81)	(0.88)	(0.87)	(0.78)	(0)
R. Forest	0.86	**0.72**	**0.69**	**0.73**	**0.71**	**0.71**	**0.71**	**0.70**	**0.71**	**0.75**	**0.76**	**0.68**	12
	(0.81)	**(0.70)**	**(0.66)**	**(0.74)**	**(0.71)**	**(0.70)**	**(0.67)**	**(0.66)**	**(0.67)**	**(0.70)**	(0.72)	**(0.63)**	(12)
Mean	0.84	0.74	0.72	0.75	0.74	0.74	0.75	0.74	0.73	0.76	0.77	0.69	12
	(0.80)	(0.71)	(0.69)	(0.74)	(0.75)	(0.73)	(0.70)	(0.70)	(0.70)	(0.71)	**(0.72)**	(0.65)	(10)
25T. Mean	0.85	0.73	0.71	0.75	0.73	0.74	0.74	0.73	0.73	0.77	0.78	0.70	11
	(0.80)	(0.71)	(0.67)	(0.74)	(0.74)	(0.72)	(0.69)	(0.68)	(0.69)	(0.72)	(0.72)	(0.64)	(12)
Median	0.85	0.73	0.71	0.75	0.73	0.74	0.74	0.73	0.73	0.77	0.78	0.70	11
	(0.80)	(0.70)	(0.67)	(0.74)	(0.75)	(0.72)	(0.69)	(0.68)	(0.69)	(0.72)	(0.73)	(0.65)	(12)
RMSE count	11	14	9	17	15	15	14	14	18	17	16	13	
MAE count	(11)	(13)	(14)	(16)	(13)	(13)	(8)	(9)	(9)	(8)	(6)	(8)	

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk. The error measures were calculated from 180 rolling windows.
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the squared error (absolute error) as loss function.

Table 5. Forecasting errors for the CPI from 2005 to 2015 with MCS combinations

	Consumer Price Index 2005-2015 - MCS											
	Forecasting Horizon											
$RMSE/(MAE)$	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
AR	0.92	0.83	0.81	0.81	0.76	0.76	0.77	0.76	0.77	0.80	0.79	0.72
	(0.85)	(0.81)	(0.78)	(0.78)	(0.76)	(0.77)	(0.75)	(0.75)	(0.75)	(0.78)	(0.77)	(0.69)
UCSV	1.00	0.82	0.80	0.80	0.75	0.74	0.74	0.75	0.75	0.77	0.78	0.73
	(0.91)	(0.81)	(0.77)	(0.77)	(0.75)	(0.74)	(0.74)	(0.76)	(0.73)	(0.72)	(0.76)	(0.69)
BVAR	0.83	0.77	0.74	0.75	0.71	0.71	0.73	0.72	0.72	0.75	0.75	0.69
	(0.81)	(0.74)	(0.70)	(0.74)	(0.70)	(0.68)	(0.66)	(0.66)	(0.66)	(0.68)	(0.69)	(0.63)
LASSO	0.85	0.76	0.73	0.74	0.70	0.71	0.72	0.71	0.73	0.75	0.76	0.67
	(0.79)	(0.72)	(0.68)	(0.72)	(0.68)	(0.67)	(0.67)	(0.65)	(0.66)	(0.69)	(0.72)	(0.62)
Ridge	0.87	0.74	0.72	0.73	0.69	0.69	0.72	0.72	0.71	0.72	0.73	0.66
	(0.83)	(0.72)	(0.68)	(0.70)	(0.68)	(0.68)	(0.67)	(0.67)	(0.65)	(0.66)	(0.68)	(0.64)
Elnet	0.85	0.76	0.73	0.74	0.70	0.69	0.71	0.72	0.72	0.76	0.75	0.67
	(0.80)	(0.72)	(0.69)	(0.70)	(0.68)	(0.66)	(0.66)	(0.65)	(0.66)	(0.69)	(0.70)	(0.62)
adaLASSO	0.85	0.77	0.75	0.75	0.72	0.72	0.73	0.74	0.74	0.77	0.78	0.68
	(0.80)	(0.74)	(0.70)	(0.73)	(0.71)	(0.69)	(0.68)	(0.68)	(0.68)	(0.71)	(0.74)	(0.66)
adaElnet	0.86	0.76	0.74	0.76	0.72	0.72	0.72	0.73	0.73	0.76	0.77	0.68
	(0.81)	(0.73)	(0.70)	(0.73)	(0.71)	(0.70)	(0.67)	(0.67)	(0.67)	(0.71)	(0.73)	(0.66)
Fact.	0.89	0.78	0.76	0.75	0.72	0.73	0.78	0.81	0.79	0.79	0.78	0.72
	(0.85)	(0.76)	(0.71)	(0.72)	(0.72)	(0.71)	(0.73)	(0.79)	(0.75)	(0.74)	(0.73)	(0.66)
T. Fact.	0.87	0.76	0.74	0.75	0.72	0.72	0.75	0.76	0.75	0.76	0.77	0.71
	(0.83)	(0.74)	(0.68)	(0.71)	(0.71)	(0.69)	(0.71)	(0.72)	(0.70)	(0.71)	(0.72)	(0.65)
CSR	0.86	0.78	0.77	0.78	0.74	0.75	0.78	0.77	0.78	0.80	0.80	0.73
	(0.80)	(0.73)	(0.72)	(0.75)	(0.73)	(0.74)	(0.74)	(0.73)	(0.73)	(0.74)	(0.77)	(0.71)
Bagging	**0.83**	0.76	0.73	0.74	0.70	0.72	0.80	0.81	0.76	0.78	0.78	0.70
	(0.87)	(0.77)	(0.72)	(0.77)	(0.75)	(0.77)	(0.79)	(0.82)	(0.74)	(0.78)	(0.78)	(0.72)
Boosting	0.97	0.76	0.72	**0.71**	**0.67**	0.68	0.71	0.71	0.71	0.74	0.76	0.69
	(0.89)	(0.74)	(0.69)	(0.71)	(0.67)	(0.69)	(0.70)	(0.70)	(0.68)	(0.70)	(0.71)	(0.64)
Jackknife	1.03	0.80	0.80	0.78	0.74	0.70	0.89	0.85	0.78	0.91	0.86	0.73
	(1.03)	(0.82)	(0.81)	(0.84)	(0.82)	(0.78)	(0.87)	(0.86)	(0.78)	(0.88)	(0.84)	(0.74)
R. Forest	0.90	0.75	**0.70**	0.72	0.67	**0.67**	**0.69**	**0.70**	**0.70**	**0.72**	**0.73**	**0.66**
	(0.83)	(0.73)	**(0.68)**	**(0.70)**	**(0.67)**	**(0.66)**	**(0.65)**	**(0.65)**	(0.64)	(0.67)	(0.68)	**(0.61)**
Mean	0.85	0.75	0.73	0.74	0.70	0.70	0.73	0.73	0.73	0.73	0.73	0.67
	(0.79)	(0.72)	(0.69)	(0.71)	(0.69)	(0.68)	(0.68)	(0.68)	(0.66)	(0.67)	(0.67)	(0.61)
25T. Mean	0.85	0.75	0.73	0.74	0.70	0.70	0.72	0.72	0.72	0.74	0.74	0.67
	(0.79)	(0.72)	(0.69)	(0.71)	(0.69)	(0.67)	(0.67)	(0.67)	(0.65)	(0.67)	(0.68)	(0.61)
Median	0.86	0.75	0.73	0.74	0.70	0.70	0.72	0.72	0.72	0.74	0.74	0.67
	(0.80)	(0.72)	(0.69)	(0.71)	(0.69)	(0.67)	(0.67)	(0.66)	(0.65)	(0.67)	(0.68)	(0.61)
MCS50	0.84	0.74	0.72	0.73	0.70	0.70	0.72	0.73	0.72	0.73	0.73	0.66
	(0.79)	(0.71)	(0.68)	(0.70)	(0.68)	(0.67)	(0.67)	(0.68)	(0.66)	(0.66)	(0.66)	(0.61)
MCS75	0.84	**0.74**	0.72	0.74	0.70	0.70	0.72	0.72	0.72	0.73	0.73	0.66
	(0.81)	**(0.71)**	(0.68)	(0.70)	(0.68)	(0.67)	(0.67)	(0.68)	(0.66)	**(0.66)**	(0.67)	(0.62)
MCS90	0.85	0.77	0.73	0.74	0.70	0.70	0.73	0.72	0.71	0.74	0.74	0.66
	(0.83)	(0.74)	(0.69)	(0.72)	(0.69)	(0.68)	(0.68)	(0.66)	**(0.63)**	(0.67)	(0.69)	(0.61)
MCS50-IRMSE	0.84	0.74	0.72	0.74	0.70	0.70	0.72	0.73	0.72	0.73	0.73	0.66
	(0.79)	(0.71)	(0.68)	(0.70)	(0.68)	(0.67)	(0.67)	(0.67)	(0.66)	(0.66)	**(0.66)**	(0.61)
MCS75-IRMSE	0.84	0.74	0.72	0.74	0.70	0.70	0.72	0.72	0.72	0.73	0.73	0.66
	(0.81)	(0.71)	(0.68)	(0.70)	(0.68)	(0.67)	(0.67)	(0.67)	(0.66)	(0.66)	(0.67)	(0.62)
MCS90-IRMSE	0.85	0.77	0.73	0.74	0.70	0.70	0.72	0.72	0.71	0.74	0.74	0.66
	(0.83)	(0.74)	(0.69)	(0.72)	(0.69)	(0.68)	(0.68)	(0.66)	(0.63)	(0.67)	(0.69)	(0.61)

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk.
[b] The 180 rolling window forecasts were divided into a training sample (2001-2004) and test sample (2005-2015) and the error measures were calculated in the test sample.
[c] The MCS used for the combinations were calculated in a expanding window starting with the training sample to avoid look ahead bias.

TABLE 6. Percentage of times each model had the smallest (biggest) error for the CPI from 2001 to 2015

	Consumer Price Index - Ranking - 2000-2015											
	Forecasting Horizon											
%best/(%worst)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
RW	14.44	12.22	11.67	**16.67**	**17.78**	11.11	**11.11**	**13.33**	12.22	10.56	10.00	6.67
	(22.78)	**(34.44)**	**(36.11)**	**(29.44)**	**(30.56)**	**(29.44)**	**(35.00)**	**(33.33)**	**(30.00)**	**(28.33)**	**(30.00)**	**(33.33)**
AR	3.89	5.56	5.00	6.67	6.11	5.00	3.89	3.89	4.44	6.11	6.67	5.00
	(2.78)	(5.00)	(6.67)	(8.33)	(8.89)	(7.22)	(6.11)	(5.56)	(7.22)	(5.56)	(7.78)	(4.44)
UCSV	5.00	4.44	3.33	7.22	5.56	6.67	6.67	5.56	6.11	10.56	5.56	7.22
	(9.44)	(4.44)	(3.89)	(2.22)	(1.11)	(3.89)	(2.22)	(0.00)	(1.67)	(3.89)	(7.22)	(3.89)
BVAR	5.56	2.78	5.00	3.89	0.56	3.89	3.89	4.44	6.11	5.00	5.00	6.67
	(2.22)	(0.56)	(0.00)	(0.00)	(0.00)	(0.56)	(0.00)	(0.56)	(1.11)	(1.11)	(2.22)	(1.11)
LASSO	2.78	1.67	3.89	0.56	1.11	3.89	2.78	1.11	2.22	1.11	2.78	2.22
	(0.00)	(0.56)	(0.00)	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)	(0.00)
Ridge	2.22	3.33	3.89	3.89	6.67	3.89	3.89	6.11	7.78	5.00	7.78	3.33
	(0.56)	(0.00)	(0.56)	(0.56)	(0.56)	(0.00)	(0.00)	(1.11)	(0.56)	(1.11)	(1.11)	(0.00)
Elnet	0.56	1.11	1.11	3.89	2.78	5.00	3.89	2.78	1.11	3.33	1.67	3.33
	(0.56)	(0.56)	(1.11)	(1.11)	(0.56)	(0.56)	(1.11)	(0.00)	(1.67)	(2.22)	(0.56)	(0.00)
adaLASSO	3.33	4.44	2.78	2.22	2.78	3.89	3.33	4.44	2.22	2.22	1.67	7.22
	(0.00)	(1.67)	(0.56)	(0.56)	(0.56)	(0.00)	(1.67)	(2.22)	(1.11)	(2.78)	(2.78)	(3.33)
adaElnet	1.11	2.22	1.11	1.67	1.11	2.78	1.67	2.78	1.67	1.11	2.22	0.56
	(0.00)	(0.00)	(0.00)	(0.00)	(0.56)	(0.00)	(0.00)	(0.00)	(0.56)	(0.00)	(0.56)	(0.56)
Fact.	4.44	4.44	10.56	7.22	8.33	9.44	7.22	6.11	3.89	2.22	1.67	3.33
	(1.67)	(3.33)	(6.11)	(4.44)	(4.44)	(2.78)	(3.89)	(5.00)	(3.33)	(0.56)	(0.56)	(1.11)
T. Fact.	5.56	3.89	5.00	6.67	5.56	4.44	3.33	3.89	4.44	2.78	3.33	4.44
	(4.44)	(2.78)	(1.11)	(0.56)	(2.78)	(4.44)	(1.67)	(2.78)	(1.67)	(2.78)	(0.56)	(0.56)
CSR	2.78	5.00	5.56	2.78	2.22	1.67	3.89	6.67	1.67	5.56	4.44	4.44
	(1.11)	(1.67)	(0.56)	(1.11)	(1.67)	(3.89)	(2.78)	(3.33)	(3.33)	(1.11)	(3.33)	(4.44)
Bagging	12.22	**17.22**	**12.22**	5.56	8.89	8.33	8.89	9.44	11.11	7.78	7.78	9.44
	(10.56)	(13.89)	(8.33)	(12.22)	(11.67)	(8.89)	(11.11)	(11.67)	(11.11)	(13.89)	(12.22)	(10.00)
Boosting	**15.56**	11.67	11.67	11.67	13.89	10.00	10.00	11.11	**16.11**	10.00	11.67	7.78
	(17.78)	(11.11)	(11.11)	(14.44)	(11.11)	(15.00)	(16.67)	(13.33)	(17.22)	(13.33)	(11.11)	(11.11)
Jackknife	9.44	11.11	11.67	9.44	6.67	**11.67**	9.44	10.00	8.33	**12.78**	**17.22**	**14.44**
	(22.78)	(18.33)	(21.67)	(22.22)	(22.22)	(19.44)	(15.00)	(18.33)	(17.22)	(20.00)	(17.78)	(23.33)
R. Forest	6.67	5.56	4.44	5.00	7.22	4.44	**11.11**	7.22	7.78	6.11	5.56	6.11
	(3.33)	(1.67)	(2.22)	(2.22)	(2.78)	(3.33)	(2.22)	(2.22)	(1.67)	(2.78)	(1.67)	(2.78)
Mean	2.22	1.67	0.00	1.67	1.67	1.67	1.67	0.56	1.11	2.78	3.33	3.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
25T. Mean	0.00	0.56	1.11	1.67	1.11	1.11	1.67	0.56	1.11	2.78	0.56	2.78
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median	2.22	1.11	0.00	1.67	0.00	1.11	1.67	0.00	0.56	2.22	1.11	1.67
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

[a] This table show the percentage of times each model had the smallest (bigger) errors in the 180 rolling windows.
[b] The biggest values are in bold.

Table 7. Forecasts Root Mean Squared Errors for the CPI on NBER Expansion and Recession periods.

Consumer Price Index RMSE - Expansion and Recession

Forecasting Horizon

exp (*rec*)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.86	0.76	0.74	0.77	0.80	0.82	0.77	0.69	0.70	0.77	0.78	0.70	5
	(0.99)	(0.89)	(0.86)	(0.84)	(0.77)	(0.76)	(0.80)	(0.92)	(0.94)	(0.92)	(0.94)	(0.89)	(9)
UCSV	0.88	0.79	0.77	0.80	0.79	0.81	0.81	0.72	0.69	0.74	0.78	0.72	4
	(1.12)	(0.86)	(0.83)	(0.83)	(0.78)	(0.74)	(0.75)	(0.89)	(0.93)	(0.91)	(0.93)	(0.92)	(12)
BVAR	0.83	0.70	0.71	0.77	0.78	0.80	0.77	0.70	0.72	0.79	0.79	0.69	7
	(0.94)	(0.85)	(0.79)	(0.76)	(0.71)	(0.71)	(0.77)	(0.87)	(0.88)	(0.87)	(0.89)	(0.88)	(12)
LASSO	0.80	0.72	0.70	0.77	0.78	0.78	0.76	0.66	0.67	0.75	0.76	0.66	7
	(0.91)	(0.81)	(0.77)	(0.75)	(0.71)	(0.72)	(0.75)	(0.88)	(0.91)	(0.90)	(0.93)	(0.88)	(12)
Ridge	0.80	**0.69**	0.70	0.77	0.78	0.81	0.76	0.67	0.66	0.71	0.72	0.63	8
	(0.95)	(0.80)	(0.76)	(0.74)	(0.69)	(0.68)	(0.74)	(0.87)	(0.88)	(0.87)	(0.89)	(0.86)	(12)
Elnet	0.80	0.71	0.70	0.76	0.78	0.78	0.75	0.67	0.68	0.74	0.76	0.67	6
	(0.92)	(0.81)	(0.77)	(0.76)	(0.70)	(0.70)	(0.75)	(0.88)	(0.91)	(0.91)	(0.92)	(0.88)	(12)
adaLASSO	0.80	0.72	0.71	0.77	0.76	0.78	0.77	0.68	0.69	0.74	0.76	0.66	9
	(0.92)	(0.82)	(0.78)	(0.76)	(0.73)	(0.72)	(0.75)	(0.88)	(0.90)	(0.91)	(0.94)	(0.87)	(12)
adaElnet	0.80	0.72	0.70	0.76	0.76	0.78	0.75	0.67	0.68	0.74	0.75	0.67	8
	(0.95)	(0.81)	(0.79)	(0.78)	(0.73)	(0.73)	(0.75)	(0.88)	(0.90)	(0.91)	(0.93)	(0.87)	(12)
Fact.	0.85	0.78	0.79	0.82	0.83	0.81	0.79	0.75	0.77	0.80	0.79	0.73	1
	(0.93)	(0.79)	(0.77)	(0.76)	(0.72)	(0.75)	(0.80)	(0.93)	(0.92)	(0.91)	(0.94)	(0.91)	(12)
T. Fact.	0.86	0.79	0.79	0.81	0.81	0.84	0.79	0.73	0.72	0.77	0.77	0.71	1
	(0.91)	(0.79)	(0.77)	(0.78)	(0.73)	(0.74)	(0.80)	(0.94)	(0.94)	(0.90)	(0.94)	(0.92)	(9)
CSR	0.82	0.73	0.72	0.77	0.79	0.83	0.81	0.73	0.74	0.80	0.81	0.72	6
	(0.92)	(0.83)	(0.82)	(0.81)	(0.75)	(0.74)	(0.77)	(0.87)	(0.89)	(0.89)	(0.90)	(0.85)	(11)
Bagging	0.84	0.77	0.78	0.87	0.89	0.89	0.86	0.76	0.71	0.76	0.79	0.68	3
	(0.81)	**(0.76)**	**(0.73)**	**(0.70)**	(0.66)	(0.67)	(0.78)	(0.90)	(0.93)	(0.90)	(0.91)	(0.87)	(12)
Boosting	0.89	0.75	0.77	0.84	0.86	0.89	0.85	0.75	0.76	0.82	0.80	0.68	0
	(1.10)	(0.81)	(0.76)	(0.71)	**(0.65)**	(0.66)	**(0.72)**	**(0.86)**	**(0.86)**	**(0.85)**	(0.90)	(0.88)	(12)
Jackknife	0.96	0.83	0.85	0.93	0.98	0.95	0.99	0.85	0.79	0.96	0.91	0.76	0
	(1.07)	(0.80)	(0.81)	(0.75)	(0.66)	**(0.63)**	(0.79)	(0.88)	(0.96)	(0.93)	(0.94)	(0.88)	(12)
R. Forest	**0.79**	0.70	**0.68**	**0.75**	**0.75**	**0.76**	**0.71**	**0.63**	**0.63**	**0.70**	0.71	**0.62**	12
	(0.98)	(0.79)	(0.74)	(0.73)	(0.66)	(0.67)	(0.72)	(0.87)	(0.90)	(0.87)	**(0.89)**	**(0.84)**	(12)
Mean	0.80	0.71	0.71	0.76	0.77	0.77	0.74	0.67	0.67	0.70	**0.71**	0.64	7
	(0.92)	(0.80)	(0.77)	(0.76)	(0.71)	(0.71)	(0.76)	(0.88)	(0.90)	(0.89)	(0.91)	(0.87)	(12)
25T. Mean	0.80	0.71	0.70	0.75	0.76	0.77	0.74	0.66	0.66	0.71	0.72	0.64	6
	(0.92)	(0.80)	(0.77)	(0.76)	(0.71)	(0.71)	(0.76)	(0.88)	(0.90)	(0.89)	(0.91)	(0.87)	(12)
Median	0.80	0.71	0.70	0.75	0.76	0.77	0.74	0.66	0.66	0.71	0.72	0.64	6
	(0.93)	(0.80)	(0.76)	(0.76)	(0.71)	(0.71)	(0.75)	(0.88)	(0.90)	(0.90)	(0.92)	(0.87)	(12)
RMSE count	11	3	10	13	11	7	10	7	7	9	7	1	
MAE count	(18)	(18)	(18)	(16)	(17)	(17)	(17)	(17)	(17)	(18)	(18)	(18)	

[a] This table shows the forecasting RMSE during expansion (recession) for all models relative to the Random Walk. The error measures were calculated from 300 rolling windows (1990-2000 and 2001-2015).
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the squared error as loss function.

Table 8. Forecasts Mean Absolute Errors for the CPI on NBER Expansion and Recession periods.

	Consumer Price Index MAE - Expansion and Recession												
	Forecasting Horizon												
exp (*rec*)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.88	0.76	0.76	0.78	0.83	0.83	0.76	0.72	0.78	0.84	0.84	0.74	1
	(0.86)	(0.92)	(0.84)	(0.88)	(0.72)	(0.73)	(0.84)	(0.94)	(0.91)	(0.89)	(0.96)	(0.90)	(7)
UCSV	0.90	0.81	0.79	0.80	0.83	0.83	0.80	0.77	0.76	0.78	0.83	0.75	1
	(0.98)	(0.85)	(0.77)	(0.81)	(0.72)	(0.70)	(0.77)	(0.88)	(0.88)	(0.86)	(0.93)	(0.93)	(11)
BVAR	0.85	0.70	0.75	0.78	0.81	0.81	0.76	0.74	0.80	0.84	0.85	0.74	3
	(0.94)	(0.85)	(0.77)	(0.81)	(0.70)	(0.69)	(0.78)	**(0.83)**	**(0.82)**	**(0.79)**	**(0.88)**	(0.88)	(11)
LASSO	0.83	0.73	0.73	0.78	0.81	0.77	0.73	0.68	0.73	0.80	0.82	0.71	6
	(0.78)	(0.81)	(0.74)	(0.76)	(0.66)	(0.69)	(0.77)	(0.87)	(0.85)	(0.83)	(0.94)	(0.89)	(12)
Ridge	0.82	0.70	0.72	0.76	0.79	0.80	0.73	0.68	0.72	0.76	0.77	0.68	7
	(0.87)	(0.81)	(0.73)	(0.77)	(0.65)	(0.66)	(0.76)	(0.85)	(0.84)	(0.81)	(0.90)	(0.88)	(10)
Elnet	0.82	0.73	0.73	0.78	0.82	0.78	0.74	0.67	0.75	0.80	0.83	0.72	4
	(0.80)	(0.81)	(0.75)	(0.77)	(0.66)	(0.68)	(0.77)	(0.87)	(0.85)	(0.85)	(0.93)	(0.88)	(12)
adaLASSO	0.81	0.73	0.71	0.77	0.77	0.76	0.72	0.68	0.73	0.78	0.81	0.70	8
	(0.81)	(0.83)	(0.75)	(0.77)	(0.68)	(0.69)	(0.77)	(0.87)	(0.84)	(0.84)	(0.96)	(0.87)	(12)
adaElnet	0.81	0.73	**0.71**	0.76	0.77	0.76	0.72	0.68	0.73	0.78	0.80	0.72	6
	(0.85)	(0.82)	(0.75)	(0.80)	(0.68)	(0.70)	(0.77)	(0.87)	(0.84)	(0.84)	(0.94)	(0.87)	(12)
Fact.	0.89	0.80	0.83	0.84	0.87	0.81	0.77	0.78	0.86	0.87	0.85	0.80	0
	(0.80)	(0.80)	(0.70)	(0.77)	(0.68)	(0.75)	(0.83)	(0.91)	(0.88)	(0.87)	(0.96)	(0.91)	(12)
T. Fact.	0.89	0.82	0.84	0.84	0.87	0.88	0.79	0.76	0.82	0.87	0.84	0.78	0
	(0.80)	(0.81)	(0.73)	(0.83)	(0.71)	(0.71)	(0.83)	(0.95)	(0.91)	(0.88)	(0.96)	(0.93)	(10)
CSR	0.85	0.74	0.74	0.78	0.82	0.82	0.75	0.71	0.77	0.82	0.83	0.75	1
	(0.81)	(0.83)	(0.78)	(0.85)	(0.70)	(0.71)	(0.80)	(0.88)	(0.86)	(0.86)	(0.93)	(0.86)	(11)
Bagging	0.85	0.78	0.82	0.90	0.93	0.91	0.83	0.78	0.78	0.83	0.85	0.75	1
	(0.81)	**(0.74)**	(0.71)	(0.74)	(0.67)	(0.67)	(0.82)	(0.90)	(0.88)	(0.86)	(0.93)	(0.91)	(12)
Boosting	0.96	0.79	0.84	0.88	0.91	0.92	0.86	0.81	0.85	0.87	0.84	0.71	0
	(0.99)	(0.80)	(0.71)	(0.74)	(0.62)	(0.67)	(0.79)	(0.89)	(0.84)	(0.82)	(0.93)	(0.91)	(11)
Jackknife	1.00	0.85	0.92	0.98	1.05	0.97	0.92	0.86	0.91	0.97	0.95	0.81	0
	(0.97)	(0.84)	(0.79)	(0.81)	(0.69)	(0.70)	(0.86)	(0.92)	(1.00)	(0.93)	(1.00)	(0.93)	(10)
R. Forest	0.81	**0.70**	0.71	0.75	**0.77**	**0.75**	**0.68**	**0.64**	**0.68**	**0.73**	**0.73**	**0.63**	12
	(0.82)	(0.80)	**(0.70)**	**(0.74)**	**(0.60)**	**(0.65)**	**(0.76)**	(0.87)	(0.85)	(0.83)	(0.90)	**(0.85)**	(12)
Mean	**0.81**	0.72	0.73	0.75	0.78	0.77	0.72	0.68	0.72	0.74	0.74	0.67	7
	(0.80)	(0.81)	(0.74)	(0.78)	(0.68)	(0.69)	(0.78)	(0.85)	(0.86)	(0.84)	(0.92)	(0.86)	(12)
25T. Mean	0.81	0.72	0.72	**0.75**	0.78	0.76	0.71	0.67	0.72	0.75	0.76	0.67	7
	(0.80)	(0.80)	(0.74)	(0.77)	(0.67)	(0.68)	(0.77)	(0.86)	(0.85)	(0.84)	(0.92)	(0.87)	(12)
Median	0.82	0.72	0.72	0.75	0.78	0.76	0.71	0.67	0.72	0.75	0.76	0.67	6
	(0.81)	(0.80)	(0.73)	(0.77)	(0.67)	(0.69)	(0.77)	(0.86)	(0.85)	(0.84)	(0.93)	(0.87)	(12)
RMSE count	11	6	9	12	8	7	3	7	1	3	2	1	
MAE count	(13)	(17)	(16)	(17)	(17)	(18)	(18)	(16)	(15)	(18)	(18)	(18)	

[a] This table shows the forecasting MAE during expansion (recession) for all models relative to the Random Walk. The error measures were calculated from 300 rolling windows (1990-2000 and 2001-2015).
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the absolute error as loss function.

Table 9. Conditional Giacomini & White test using the Random Walk as benchmark

Consumer Price Index - Conditional Giacomini & White Test Results

t+1

	Intercept	Rec.	VIX	Uncert.	Rec.*VIX	Rec*Uncert.
AR	7.71	39.44	0.19	-1.42	-41.56	19.88
	(0.190)	(0.580)	(0.910)	(0.310)	(0.340)	(0.270)
UCSV	4.74	47.76	1.70	-1.76	-82.63	44.68
	(0.490)	(0.630)	(0.360)	(0.260)	(0.280)	(0.210)
BVAR	14.68**	-24.25	-1.57	-1.74	0.30	5.03
	(0.020)	(0.750)	(0.430)	(0.340)	(0.990)	(0.660)
LASSO	13.06**	-0.35	-0.94	-1.73	-23.57	16.43
	(0.040)	(1.000)	(0.630)	(0.290)	(0.480)	(0.340)
Ridge	13.86**	10.67	-0.53	-2.16	-30.10	18.29
	(0.020)	(0.870)	(0.800)	(0.200)	(0.310)	(0.240)
Elnet	13.86**	-1.16	-0.87	-1.94	-24.80	17.40
	(0.030)	(0.980)	(0.650)	(0.230)	(0.470)	(0.330)
adaLASSO	13.56**	-3.98	-0.59	-2.06	-18.19	13.47
	(0.020)	(0.940)	(0.750)	(0.200)	(0.520)	(0.340)
adaElnet	13.62**	10.05	-0.59	-2.07	-23.53	14.04
	(0.030)	(0.840)	(0.740)	(0.190)	(0.440)	(0.360)
Fact.	14.42**	3.41	-0.95	-2.14	-27.57	18.42
	(0.040)	(0.960)	(0.560)	(0.120)	(0.540)	(0.350)
T. Fact.	7.54	-10.26	-0.49	-0.96	-21.66	17.22
	(0.200)	(0.870)	(0.790)	(0.500)	(0.570)	(0.360)
CSR	10.54	0.23	-0.84	-1.29	-24.85	17.13
	(0.100)	(1.000)	(0.670)	(0.420)	(0.530)	(0.300)
Bagging	21.67***	-25.41	-2.31	-2.83	21.52	-7.86
	(0.000)	(0.760)	(0.180)	(0.130)	(0.320)	(0.620)
Boosting	10.15	52.64	-1.76	-0.80	-69.60	35.35
	(0.310)	(0.630)	(0.470)	(0.700)	(0.320)	(0.290)
Jackknife	11.84	5.06	-0.54	-2.11	-66.08	43.08
	(0.240)	(0.950)	(0.820)	(0.300)	(0.270)	(0.200)
R. Forest	17.48***	4.79	-1.49	-2.31	-39.51	25.71
	(0.010)	(0.910)	(0.420)	(0.150)	(0.280)	(0.200)
Mean	13.89**	-5.93	-0.82	-1.98	-22.55	16.86
	(0.020)	(0.930)	(0.640)	(0.190)	(0.530)	(0.320)
25T. Mean	12.88**	-0.82	-0.71	-1.83	-25.08	17.48
	(0.030)	(0.990)	(0.690)	(0.230)	(0.490)	(0.320)
Median	13.07**	1.41	-0.71	-1.87	-26.35	17.84
	(0.030)	(0.980)	(0.700)	(0.230)	(0.450)	(0.300)

t+3

	Intercept	Rec.	VIX	Uncert.	Rec.*VIX	Rec*Uncert.
AR	29.93	-276.70	-6.71*	-1.32	14.07	49.03
	(0.190)	(0.250)	(0.090)	(0.720)	(0.860)	(0.400)
UCSV	30.20	-282.22	-4.93	-2.62	29.88	40.15
	(0.150)	(0.270)	(0.140)	(0.410)	(0.720)	(0.440)
BVAR	31.10	-339.21*	-8.02**	-0.69	64.41	28.99
	(0.170)	(0.060)	(0.040)	(0.860)	(0.230)	(0.490)
LASSO	31.37	-358.28	-8.10*	-0.65	56.95	38.16
	(0.200)	(0.140)	(0.050)	(0.870)	(0.480)	(0.470)
Ridge	30.72	-391.57*	-7.23*	-1.05	76.82	31.71
	(0.180)	(0.090)	(0.060)	(0.780)	(0.300)	(0.510)
Elnet	31.55	-379.02	-8.01*	-0.74	65.75	36.46
	(0.200)	(0.120)	(0.060)	(0.850)	(0.380)	(0.480)
adaLASSO	30.72	-364.17	-8.05*	-0.56	58.35	38.26
	(0.220)	(0.140)	(0.060)	(0.890)	(0.450)	(0.470)
adaElnet	31.84	-358.66	-7.96*	-0.84	54.98	39.37
	(0.200)	(0.150)	(0.060)	(0.840)	(0.490)	(0.470)
Fact.	29.89	-320.76	-7.76**	-0.82	60.57	28.47
	(0.140)	(0.170)	(0.040)	(0.800)	(0.380)	(0.560)
T. Fact.	21.52	-341.65	-8.20**	1.28	74.38	23.25
	(0.280)	(0.130)	(0.020)	(0.700)	(0.250)	(0.620)
CSR	28.31	-330.19	-7.86*	-0.19	40.76	42.66
	(0.230)	(0.180)	(0.060)	(0.960)	(0.580)	(0.440)
Bagging	29.51	-453.50*	-6.84	-1.29	101.80	28.00
	(0.240)	(0.060)	(0.110)	(0.760)	(0.150)	(0.540)
Boosting	25.99	-386.12	-9.31**	1.05	82.76	26.86
	(0.230)	(0.110)	(0.030)	(0.780)	(0.270)	(0.610)
Jackknife	28.74	-492.72**	-6.86*	-1.38	83.39	47.26
	(0.280)	(0.030)	(0.090)	(0.770)	(0.160)	(0.330)
R. Forest	31.93	-382.24	-7.85**	-0.89	80.91	27.34
	(0.190)	(0.110)	(0.050)	(0.820)	(0.300)	(0.590)
Mean	30.01	-362.25	-7.23*	-0.92	66.99	32.20
	(0.180)	(0.120)	(0.060)	(0.800)	(0.360)	(0.500)
25T. Mean	29.86	-368.99	-7.52*	-0.68	68.00	32.94
	(0.200)	(0.120)	(0.060)	(0.860)	(0.360)	(0.510)
Median	29.68	-371.72	-7.59*	-0.60	69.61	32.48
	(0.200)	(0.120)	(0.060)	(0.880)	(0.340)	(0.520)

t+6

	Intercept	Rec.	VIX	Uncert.	Rec.*VIX	Rec*Uncert.
AR	29.84	66.22	-2.40	-4.41	84.35***	-64.77*
	(0.150)	(0.640)	(0.390)	(0.200)	(0.000)	(0.060)
UCSV	26.68	91.18	-1.77	-4.09	79.90***	-66.57
	(0.160)	(0.590)	(0.370)	(0.200)	(0.000)	(0.110)
BVAR	25.49	17.98	-3.92	-2.44	107.81***	-70.05**
	(0.240)	(0.890)	(0.150)	(0.510)	(0.000)	(0.040)
LASSO	25.46	75.07	-2.59	-3.22	97.92***	-75.12*
	(0.220)	(0.640)	(0.350)	(0.370)	(0.000)	(0.060)
Ridge	26.10	27.11	-2.67	-3.38	118.58***	-78.63**
	(0.230)	(0.860)	(0.340)	(0.360)	(0.000)	(0.040)
Elnet	25.33	68.23	-2.80	-3.07	108.42***	-80.44**
	(0.230)	(0.670)	(0.320)	(0.400)	(0.000)	(0.040)
adaLASSO	28.17	61.11	-3.18	-3.44	103.18***	-75.75**
	(0.150)	(0.690)	(0.260)	(0.320)	(0.000)	(0.050)
adaElnet	27.67	74.03	-3.08	-3.38	95.93***	-73.68*
	(0.160)	(0.630)	(0.260)	(0.330)	(0.000)	(0.050)
Fact.	26.68	-3.51	-3.14	-3.22	101.99***	-62.55*
	(0.180)	(0.970)	(0.250)	(0.350)	(0.010)	(0.060)
T. Fact.	19.52	48.64	-2.85	-1.94	96.85***	-69.32**
	(0.290)	(0.700)	(0.300)	(0.550)	(0.000)	(0.030)
CSR	27.54	-1.77	-3.25	-3.40	111.47***	-68.96**
	(0.190)	(0.990)	(0.310)	(0.350)	(0.000)	(0.040)
Bagging	30.88	-9.79	-3.28	-4.29	135.90***	-82.33**
	(0.170)	(0.950)	(0.300)	(0.260)	(0.000)	(0.040)
Boosting	17.40	57.01	-4.59	-0.55	145.71***	-102.43**
	(0.460)	(0.740)	(0.140)	(0.890)	(0.000)	(0.020)
Jackknife	33.18	-72.29	-5.36	-3.68	196.23**	-109.43*
	(0.150)	(0.590)	(0.140)	(0.350)	(0.010)	(0.050)
R. Forest	26.32	45.23	-2.11	-3.64	116.45***	-80.84*
	(0.190)	(0.800)	(0.410)	(0.300)	(0.000)	(0.060)
Mean	25.89	36.67	-2.59	-3.29	111.08***	-76.11**
	(0.200)	(0.800)	(0.310)	(0.340)	(0.000)	(0.040)
25T. Mean	26.49	42.02	-2.58	-3.43	108.64***	-75.49**
	(0.190)	(0.780)	(0.330)	(0.330)	(0.000)	(0.040)
Median	26.41	41.16	-2.60	-3.40	107.80***	-74.80**
	(0.200)	(0.780)	(0.330)	(0.330)	(0.000)	(0.040)

t+12

	Intercept	Rec.	VIX	Uncert.	Rec.*VIX	Rec*Uncert.
AR	22.08	-72.66*	9.95	-9.58*	38.21	-11.02
	(0.300)	(0.060)	(0.320)	(0.070)	(0.340)	(0.680)
UCSV	14.63	-60.58*	10.35	-8.31	27.93	-7.08
	(0.480)	(0.070)	(0.320)	(0.100)	(0.380)	(0.740)
BVAR	16.56	-78.24*	8.37	-7.34	43.09	-13.20
	(0.460)	(0.050)	(0.390)	(0.150)	(0.300)	(0.640)
LASSO	16.22	-104.90**	10.76	-8.66	51.57	-13.73
	(0.490)	(0.020)	(0.310)	(0.120)	(0.280)	(0.670)
Ridge	23.16	-157.51***	10.46	-9.89*	65.43	-12.09
	(0.330)	(0.010)	(0.320)	(0.080)	(0.250)	(0.740)
Elnet	14.07	-110.58**	10.96	-8.35	52.38	-13.12
	(0.560)	(0.020)	(0.300)	(0.140)	(0.290)	(0.690)
adaLASSO	22.88	-136.63**	10.30	-9.84*	62.30	-14.19
	(0.340)	(0.010)	(0.320)	(0.080)	(0.240)	(0.690)
adaElnet	18.09	-127.30**	10.94	-9.23*	59.28	-14.12
	(0.430)	(0.020)	(0.300)	(0.090)	(0.260)	(0.680)
Fact.	12.91	-31.46	7.02	-5.88	26.45	-11.66
	(0.550)	(0.290)	(0.470)	(0.240)	(0.340)	(0.570)
T. Fact.	11.19	-31.21	8.01	-6.06	25.60	-11.43
	(0.590)	(0.330)	(0.420)	(0.230)	(0.350)	(0.580)
CSR	19.45	-125.34**	9.22	-8.64*	66.39	-18.80
	(0.280)	(0.010)	(0.310)	(0.070)	(0.210)	(0.570)
Bagging	23.07	-189.98**	10.33	-9.97*	62.25	-3.32
	(0.410)	(0.010)	(0.280)	(0.080)	(0.260)	(0.920)
Boosting	7.85	-94.72*	9.00	-5.82	56.49	-19.10
	(0.690)	(0.070)	(0.370)	(0.250)	(0.230)	(0.560)
Jackknife	48.95	-199.93***	9.31	-15.28**	55.91	3.54
	(0.190)	(0.000)	(0.390)	(0.030)	(0.210)	(0.910)
R. Forest	17.17	-138.05**	11.52	-9.20*	68.24	-17.82
	(0.450)	(0.010)	(0.260)	(0.090)	(0.240)	(0.630)
Mean	17.91	-101.36**	10.37	-8.71	47.75	-11.77
	(0.450)	(0.020)	(0.310)	(0.110)	(0.260)	(0.680)
25T. Mean	16.45	-103.35**	10.48	-8.47	50.18	-13.02
	(0.470)	(0.020)	(0.310)	(0.110)	(0.270)	(0.670)
Median	16.24	-104.90**	10.49	-8.43	51.40	-13.56
	(0.470)	(0.020)	(0.310)	(0.110)	(0.270)	(0.670)

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Table 10. Conditional GW test (uncertainty only) using the Random Walk as benchmark

Consumer Price Index - Conditional Giacomini & White (uncertainty only)

	t+1					t+3			
	Intercept	Rec.	Uncert.	Rec*Uncert.		Intercept	Rec.	Uncert.	Rec*Uncert.
AR	7.95	28.57	-1.36	-5.98	AR	21.76	-266.64	-3.75	56.04
	(0.160)	(0.700)	(0.260)	(0.710)		(0.300)	(0.260)	(0.390)	(0.260)
UCSV	6.81	24.87	-1.15	-6.40	UCSV	24.20	-269.80	-4.40	57.49
	(0.220)	(0.790)	(0.330)	(0.760)		(0.200)	(0.290)	(0.270)	(0.290)
BVAR	12.76*	-22.67	-2.31	4.81	BVAR	21.34	-314.94	-3.58	67.05
	(0.060)	(0.760)	(0.110)	(0.750)		(0.320)	(0.120)	(0.430)	(0.120)
LASSO	11.91*	-5.51	-2.07	1.49	LASSO	21.51	-335.85	-3.58	71.54
	(0.060)	(0.920)	(0.120)	(0.900)		(0.340)	(0.190)	(0.460)	(0.190)
Ridge	13.22**	3.43	-2.35*	-0.61	Ridge	21.92	-364.86	-3.66	77.72
	(0.040)	(0.960)	(0.080)	(0.970)		(0.310)	(0.150)	(0.420)	(0.150)
Elnet	12.80**	-6.70	-2.25*	1.71	Elnet	21.79	-354.41	-3.64	75.35
	(0.050)	(0.910)	(0.100)	(0.890)		(0.340)	(0.180)	(0.450)	(0.170)
adaLASSO	12.85**	-8.10	-2.27*	1.97	adaLASSO	20.92	-341.43	-3.47	72.53
	(0.040)	(0.870)	(0.080)	(0.850)		(0.360)	(0.190)	(0.470)	(0.190)
adaElnet	12.90**	4.57	-2.28*	-0.79	adaElnet	22.15	-336.87	-3.71	71.56
	(0.040)	(0.920)	(0.080)	(0.940)		(0.330)	(0.190)	(0.440)	(0.190)
Fact.	13.26**	-2.77	-2.48*	0.98	Fact.	20.44	-297.72	-3.63	64.20
	(0.040)	(0.970)	(0.060)	(0.950)		(0.280)	(0.230)	(0.360)	(0.220)
T. Fact.	6.95	-15.36	-1.14	3.59	T. Fact.	11.53	-314.64	-1.68	67.48
	(0.220)	(0.790)	(0.350)	(0.780)		(0.540)	(0.200)	(0.670)	(0.200)
CSR	9.52	-5.36	-1.60	1.41	CSR	18.74	-312.16	-3.03	66.02
	(0.140)	(0.940)	(0.240)	(0.930)		(0.390)	(0.220)	(0.510)	(0.220)
Bagging	18.86**	-17.66	-3.66**	4.95	Bagging	21.18	-420.74	-3.76	89.68
	(0.020)	(0.820)	(0.030)	(0.760)		(0.360)	(0.120)	(0.440)	(0.120)
Boosting	8.01	36.43	-1.44	-8.51	Boosting	14.65	-355.89	-2.31	76.02
	(0.370)	(0.730)	(0.450)	(0.700)		(0.470)	(0.190)	(0.590)	(0.180)
Jackknife	11.18	-11.42	-2.30	1.74	Jackknife	20.40	-464.69*	-3.86	97.45*
	(0.220)	(0.890)	(0.230)	(0.920)		(0.390)	(0.070)	(0.440)	(0.080)
R. Forest	15.67**	-3.94	-2.85**	0.69	R. Forest	22.38	-353.88	-3.72	75.73
	(0.020)	(0.940)	(0.040)	(0.950)		(0.320)	(0.180)	(0.440)	(0.180)
Mean	12.89**	-10.94	-2.27*	2.58	Mean	21.21	-338.07	-3.53	72.07
	(0.030)	(0.860)	(0.070)	(0.850)		(0.310)	(0.180)	(0.420)	(0.170)
25T. Mean	12.01**	-6.59	-2.09*	1.65	25T. Mean	20.70	-344.27	-3.40	73.36
	(0.040)	(0.910)	(0.100)	(0.900)		(0.340)	(0.180)	(0.450)	(0.180)
Median	12.21**	-4.68	-2.13*	1.22	Median	20.44	-346.52	-3.35	73.89
	(0.050)	(0.940)	(0.100)	(0.920)		(0.340)	(0.180)	(0.460)	(0.180)

	t+6					t+12			
	Intercept	Rec.	Uncert.	Rec*Uncert.		Intercept	Rec.	Uncert.	Rec*Uncert.
AR	26.92	90.23	-5.28	-12.81	AR	34.19**	-72.38	-5.98*	15.41
	(0.130)	(0.550)	(0.150)	(0.640)		(0.050)	(0.110)	(0.090)	(0.120)
UCSV	24.53	113.44	-4.73	-17.22	UCSV	27.23*	-63.33*	-4.57	13.05
	(0.150)	(0.520)	(0.180)	(0.590)		(0.090)	(0.090)	(0.160)	(0.110)
BVAR	20.73	49.48	-3.86	-3.86	BVAR	26.74	-75.18	-4.32	15.85
	(0.240)	(0.730)	(0.300)	(0.890)		(0.150)	(0.120)	(0.250)	(0.130)
LASSO	22.31	102.74	-4.15	-14.75	LASSO	29.32	-101.96*	-4.78	21.24*
	(0.180)	(0.550)	(0.240)	(0.640)		(0.130)	(0.080)	(0.220)	(0.090)
Ridge	22.85	60.18	-4.34	-5.40	Ridge	35.89*	-150.72**	-6.11	31.45**
	(0.180)	(0.710)	(0.230)	(0.860)		(0.070)	(0.040)	(0.130)	(0.040)
Elnet	21.92	98.81	-4.08	-13.57	Elnet	27.41	-107.62*	-4.39	22.41*
	(0.200)	(0.560)	(0.260)	(0.660)		(0.160)	(0.070)	(0.270)	(0.080)
adaLASSO	24.31	90.71	-4.59	-12.25	adaLASSO	35.42*	-130.49*	-6.12	27.35*
	(0.130)	(0.590)	(0.170)	(0.690)		(0.070)	(0.050)	(0.130)	(0.060)
adaElnet	23.92	101.67	-4.50	-14.67	adaElnet	31.41*	-122.55*	-5.28	25.71*
	(0.140)	(0.540)	(0.190)	(0.630)		(0.100)	(0.060)	(0.170)	(0.070)
Fact.	22.86	25.74	-4.35	0.22	Fact.	21.45	-31.40	-3.34	6.66
	(0.200)	(0.830)	(0.240)	(0.990)		(0.220)	(0.310)	(0.350)	(0.310)
T. Fact.	16.05	76.29	-2.97	-9.68	T. Fact.	20.95	-32.32	-3.17	6.63
	(0.320)	(0.560)	(0.370)	(0.690)		(0.210)	(0.320)	(0.360)	(0.330)
CSR	23.59	30.02	-4.57	-0.31	CSR	30.67**	-117.11*	-5.31*	25.01*
	(0.190)	(0.820)	(0.220)	(0.990)		(0.040)	(0.080)	(0.080)	(0.090)
Bagging	26.89	28.32	-5.48	1.55	Bagging	35.65	-183.88**	-6.24	38.20**
	(0.140)	(0.860)	(0.150)	(0.960)		(0.130)	(0.030)	(0.200)	(0.030)
Boosting	11.82	98.90	-2.21	-12.78	Boosting	18.80	-88.82	-2.57	18.48
	(0.410)	(0.620)	(0.470)	(0.730)		(0.230)	(0.150)	(0.430)	(0.160)
Jackknife	26.66	-16.66	-5.62	11.52	Jackknife	60.28*	-194.48***	-11.92*	40.84***
	(0.130)	(0.920)	(0.130)	(0.740)		(0.060)	(0.000)	(0.070)	(0.000)
R. Forest	23.76	77.21	-4.40	-8.79	R. Forest	31.19*	-131.55*	-5.04	27.75*
	(0.150)	(0.690)	(0.210)	(0.810)		(0.100)	(0.060)	(0.190)	(0.070)
Mean	22.74	67.73	-4.23	-7.53	Mean	30.54	-99.04*	-4.96	20.72*
	(0.170)	(0.660)	(0.220)	(0.800)		(0.110)	(0.060)	(0.200)	(0.070)
25T. Mean	23.35	72.45	-4.36	-8.42	25T. Mean	29.21	-100.51*	-4.68	21.01*
	(0.160)	(0.650)	(0.210)	(0.780)		(0.110)	(0.070)	(0.210)	(0.080)
Median	23.25	71.38	-4.34	-8.27	Median	29.01	-101.74*	-4.64	21.24*
	(0.160)	(0.660)	(0.210)	(0.780)		(0.110)	(0.070)	(0.220)	(0.080)

[a]

Table 11. Conditional GW test (VIX only) using the Random Walk as benchmark

Consumer Price Index - Conditional Giacomini & White (VIX only)

	t+1					t+3			
	Intercept	Rec.	VIX.	Rec*VIX.		Intercept	Rec.	VIX.	Rec*VIX.
AR	2.87	94.99	-0.40	-28.86	AR	25.43*	-141.14	-7.26	45.93
	(0.530)	(0.380)	(0.800)	(0.390)		(0.070)	(0.500)	(0.100)	(0.480)
UCSV	-1.25	171.65	0.96	-53.74	UCSV	21.29*	-170.20	-6.02	55.60
	(0.810)	(0.340)	(0.580)	(0.350)		(0.090)	(0.460)	(0.140)	(0.450)
BVAR	8.75*	-9.29	-2.30	3.18	BVAR	28.77**	-259.13*	-8.31*	83.27*
	(0.060)	(0.870)	(0.140)	(0.860)		(0.030)	(0.090)	(0.050)	(0.090)
LASSO	7.19	45.92	-1.66	-13.20	LASSO	29.16**	-253.03	-8.37*	81.83
	(0.130)	(0.560)	(0.310)	(0.590)		(0.040)	(0.260)	(0.070)	(0.250)
Ridge	6.51	62.34	-1.43	-18.62	Ridge	27.16**	-303.76	-7.67*	97.38
	(0.190)	(0.410)	(0.400)	(0.430)		(0.040)	(0.160)	(0.080)	(0.160)
Elnet	7.28	47.91	-1.68	-13.85	Elnet	29.02**	-278.38	-8.32*	89.49
	(0.130)	(0.560)	(0.310)	(0.590)		(0.050)	(0.200)	(0.080)	(0.190)
adaLASSO	6.57	34.36	-1.44	-9.85	adaLASSO	28.81*	-258.69	-8.28*	83.32
	(0.130)	(0.610)	(0.340)	(0.640)		(0.050)	(0.240)	(0.080)	(0.230)
adaElnet	6.59	49.96	-1.46	-14.81	adaElnet	29.00*	-249.96	-8.31*	80.61
	(0.140)	(0.480)	(0.350)	(0.510)		(0.050)	(0.260)	(0.080)	(0.250)
Fact.	7.15	55.42	-1.84	-15.99	Fact.	27.09**	-242.01	-8.11*	79.06
	(0.120)	(0.620)	(0.240)	(0.650)		(0.030)	(0.220)	(0.050)	(0.200)
T. Fact.	4.28	37.68	-0.89	-10.59	T. Fact.	25.86**	-278.60	-7.67**	89.94
	(0.350)	(0.680)	(0.580)	(0.710)		(0.030)	(0.130)	(0.050)	(0.130)
CSR	6.15	48.12	-1.38	-13.92	CSR	27.66*	-212.86	-7.94*	68.71
	(0.220)	(0.640)	(0.420)	(0.660)		(0.050)	(0.300)	(0.080)	(0.290)
Bagging	12.06***	-45.17	-3.49**	15.68	Bagging	25.12*	-375.73*	-7.38	119.87*
	(0.010)	(0.500)	(0.020)	(0.450)		(0.090)	(0.080)	(0.120)	(0.080)
Boosting	7.43	150.28	-2.10	-46.59	Boosting	29.57**	-313.01	-8.87**	100.63
	(0.280)	(0.380)	(0.370)	(0.390)		(0.030)	(0.140)	(0.050)	(0.140)
Jackknife	4.69	124.80	-1.42	-38.32	Jackknife	24.06	-362.00**	-7.43	114.07**
	(0.490)	(0.360)	(0.530)	(0.370)		(0.110)	(0.030)	(0.120)	(0.030)
R. Forest	9.62**	76.94	-2.45	-23.19	R. Forest	28.92**	-306.53	-8.22*	98.64
	(0.040)	(0.340)	(0.130)	(0.350)		(0.040)	(0.170)	(0.070)	(0.160)
Mean	7.18	41.66	-1.65	-11.96	Mean	26.88**	-273.19	-7.61*	87.89
	(0.100)	(0.640)	(0.270)	(0.670)		(0.050)	(0.190)	(0.080)	(0.180)
25T. Mean	6.66	48.39	-1.48	-14.05	25T. Mean	27.55**	-278.05	-7.81*	89.45
	(0.140)	(0.580)	(0.340)	(0.610)		(0.050)	(0.190)	(0.080)	(0.180)
Median	6.72	51.64	-1.49	-15.09	Median	27.63**	-282.10	-7.85*	90.78
	(0.140)	(0.540)	(0.340)	(0.570)		(0.050)	(0.180)	(0.080)	(0.170)

	t+6					t+12			
	Intercept	Rec.	VIX.	Rec*VIX.		Intercept	Rec.	VIX.	Rec*VIX.
AR	14.86	-108.85***	-4.24	40.79***	AR	-10.46	-96.71	5.95	28.69
	(0.150)	(0.000)	(0.200)	(0.000)		(0.660)	(0.210)	(0.500)	(0.240)
UCSV	12.79	-89.05*	-3.48	35.24***	UCSV	-13.60	-74.63	6.89	21.30
	(0.160)	(0.060)	(0.220)	(0.000)		(0.580)	(0.210)	(0.450)	(0.270)
BVAR	17.19	-172.88***	-4.94	61.26***	BVAR	-8.38	-109.74	5.30	32.67
	(0.110)	(0.000)	(0.150)	(0.000)		(0.720)	(0.160)	(0.540)	(0.180)
LASSO	14.52	-129.22***	-3.93	47.85***	LASSO	-13.22	-136.99	7.14	40.49
	(0.150)	(0.000)	(0.220)	(0.000)		(0.600)	(0.140)	(0.450)	(0.160)
Ridge	14.62	-186.71***	-4.08	66.17***	Ridge	-10.43	-184.29*	6.33	55.13
	(0.170)	(0.000)	(0.230)	(0.000)		(0.680)	(0.090)	(0.500)	(0.110)
Elnet	14.91	-150.78***	-4.08	54.90***	Elnet	-14.29	-141.21	7.47	41.77
	(0.150)	(0.000)	(0.220)	(0.000)		(0.580)	(0.140)	(0.430)	(0.160)
adaLASSO	16.47*	-144.77***	-4.61	52.65***	adaLASSO	-10.55	-169.21	6.19	50.64
	(0.090)	(0.000)	(0.150)	(0.000)		(0.670)	(0.100)	(0.500)	(0.120)
adaElnet	16.18*	-126.18***	-4.49	46.77***	adaElnet	-13.28	-160.09	7.09	47.81
	(0.100)	(0.000)	(0.150)	(0.000)		(0.600)	(0.120)	(0.440)	(0.140)
Fact.	15.75	-173.27***	-4.48	60.18***	Fact.	-7.06	-59.68	4.57	17.39
	(0.120)	(0.010)	(0.170)	(0.000)		(0.760)	(0.220)	(0.600)	(0.270)
T. Fact.	12.93	-140.54***	-3.65	50.90***	T. Fact.	-9.41	-58.67	5.48	16.65
	(0.190)	(0.000)	(0.250)	(0.000)		(0.690)	(0.220)	(0.530)	(0.280)
CSR	16.00	-189.02***	-4.66	65.41***	CSR	-9.92	-171.38*	5.62	51.99
	(0.150)	(0.000)	(0.200)	(0.000)		(0.640)	(0.100)	(0.470)	(0.110)
Bagging	16.29	-233.18***	-5.07	80.85***	Bagging	-10.81	-192.61*	6.17	57.69
	(0.150)	(0.000)	(0.170)	(0.000)		(0.660)	(0.090)	(0.480)	(0.100)
Boosting	15.53	-224.04***	-4.82	78.37***	Boosting	-11.94	-143.40	6.57	42.57
	(0.150)	(0.000)	(0.170)	(0.000)		(0.610)	(0.110)	(0.450)	(0.130)
Jackknife	20.67*	-370.53***	-6.89*	123.55***	Jackknife	-2.98	-180.26**	2.93	54.58**
	(0.100)	(0.010)	(0.090)	(0.000)		(0.920)	(0.030)	(0.780)	(0.040)
R. Forest	13.95	-174.49***	-3.62	62.53***	R. Forest	-14.10	-181.01	7.68	54.35
	(0.150)	(0.000)	(0.240)	(0.000)		(0.560)	(0.110)	(0.400)	(0.120)
Mean	14.70	-170.28***	-3.96	60.35***	Mean	-11.68	-128.03	6.74	37.95
	(0.140)	(0.000)	(0.210)	(0.000)		(0.640)	(0.110)	(0.460)	(0.130)
25T. Mean	14.85	-163.14***	-4.01	58.29***	25T. Mean	-12.34	-133.62	6.95	39.61
	(0.140)	(0.000)	(0.210)	(0.000)		(0.620)	(0.120)	(0.450)	(0.150)
Median	14.86	-162.13***	-4.01	57.90***	Median	-12.41	-136.66	6.97	40.49
	(0.140)	(0.000)	(0.210)	(0.000)		(0.610)	(0.130)	(0.450)	(0.150)

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Appendix A. Supplementary Material

Table 12. Forecasting Errors for the PCE from 1990 to 2000

	Personal Consumption Expenditures 1990-2000												
	Forecasting Horizon												
RMSE/(MAE)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.84	0.80	0.86	0.82	0.79	0.80	0.83	0.84	0.90	0.86	0.95	0.92	7
	(0.86)	(0.79)	(0.88)	(0.85)	(0.79)	(0.84)	(0.89)	(0.80)	(0.89)	(0.90)	(1.00)	(0.98)	(10)
UCSV	0.89	0.85	0.86	0.88	0.85	0.84	0.86	0.87	0.89	0.87	0.90	0.89	7
	(0.90)	(0.84)	(0.87)	(0.88)	(0.84)	(0.85)	(0.89)	(0.86)	(0.86)	(0.87)	(0.93)	(0.89)	(10)
BVAR	0.99	0.83	0.95	0.91	0.87	0.94	1.02	1.07	1.15	1.05	1.16	1.10	3
	(1.00)	(0.80)	(1.00)	(0.99)	(0.95)	(1.05)	(1.14)	(1.08)	(1.22)	(1.15)	(1.29)	(1.22)	(1)
LASSO	0.83	0.83	0.86	0.89	0.85	0.88	0.89	0.89	0.96	0.88	0.95	0.88	2
	(0.83)	(0.82)	(0.87)	(0.94)	(0.89)	(0.93)	(1.00)	(0.86)	(0.96)	(0.91)	(1.02)	(0.95)	(3)
Ridge	0.82	0.77	0.85	0.83	0.78	0.82	0.83	0.84	0.90	0.83	0.91	0.84	10
	(0.82)	**(0.75)**	(0.86)	(0.85)	(0.82)	(0.87)	(0.90)	(0.80)	(0.90)	(0.87)	(0.96)	(0.87)	(11)
Elnet	**0.80**	0.83	0.87	0.90	0.86	0.89	0.92	0.91	0.95	0.88	1.00	0.91	2
	(0.81)	(0.83)	(0.89)	(0.97)	(0.92)	(0.96)	(1.02)	(0.88)	(0.96)	(0.92)	(1.08)	(0.98)	(2)
adaLASSO	0.84	0.84	0.86	0.85	0.81	0.83	0.86	0.88	0.93	0.83	0.90	0.87	6
	(0.84)	(0.83)	(0.87)	(0.87)	(0.82)	(0.85)	(0.92)	(0.83)	(0.91)	(0.85)	(0.94)	(0.92)	(7)
adaElnet	0.85	0.84	0.86	0.86	0.80	0.84	0.86	0.88	0.95	0.84	0.92	0.88	4
	(0.86)	(0.84)	(0.87)	(0.90)	(0.82)	(0.87)	(0.93)	(0.84)	(0.93)	(0.87)	(0.97)	(0.94)	(6)
Fact.	0.89	0.89	0.96	0.88	0.86	0.92	0.91	0.92	1.05	0.98	1.05	1.04	1
	(0.91)	(0.89)	(1.01)	(0.89)	(0.87)	(0.95)	(0.98)	(0.89)	(1.09)	(1.04)	(1.10)	(1.13)	(1)
T. Fact.	0.95	0.91	1.01	0.84	0.83	0.88	0.89	0.88	1.00	0.96	0.99	0.97	2
	(0.96)	(0.91)	(1.07)	(0.85)	(0.84)	(0.91)	(0.98)	(0.86)	(1.01)	(1.01)	(1.03)	(1.02)	(2)
CSR	0.83	0.83	0.86	**0.81**	**0.76**	**0.78**	0.80	**0.81**	0.87	0.83	0.90	0.85	9
	(0.83)	(0.81)	(0.87)	**(0.83)**	**(0.78)**	**(0.80)**	**(0.85)**	**(0.76)**	(0.86)	(0.86)	(0.93)	(0.89)	(12)
Bagging	0.85	0.82	0.94	0.90	0.86	0.86	0.84	0.83	0.91	0.86	0.97	0.89	10
	(0.85)	(0.80)	(0.95)	(0.94)	(0.93)	(0.92)	(0.91)	(0.80)	(0.90)	(0.88)	(1.00)	(0.91)	(9)
Boosting	0.99	0.90	1.01	0.96	0.91	0.98	1.00	1.04	1.06	0.94	0.99	0.92	0
	(1.03)	(0.91)	(1.09)	(1.02)	(0.97)	(1.05)	(1.09)	(1.01)	(1.06)	(0.96)	(1.03)	(0.94)	(2)
Jackknife	0.94	1.00	1.06	1.04	1.00	0.92	1.02	1.01	1.17	1.00	1.08	1.00	0
	(0.97)	(1.03)	(1.10)	(1.06)	(1.06)	(0.95)	(1.11)	(0.92)	(1.15)	(1.03)	(1.06)	(0.99)	(2)
R. Forest	0.82	**0.77**	0.86	0.83	0.78	0.80	**0.80**	0.81	**0.84**	**0.78**	**0.85**	**0.79**	12
	(0.82)	(0.77)	(0.90)	(0.87)	(0.81)	(0.85)	(0.85)	(0.76)	**(0.82)**	**(0.80)**	**(0.90)**	**(0.82)**	(12)
Mean	0.82	0.79	**0.84**	0.82	0.78	0.80	0.81	0.81	0.88	0.82	0.87	0.84	8
	(0.83)	(0.79)	(0.85)	(0.84)	(0.79)	(0.83)	(0.88)	(0.77)	(0.86)	(0.84)	(0.92)	(0.88)	(10)
25T. Mean	0.82	0.80	0.85	0.82	0.79	0.80	0.82	0.83	0.90	0.82	0.89	0.85	9
	(0.83)	(0.79)	(0.86)	(0.84)	(0.80)	(0.83)	(0.89)	(0.79)	(0.88)	(0.85)	(0.94)	(0.90)	(11)
Median	0.82	0.80	0.84	0.82	0.79	0.81	0.83	0.84	0.90	0.82	0.89	0.85	8
	(0.83)	(0.79)	**(0.85)**	(0.85)	(0.81)	(0.83)	(0.89)	(0.79)	(0.89)	(0.85)	(0.94)	(0.90)	(11)
RMSE count	11	5	12	12	7	10	8	5	9	7	9	5	
MAE count	(11)	(11)	(12)	(11)	(11)	(9)	(9)	(8)	(9)	(7)	(13)	(11)	

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk. The error measures were calculated from 120 rolling windows.
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the squared error (absolute error) as loss function.

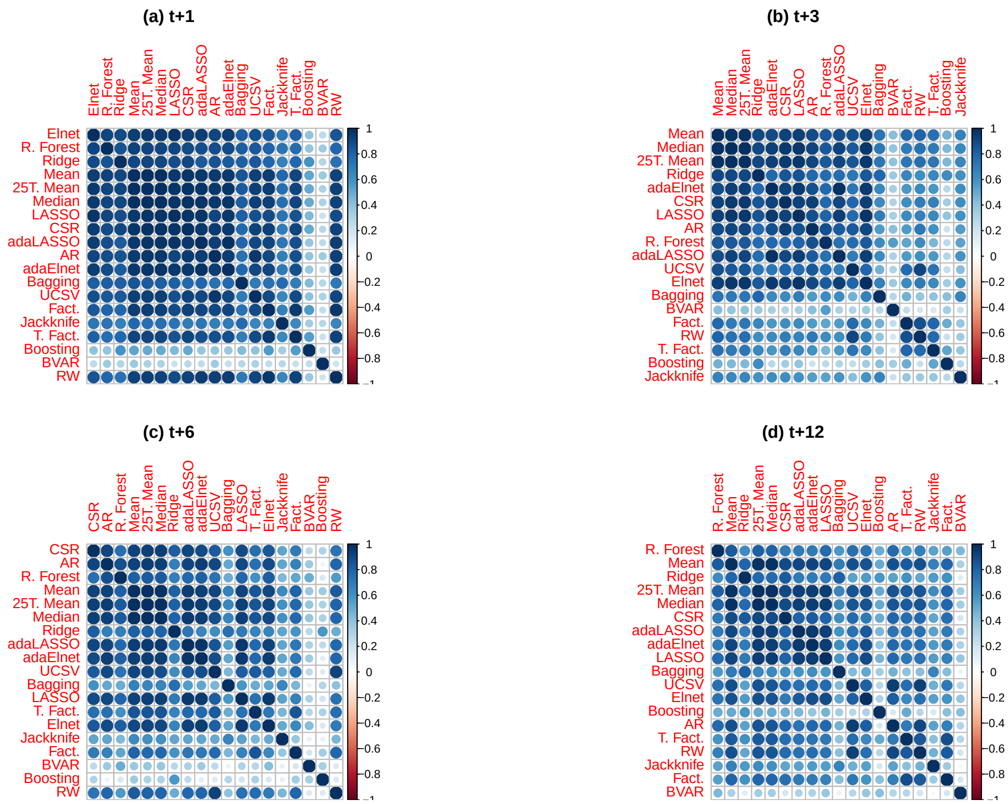
A.1. Results for the PCE - 1990–1999.

A.2. Results for the PCE - 2000–2015.

A.3. Results for the PCE - NBER expansion and recession.

A.4. Variable Selection for the PCE.

FIGURE 6. Forecast Correlation for the PCE from 1990 2000



This figure shows the correlations between forecasts obtained in a 120 rolling window scheme for horizons 1, 3, 6 and 12.

Table 13. Forecasting errors for the PCE from 1995 to 2000 with MCS combinations

	Personal Consumption Expenditures 1995-2000 - MCS											
	Forecasting Horizon											
$RMSE/(MAE)$	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
AR	0.82	0.77	**0.83**	**0.79**	**0.80**	**0.91**	0.82	0.83	0.95	0.87	1.05	0.98
	(0.84)	(0.79)	**(0.82)**	**(0.81)**	**(0.82)**	(0.90)	(0.90)	(0.80)	(0.96)	(0.90)	(1.07)	(1.03)
UCSV	0.86	0.82	0.87	0.87	0.85	0.92	0.87	0.87	0.92	0.89	**0.94**	0.91
	(0.88)	(0.84)	(0.85)	(0.86)	(0.85)	**(0.90)**	(0.90)	(0.86)	(0.91)	(0.89)	**(0.96)**	(0.93)
BVAR	0.90	0.82	1.11	1.00	1.03	1.31	1.12	1.21	1.43	1.23	1.53	1.35
	(0.93)	(0.84)	(1.13)	(1.02)	(1.11)	(1.36)	(1.26)	(1.20)	(1.52)	(1.30)	(1.63)	(1.51)
LASSO	0.83	0.85	0.91	0.95	0.95	1.11	0.94	0.92	1.10	0.98	1.17	1.02
	(0.85)	(0.87)	(0.89)	(0.97)	(1.00)	(1.09)	(1.07)	(0.89)	(1.12)	(1.02)	(1.25)	(1.09)
Ridge	0.82	0.80	0.92	0.87	0.91	1.07	0.87	0.88	1.01	0.89	1.08	0.95
	(0.84)	(0.81)	(0.92)	(0.87)	(0.94)	(1.07)	(0.95)	(0.83)	(1.04)	(0.93)	(1.14)	(1.03)
Elnet	**0.78**	0.84	0.93	0.93	0.96	1.15	0.99	0.97	1.10	0.99	1.23	1.03
	(0.81)	(0.87)	(0.91)	(0.95)	(1.01)	(1.14)	(1.10)	(0.94)	(1.14)	(1.04)	(1.30)	(1.11)
adaLASSO	0.81	0.81	0.92	0.87	0.89	1.00	0.91	0.94	1.07	0.90	1.09	0.99
	(0.84)	(0.82)	(0.88)	(0.89)	(0.91)	(0.94)	(0.98)	(0.89)	(1.06)	(0.92)	(1.13)	(1.04)
adaElnet	0.83	0.83	0.90	0.88	0.87	1.00	0.91	0.94	1.10	0.92	1.12	1.00
	(0.86)	(0.84)	(0.88)	(0.89)	(0.90)	(0.95)	(1.01)	(0.89)	(1.10)	(0.95)	(1.17)	(1.07)
Fact.	0.92	0.98	1.12	0.90	0.94	1.17	1.00	1.03	1.26	1.12	1.35	1.27
	(0.95)	(1.00)	(1.14)	(0.92)	(0.97)	(1.13)	(1.11)	(0.96)	(1.31)	(1.20)	(1.42)	(1.38)
T. Fact.	0.98	0.96	1.17	0.86	0.93	1.11	0.98	0.97	1.19	1.09	1.23	1.14
	(1.01)	(0.98)	(1.22)	(0.85)	(0.96)	(1.09)	(1.08)	(0.94)	(1.23)	(1.17)	(1.28)	(1.20)
CSR	0.83	0.83	0.85	0.80	0.81	0.93	0.83	0.83	0.98	0.88	1.05	0.97
	(0.85)	(0.85)	(0.84)	(0.81)	(0.83)	(0.91)	(0.91)	(0.78)	(0.99)	(0.92)	(1.08)	(1.01)
Bagging	0.86	0.86	1.02	0.94	0.96	1.00	0.80	**0.75**	**0.88**	0.82	1.02	0.93
	(0.87)	(0.86)	(0.99)	(0.94)	(1.02)	(0.99)	(0.85)	**(0.73)**	**(0.89)**	(0.82)	(1.02)	(0.97)
Boosting	1.11	1.08	1.30	1.15	1.20	1.45	1.18	1.26	1.38	1.13	1.32	1.12
	(1.20)	(1.15)	(1.36)	(1.16)	(1.28)	(1.49)	(1.34)	(1.23)	(1.42)	(1.16)	(1.36)	(1.19)
Jackknife	0.94	1.00	1.17	1.09	1.15	1.16	1.05	1.01	1.25	0.97	1.17	1.00
	(0.95)	(1.06)	(1.18)	(1.08)	(1.22)	(1.10)	(1.14)	(0.91)	(1.23)	(0.93)	(1.10)	(1.02)
R. Forest	0.79	**0.77**	0.88	0.82	0.82	0.94	**0.77**	0.80	0.90	**0.78**	0.96	**0.85**
	(0.80)	**(0.79)**	(0.89)	(0.82)	(0.87)	(0.96)	**(0.84)**	(0.75)	(0.90)	**(0.80)**	(0.98)	**(0.89)**
Mean	0.81	0.81	0.90	0.84	0.86	0.98	0.85	0.85	1.00	0.87	1.02	0.94
	(0.84)	(0.83)	(0.88)	(0.87)	(0.89)	(0.96)	(0.94)	(0.80)	(1.00)	(0.91)	(1.06)	(0.98)
25T. Mean	0.81	0.81	0.90	0.85	0.87	0.99	0.87	0.87	1.02	0.89	1.07	0.96
	(0.84)	(0.82)	(0.89)	(0.86)	(0.90)	(0.97)	(0.96)	(0.82)	(1.03)	(0.93)	(1.11)	(1.02)
Median	0.82	0.81	0.90	0.85	0.88	1.00	0.87	0.87	1.03	0.89	1.07	0.98
	(0.84)	(0.82)	(0.88)	(0.86)	(0.90)	(0.97)	(0.95)	(0.83)	(1.03)	(0.93)	(1.12)	(1.03)
MCS50	0.80	0.80	0.89	0.85	0.86	0.98	0.83	0.84	0.96	0.86	1.00	0.92
	(0.82)	(0.83)	(0.86)	(0.86)	(0.89)	(0.96)	(0.92)	(0.81)	(0.96)	(0.90)	(1.05)	(0.96)
MCS75	0.80	0.80	0.89	0.85	0.86	0.99	0.85	0.84	0.97	0.87	1.00	0.92
	(0.83)	(0.82)	(0.87)	(0.87)	(0.88)	(0.97)	(0.94)	(0.80)	(0.97)	(0.90)	(1.04)	(0.96)
MCS90	0.81	0.80	0.89	0.84	0.86	0.98	0.86	0.85	0.98	0.86	1.01	0.92
	(0.84)	(0.83)	(0.87)	(0.86)	(0.89)	(0.97)	(0.95)	(0.80)	(0.98)	(0.90)	(1.05)	(0.96)
MCS50-IRMSE	0.80	0.80	0.89	0.85	0.86	0.98	0.84	0.84	0.96	0.86	1.01	0.92
	(0.82)	(0.83)	(0.87)	(0.86)	(0.89)	(0.96)	(0.92)	(0.81)	(0.96)	(0.90)	(1.05)	(0.96)
MCS75-IRMSE	0.80	0.80	0.89	0.85	0.86	0.99	0.85	0.84	0.97	0.87	1.01	0.92
	(0.82)	(0.82)	(0.87)	(0.87)	(0.89)	(0.97)	(0.94)	(0.80)	(0.97)	(0.90)	(1.05)	(0.97)
MCS90-IRMSE	0.81	0.80	0.89	0.84	0.86	0.99	0.86	0.85	0.98	0.87	1.02	0.92
	(0.83)	(0.83)	(0.88)	(0.86)	(0.89)	(0.97)	(0.95)	(0.80)	(0.99)	(0.90)	(1.06)	(0.97)

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk.
[b] The 120 rolling window forecasts were divided into a training sample (1990-1994) and test sample (1995-2000) and the error measures were calculated in the test sample.
[c] The MCS used for the combinations were calculated in a expanding window starting with the training sample to avoid look ahead bias.

Table 14. Percentage of times each model had the smallest (biggest) error for the PCE from 1990 to 2000

	Personal Consumption Expenditure - Ranking - 1990-2000											
	Forecasting Horizon											
%best/(%worst)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
RW	9.23	6.20	11.45	**12.98**	6.20	11.45	**13.08**	7.69	9.09	6.92	8.33	9.09
	(22.14)	**(23.85)**	(13.64)	(16.92)	(19.85)	(18.32)	(20.00)	**(21.54)**	(12.40)	(16.15)	(13.74)	(12.98)
AR	2.31	1.55	3.05	2.29	5.43	0.76	3.08	3.08	4.55	6.92	3.03	3.03
	(0.00)	(1.54)	(2.27)	(2.31)	(0.76)	(0.00)	(0.00)	(1.54)	(0.00)	(3.08)	(3.05)	(3.05)
UCSV	4.62	7.75	8.40	8.40	**10.08**	9.92	6.15	9.23	7.58	10.77	8.33	8.33
	(1.53)	(1.54)	(2.27)	(0.77)	(0.76)	(2.29)	(0.00)	(1.54)	(3.10)	(0.77)	(3.05)	(3.05)
BVAR	10.77	12.40	6.87	6.11	6.20	4.58	7.69	3.08	2.27	8.46	6.06	7.58
	(16.03)	(11.54)	(9.85)	(13.08)	(9.16)	(15.27)	(16.15)	(13.85)	(21.71)	**(25.38)**	**(22.14)**	**(28.24)**
LASSO	2.31	3.88	1.53	3.05	4.65	3.05	0.77	2.31	3.79	5.38	5.30	2.27
	(0.00)	(0.00)	(0.00)	(0.77)	(3.05)	(3.82)	(3.85)	(3.08)	(3.88)	(0.77)	(0.76)	(0.00)
Ridge	4.62	3.88	3.82	1.53	4.65	3.05	5.38	5.38	3.79	2.31	2.27	5.30
	(0.76)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(0.76)
Elnet	3.08	2.33	1.53	4.58	5.43	3.82	3.85	6.15	4.55	0.77	2.27	2.27
	(0.00)	(0.77)	(2.27)	(9.23)	(8.40)	(3.05)	(1.54)	(3.08)	(2.33)	(0.00)	(2.29)	(3.05)
adaLASSO	3.08	3.10	3.82	3.82	1.55	3.05	3.08	1.54	3.03	5.38	3.03	3.03
	(0.00)	(0.77)	(0.76)	(0.77)	(0.00)	(0.76)	(0.00)	(1.54)	(0.78)	(0.77)	(1.53)	(0.76)
adaElnet	0.77	2.33	2.29	0.00	2.33	3.05	0.77	1.54	1.52	3.08	0.76	1.52
	(5.34)	(3.08)	(0.76)	(0.77)	(0.00)	(0.76)	(0.00)	(0.00)	(1.55)	(0.00)	(0.00)	(0.00)
Fact.	2.31	3.88	5.34	6.11	7.75	5.34	4.62	0.77	3.03	2.31	6.82	3.79
	(0.00)	(3.85)	(6.82)	(5.38)	(3.05)	(7.63)	(5.38)	(5.38)	(9.30)	(11.54)	(14.50)	(9.16)
T. Fact.	2.31	3.88	5.34	7.63	6.20	4.58	2.31	4.62	3.03	6.15	4.55	3.03
	(3.82)	(5.38)	(6.82)	(3.85)	(3.05)	(3.82)	(0.77)	(1.54)	(0.00)	(1.54)	(1.53)	(0.76)
CSR	0.00	2.33	1.53	3.05	2.33	4.58	6.15	6.15	3.79	0.77	3.79	2.27
	(0.00)	(0.00)	(0.76)	(0.77)	(0.76)	(0.76)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(1.53)
Bagging	**16.92**	**17.83**	**12.98**	9.16	**10.08**	9.92	11.54	11.54	**15.15**	10.77	12.12	15.15
	(6.11)	(10.77)	(10.61)	(9.23)	(12.98)	(9.16)	(9.23)	(6.92)	(6.20)	(9.23)	(6.87)	(11.45)
Boosting	15.38	13.18	8.40	11.45	**10.08**	12.21	10.77	9.23	14.39	9.23	7.58	6.82
	(27.48)	(13.08)	(16.67)	(16.92)	(16.79)	**(20.61)**	(16.92)	(20.00)	(13.18)	(11.54)	(8.40)	(6.11)
Jackknife	10.77	7.75	12.21	**12.98**	6.98	**12.98**	10.00	**20.00**	10.61	**16.15**	**18.94**	**17.42**
	(16.03)	**(23.85)**	**(24.24)**	**(18.46)**	**(21.37)**	(11.45)	**(23.08)**	(19.23)	**(23.26)**	(18.46)	(19.85)	(19.08)
R. Forest	9.23	6.20	5.34	4.58	3.88	3.05	6.92	3.85	6.06	3.08	4.55	6.06
	(0.76)	(0.00)	(2.27)	(0.77)	(0.00)	(1.53)	(3.08)	(0.77)	(2.33)	(0.77)	(0.76)	(0.00)
Mean	0.77	1.55	1.53	0.76	1.55	0.76	1.54	2.31	1.52	0.00	2.27	1.52
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
25T. Mean	1.54	0.00	3.05	1.53	3.10	1.53	0.77	0.77	0.76	0.77	0.00	1.52
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median	0.00	0.00	1.53	0.00	1.55	2.29	1.54	0.77	1.52	0.77	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

[a] This table show the percentage of times each model had the smallest (bigger) errors in the 120 rolling windows.
[b] The biggest values are in bold.

Table 15. Forecasting Errors for the PCE from 2001 to 2015

	Personal Consumption Expenditures 2000-2015												
					Forecasting Horizon								
RMSE/(MAE)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.91	0.84	0.81	0.84	0.82	0.80	0.79	0.77	0.80	0.83	0.85	0.77	7
	(0.88)	(0.82)	(0.75)	(0.82)	(0.83)	(0.79)	(0.74)	(0.72)	(0.78)	(0.81)	(0.83)	(0.74)	(0)
UCSV	0.96	0.86	0.84	0.86	0.83	0.83	0.82	0.81	0.82	0.83	0.85	0.81	5
	(0.94)	(0.87)	(0.81)	(0.84)	(0.84)	(0.83)	(0.82)	(0.81)	(0.83)	(0.83)	(0.88)	(0.80)	(0)
BVAR	0.85	0.79	0.75	0.78	0.77	0.77	0.76	0.76	0.79	0.81	0.82	0.76	10
	(0.83)	(0.77)	(0.70)	(0.76)	(0.77)	(0.74)	(0.69)	(0.70)	(0.75)	(0.76)	(0.78)	(0.71)	(10)
LASSO	**0.83**	0.77	0.73	0.77	0.76	0.76	0.75	0.75	0.78	0.80	0.81	0.73	8
	(0.79)	(0.74)	(0.67)	(0.74)	(0.77)	(0.72)	(0.69)	(0.68)	(0.73)	(0.76)	(0.78)	(0.68)	(7)
Ridge	0.87	0.76	0.73	0.77	0.76	0.75	0.74	0.73	0.76	0.77	0.78	0.71	6
	(0.84)	(0.74)	(0.67)	(0.75)	(0.78)	(0.75)	(0.69)	(0.68)	(0.74)	(0.74)	(0.76)	(0.70)	(9)
Elnet	0.84	0.76	0.72	0.76	0.76	0.75	0.74	0.74	0.78	0.80	0.81	0.72	5
	(0.80)	(0.74)	(0.67)	(0.73)	(0.76)	(0.72)	(0.68)	(0.67)	(0.74)	(0.76)	(0.78)	(0.68)	(8)
adaLASSO	0.84	0.77	0.74	0.78	0.78	0.77	0.76	0.77	0.79	0.81	0.83	0.73	10
	(0.80)	(0.76)	(0.69)	(0.77)	(0.78)	(0.74)	(0.71)	(0.70)	(0.74)	(0.78)	(0.81)	(0.70)	(8)
adaElnet	0.84	0.78	0.74	0.78	0.79	0.77	0.76	0.76	0.79	0.81	0.82	0.73	11
	(0.81)	(0.76)	(0.68)	(0.76)	(0.78)	(0.74)	(0.71)	(0.69)	(0.75)	(0.78)	(0.81)	(0.70)	(7)
Fact.	0.89	0.83	0.80	0.83	0.82	0.81	0.81	0.81	0.83	0.83	0.84	0.80	4
	(0.85)	(0.82)	(0.75)	(0.82)	(0.83)	(0.80)	(0.78)	(0.77)	(0.80)	(0.80)	(0.81)	(0.77)	(1)
T. Fact.	0.88	0.80	0.76	0.80	0.80	0.79	0.78	0.78	0.79	0.80	0.82	0.78	11
	(0.88)	(0.81)	(0.72)	(0.78)	(0.82)	(0.80)	(0.74)	(0.74)	(0.77)	(0.78)	(0.80)	(0.76)	(0)
CSR	0.86	0.77	0.75	0.79	0.79	0.79	0.79	0.77	0.81	0.84	0.86	0.80	10
	(0.81)	(0.76)	(0.68)	(0.79)	(0.80)	(0.77)	(0.73)	(0.71)	(0.77)	(0.81)	(0.84)	(0.77)	(4)
Bagging	0.88	0.76	0.74	0.81	0.81	0.79	0.82	0.79	0.81	0.80	0.81	0.73	11
	(0.87)	(0.75)	(0.69)	(0.82)	(0.88)	(0.83)	(0.80)	(0.80)	(0.84)	(0.80)	(0.82)	(0.72)	(3)
Boosting	1.00	0.80	0.77	0.81	0.79	0.80	0.80	0.79	0.82	0.84	0.85	0.79	9
	(0.98)	(0.79)	(0.73)	(0.82)	(0.84)	(0.82)	(0.79)	(0.78)	(0.85)	(0.84)	(0.87)	(0.78)	(2)
Jackknife	0.96	0.84	0.78	0.85	0.83	0.82	0.84	0.82	0.86	0.83	0.86	0.77	9
	(0.92)	(0.84)	(0.75)	(0.92)	(0.93)	(0.89)	(0.82)	(0.83)	(0.89)	(0.87)	(0.91)	(0.83)	(0)
R. Forest	0.88	**0.76**	**0.71**	**0.74**	**0.72**	**0.71**	**0.70**	**0.70**	**0.73**	**0.74**	**0.76**	**0.70**	12
	(0.82)	**(0.73)**	**(0.66)**	**(0.73)**	**(0.74)**	**(0.71)**	**(0.67)**	**(0.65)**	**(0.70)**	**(0.71)**	**(0.72)**	**(0.64)**	(12)
Mean	0.85	0.76	0.74	0.77	0.77	0.76	0.75	0.74	0.76	0.77	0.78	0.72	8
	(0.81)	(0.75)	(0.68)	(0.75)	(0.77)	(0.74)	(0.71)	(0.68)	(0.73)	(0.73)	(0.76)	(0.69)	(8)
25T. Mean	0.84	0.76	0.73	0.77	0.76	0.75	0.74	0.74	0.76	0.78	0.79	0.72	7
	(0.80)	(0.75)	(0.67)	(0.75)	(0.77)	(0.73)	(0.69)	(0.67)	(0.72)	(0.74)	(0.76)	(0.68)	(9)
Median	0.84	0.76	0.73	0.77	0.76	0.76	0.74	0.74	0.76	0.78	0.79	0.72	9
	(0.80)	(0.75)	(0.68)	(0.75)	(0.76)	(0.74)	(0.69)	(0.67)	(0.72)	(0.74)	(0.76)	(0.68)	(7)
RMSE count	13	15	14	15	17	16	9	11	13	14	6	9	
MAE count	(10)	(13)	(13)	(7)	(9)	(10)	(9)	(7)	(4)	(5)	(1)	(7)	

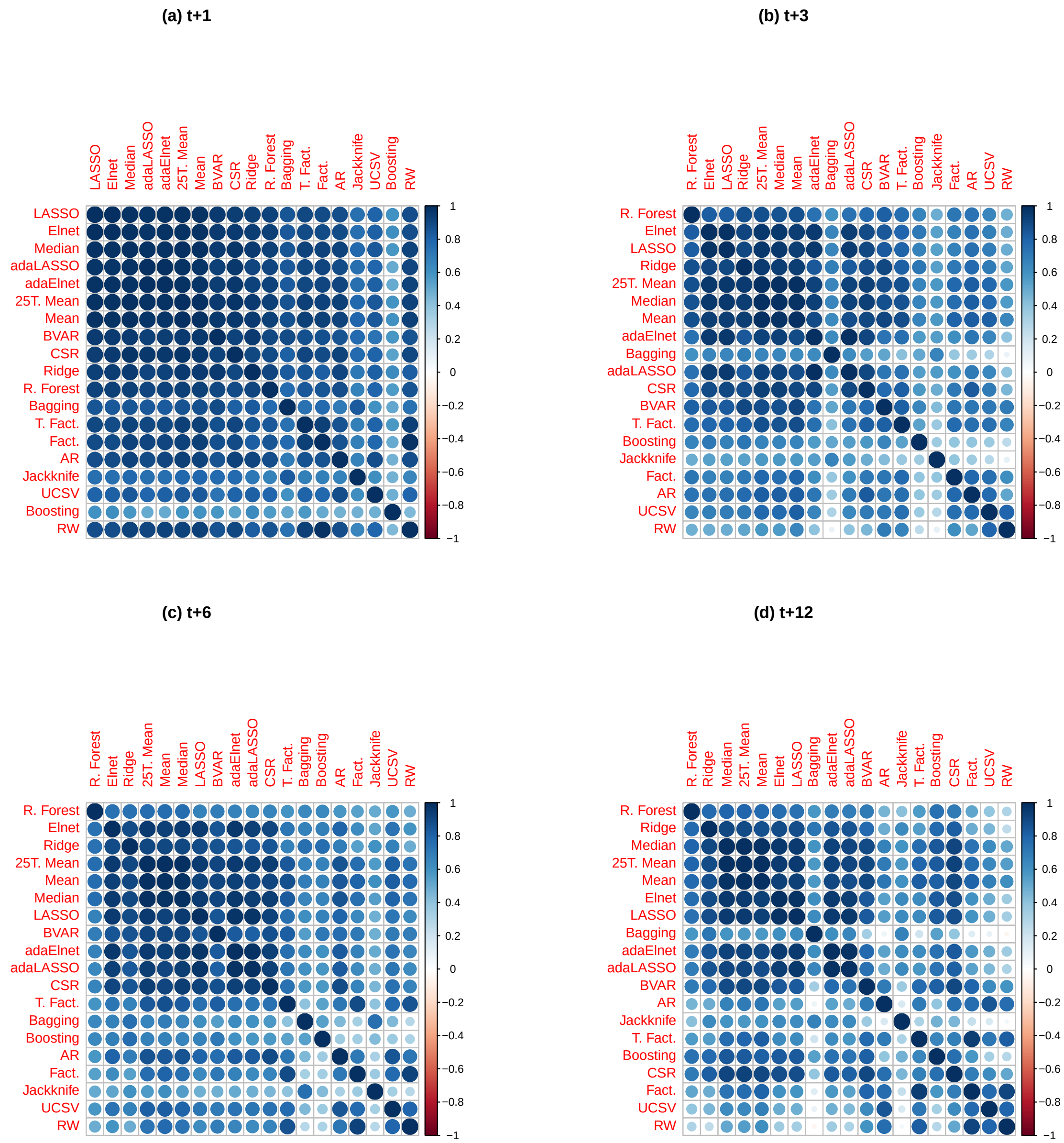
[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk. The error measures were calculated from 180 rolling windows.
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the squared error (absolute error) as loss function.

Table 16. Forecasting errors for the PCE from 2005 to 2015 with MCS combinations

	Personal Consumption Expenditures 2005-2015 - MCS											
	Forecasting Horizon											
$RMSE/(MAE)$	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
AR	0.93	0.88	0.87	0.86	0.80	0.78	0.79	0.78	0.81	0.81	0.83	0.77
	(0.87)	(0.89)	(0.82)	(0.82)	(0.77)	(0.76)	(0.76)	(0.75)	(0.78)	(0.79)	(0.82)	(0.76)
UCSV	0.99	0.88	0.86	0.87	0.82	0.80	0.80	0.81	0.82	0.82	0.83	0.80
	(0.92)	(0.88)	(0.84)	(0.85)	(0.81)	(0.79)	(0.80)	(0.82)	(0.83)	(0.81)	(0.86)	(0.78)
BVAR	0.88	0.81	0.78	0.77	0.73	0.72	0.75	0.75	0.77	0.77	0.79	0.74
	(0.84)	(0.80)	(0.72)	(0.73)	(0.70)	(0.69)	(0.68)	(0.69)	(0.72)	(0.71)	(0.75)	(0.70)
LASSO	**0.84**	0.79	0.76	0.76	0.73	0.72	0.74	0.75	0.77	0.76	0.77	0.70
	(0.78)	(0.78)	(0.71)	(0.72)	(0.69)	(0.67)	(0.69)	(0.68)	(0.70)	(0.71)	(0.74)	(0.66)
Ridge	0.89	0.78	0.76	0.76	0.71	0.70	0.72	0.73	0.75	0.73	0.75	0.70
	(0.84)	(0.78)	(0.70)	(0.72)	(0.70)	(0.68)	(0.69)	(0.69)	(0.72)	(0.69)	(0.73)	(0.69)
Elnet	0.85	0.78	0.75	0.75	0.72	0.71	0.72	0.75	0.77	0.77	0.77	0.69
	(0.79)	(0.77)	**(0.70)**	**(0.70)**	(0.68)	**(0.66)**	(0.67)	(0.68)	(0.72)	(0.70)	(0.73)	(0.65)
adaLASSO	0.86	0.79	0.78	0.78	0.75	0.74	0.75	0.78	0.79	0.77	0.79	0.70
	(0.82)	(0.80)	(0.73)	(0.75)	(0.72)	(0.69)	(0.71)	(0.71)	(0.72)	(0.70)	(0.75)	(0.67)
adaElnet	0.86	0.81	0.78	0.78	0.76	0.73	0.75	0.77	0.78	0.78	0.79	0.70
	(0.82)	(0.80)	(0.72)	(0.74)	(0.72)	(0.69)	(0.70)	(0.70)	(0.72)	(0.71)	(0.75)	(0.67)
Fact.	0.91	0.84	0.85	0.84	0.80	0.79	0.80	0.81	0.83	0.81	0.82	0.78
	(0.85)	(0.84)	(0.81)	(0.82)	(0.79)	(0.76)	(0.79)	(0.77)	(0.78)	(0.76)	(0.78)	(0.75)
T. Fact.	0.88	0.79	0.81	0.81	0.78	0.75	0.76	0.76	0.79	0.78	0.78	0.76
	(0.85)	(0.81)	(0.77)	(0.77)	(0.77)	(0.74)	(0.72)	(0.72)	(0.75)	(0.73)	(0.75)	(0.73)
CSR	0.88	0.80	0.79	0.79	0.75	0.75	0.79	0.79	0.81	0.82	0.83	0.79
	(0.81)	(0.81)	(0.74)	(0.77)	(0.73)	(0.73)	(0.74)	(0.74)	(0.76)	(0.77)	(0.81)	(0.78)
Bagging	0.92	0.79	0.76	0.77	0.74	0.73	0.80	0.81	0.80	0.77	0.78	0.72
	(0.91)	(0.79)	(0.70)	(0.77)	(0.77)	(0.75)	(0.82)	(0.84)	(0.84)	(0.77)	(0.78)	(0.71)
Boosting	0.99	0.80	0.76	0.74	0.70	0.71	0.74	0.75	0.77	0.77	0.80	0.76
	(0.93)	(0.80)	(0.72)	(0.73)	(0.70)	(0.71)	(0.74)	(0.74)	(0.77)	(0.74)	(0.81)	(0.76)
Jackknife	1.01	0.85	0.80	0.84	0.77	0.74	0.84	0.82	0.85	0.83	0.84	0.77
	(0.98)	(0.89)	(0.79)	(0.91)	(0.84)	(0.80)	(0.82)	(0.87)	(0.89)	(0.87)	(0.89)	(0.85)
R. Forest	0.92	0.79	**0.74**	**0.74**	**0.68**	**0.67**	**0.70**	**0.72**	**0.73**	**0.72**	0.74	0.69
	(0.83)	(0.78)	(0.70)	(0.71)	**(0.67)**	(0.66)	**(0.67)**	**(0.67)**	**(0.69)**	**(0.67)**	(0.70)	**(0.63)**
Mean	0.86	0.78	0.76	0.77	0.73	0.72	0.73	0.74	0.75	0.75	0.75	0.70
	(0.80)	(0.78)	(0.71)	(0.73)	(0.71)	(0.69)	(0.69)	(0.69)	(0.71)	(0.69)	(0.72)	(0.66)
25T. Mean	0.86	0.78	0.76	0.76	0.73	0.71	0.73	0.74	0.75	0.75	0.76	0.70
	(0.80)	(0.78)	(0.71)	(0.72)	(0.70)	(0.68)	(0.68)	(0.68)	(0.70)	(0.70)	(0.73)	(0.66)
Median	0.86	0.78	0.77	0.77	0.72	0.72	0.73	0.74	0.75	0.75	0.76	0.70
	(0.80)	(0.78)	(0.71)	(0.72)	(0.69)	(0.69)	(0.68)	(0.68)	(0.70)	(0.69)	(0.72)	(0.65)
MCS50	0.86	0.77	0.76	0.77	0.73	0.72	0.73	0.74	0.75	0.74	0.74	0.69
	(0.79)	(0.77)	(0.70)	(0.72)	(0.70)	(0.69)	(0.68)	(0.68)	(0.71)	(0.69)	(0.70)	(0.66)
MCS75	0.86	0.77	0.76	0.77	0.74	0.72	0.73	0.75	0.76	0.74	0.74	**0.68**
	(0.80)	(0.77)	(0.70)	(0.72)	(0.72)	(0.69)	(0.70)	(0.69)	(0.72)	(0.70)	(0.70)	(0.64)
MCS90	0.86	**0.76**	0.76	0.74	0.73	0.70	0.73	0.73	0.75	0.74	**0.73**	0.69
	(0.81)	**(0.76)**	(0.70)	(0.70)	(0.72)	(0.68)	(0.69)	(0.68)	(0.71)	(0.69)	**(0.69)**	(0.65)
MCS50-IRMSE	0.86	0.77	0.76	0.77	0.73	0.72	0.73	0.74	0.75	0.74	0.74	0.69
	(0.79)	(0.77)	(0.70)	(0.72)	(0.70)	(0.69)	(0.68)	(0.68)	(0.71)	(0.68)	(0.70)	(0.65)
MCS75-IRMSE	0.86	0.77	0.76	0.76	0.73	0.72	0.73	0.75	0.76	0.74	0.74	0.68
	(0.80)	(0.77)	(0.70)	(0.72)	(0.71)	(0.68)	(0.70)	(0.69)	(0.72)	(0.69)	(0.70)	(0.64)
MCS90-IRMSE	0.86	0.76	0.76	0.74	0.72	0.70	0.73	0.73	0.75	0.73	0.73	0.69
	(0.81)	(0.76)	(0.70)	(0.70)	(0.72)	(0.68)	(0.69)	(0.68)	(0.71)	(0.69)	(0.69)	(0.65)

[a] This table shows the forecasting RMSE (MAE) for all models relative to the Random Walk.
[b] The 180 rolling window forecasts were divided into a training sample (2001-2004) and test sample (2005-2015) and the error measures were calculated in the test sample.
[c] The MCS used for the combinations were calculated in a expanding window starting with the training sample to avoid look ahead bias.

FIGURE 7. Forecast Correlation for the PCE from 2001 to 2015



This figure shows the correlations between forecasts obtained in a 180 rolling window scheme for horizons 1, 3, 6 and 12.

Table 17. Percentage of times each model had the smallest (biggest) error for the PCE from 2001 to 2015

Personal Consumption Expenditure - Ranking - 2000-2015												
	Forecasting Horizon											
%best/(%worst)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
RW	8.89	10.00	9.44	12.22	**16.11**	10.00	9.44	7.22	10.00	9.44	7.78	6.67
	(17.22)	**(28.33)**	**(35.00)**	**(27.78)**	**(25.56)**	**(26.67)**	**(28.33)**	**(32.22)**	**(23.89)**	**(22.22)**	**(22.78)**	**(27.78)**
AR	4.44	5.56	2.22	3.33	3.89	5.00	4.44	6.11	6.11	7.78	7.22	8.89
	(4.44)	(7.22)	(8.33)	(5.56)	(7.22)	(5.56)	(5.56)	(3.89)	(5.56)	(4.44)	(5.56)	(6.67)
UCSV	5.00	4.44	3.89	3.89	2.22	4.44	5.56	3.89	3.33	3.33	5.00	5.56
	(10.00)	(3.33)	(3.89)	(2.22)	(2.22)	(4.44)	(2.78)	(1.67)	(1.11)	(3.89)	(5.00)	(3.89)
BVAR	6.67	1.67	4.44	2.78	5.56	2.78	5.00	2.78	5.00	8.33	5.56	6.11
	(1.67)	(0.56)	(0.00)	(0.00)	(0.00)	(1.11)	(1.11)	(0.56)	(1.11)	(2.78)	(2.78)	(1.67)
LASSO	3.89	3.89	2.78	2.22	1.11	4.44	2.78	4.44	5.00	1.67	2.22	3.89
	(0.00)	(0.00)	(0.00)	(0.56)	(0.56)	(0.56)	(1.11)	(0.00)	(2.22)	(2.22)	(1.11)	(0.00)
Ridge	3.33	3.33	4.44	4.44	5.00	3.89	1.67	6.67	1.67	5.56	4.44	4.44
	(0.00)	(0.00)	(0.00)	(0.00)	(0.56)	(0.00)	(0.56)	(1.11)	(0.56)	(1.11)	(0.00)	(0.00)
Elnet	1.67	1.11	2.22	3.33	3.89	2.22	3.89	3.33	1.67	5.00	2.22	1.67
	(1.11)	(0.00)	(0.00)	(0.00)	(1.11)	(0.00)	(0.00)	(2.22)	(1.67)	(0.56)	(2.22)	(0.00)
adaLASSO	5.56	1.67	3.33	2.78	3.89	2.78	2.78	3.89	4.44	4.44	1.67	2.78
	(0.56)	(1.67)	(1.67)	(1.11)	(0.56)	(0.00)	(0.56)	(1.67)	(0.56)	(2.78)	(2.78)	(2.78)
adaElnet	2.22	2.22	0.56	2.22	2.78	2.22	1.11	3.89	1.67	1.67	2.78	2.78
	(1.11)	(0.56)	(0.00)	(0.00)	(0.00)	(0.56)	(0.56)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fact.	5.56	5.00	6.67	10.00	7.78	10.00	2.22	5.00	5.56	2.22	2.22	2.78
	(3.89)	(6.67)	(6.11)	(8.33)	(4.44)	(2.78)	(4.44)	(3.33)	(2.22)	(2.78)	(1.11)	(0.56)
T. Fact.	3.89	5.00	4.44	6.11	4.44	3.33	7.78	6.11	6.67	3.89	5.00	3.33
	(3.33)	(4.44)	(1.67)	(1.11)	(1.67)	(1.11)	(2.78)	(1.11)	(2.22)	(1.11)	(1.67)	(2.78)
CSR	2.78	5.00	4.44	3.89	4.44	1.11	3.89	1.67	3.33	3.89	2.78	3.33
	(0.56)	(0.56)	(0.56)	(0.56)	(1.11)	(1.67)	(2.22)	(1.11)	(1.67)	(3.89)	(6.11)	(6.11)
Bagging	12.22	13.33	14.44	6.11	6.11	11.11	10.00	7.22	9.44	10.56	12.22	**13.33**
	(11.67)	(7.22)	(7.78)	(10.56)	(10.56)	(13.33)	(11.11)	(11.67)	(8.89)	(13.33)	(8.89)	(8.33)
Boosting	**15.00**	**16.67**	**15.00**	**19.44**	15.00	13.33	11.67	**13.33**	12.22	10.00	13.33	12.22
	(24.44)	(19.44)	(17.22)	(20.00)	(17.78)	(18.33)	(17.22)	(17.78)	(21.67)	(17.22)	(17.78)	(16.67)
Jackknife	10.00	12.22	11.67	8.33	10.00	**13.89**	**15.56**	12.78	**13.33**	**13.89**	**14.44**	12.22
	(17.78)	(17.22)	(16.67)	(20.00)	(22.78)	(20.00)	(19.44)	(18.33)	(19.44)	(18.89)	(19.44)	(21.11)
R. Forest	5.56	7.22	6.11	6.67	4.44	6.67	11.11	7.78	7.22	3.33	6.11	6.11
	(2.22)	(2.78)	(1.11)	(2.22)	(3.89)	(3.89)	(2.22)	(3.33)	(7.22)	(2.78)	(2.78)	(1.67)
Mean	1.11	1.11	2.22	0.56	1.67	1.67	0.56	1.11	1.67	3.33	2.78	2.22
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
25T. Mean	1.67	0.00	0.56	1.11	1.67	1.11	0.56	2.78	1.11	1.11	1.67	1.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median	0.56	0.56	1.11	0.56	0.00	0.00	0.00	0.00	0.56	0.56	0.56	0.56
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

[a] This table show the percentage of times each model had the smallest (bigger) errors in the 180 rolling windows.
[b] The biggest values are in bold.

Table 18. Forecasts Root Mean Squared Errors for the PCE on NBER Expansion and Recession periods.

Personal Consumption Expenditures RMSE - Expansion and Recession													
	Forecasting Horizon												
	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
AR	0.86	0.77	0.75	0.79	0.80	0.81	0.78	0.71	0.74	0.78	0.82	0.76	5
	(0.97)	(0.95)	(0.92)	(0.90)	(0.84)	(0.80)	(0.82)	(0.91)	(0.97)	(0.94)	(0.96)	(0.91)	(9)
UCSV	0.90	0.83	0.82	0.84	0.82	0.84	0.85	0.78	0.76	0.78	0.81	0.78	4
	(1.04)	(0.91)	(0.88)	(0.90)	(0.85)	(0.81)	(0.79)	(0.90)	(0.97)	(0.94)	(0.96)	(0.94)	(12)
BVAR	0.87	0.74	0.76	0.81	0.81	0.84	0.82	0.79	0.83	0.85	0.90	0.81	7
	(0.96)	(0.92)	(0.84)	(0.81)	(0.76)	(0.76)	(0.81)	(0.89)	(0.93)	(0.90)	(0.91)	(0.90)	(12)
LASSO	0.81	0.74	0.71	0.79	0.79	0.81	0.77	0.71	0.75	0.77	0.79	0.71	7
	(0.87)	(0.87)	(0.82)	(0.80)	(0.77)	(0.76)	(0.79)	(0.89)	(0.93)	(0.91)	(0.93)	(0.88)	(12)
Ridge	0.82	0.71	0.72	0.78	0.78	0.81	0.76	0.70	0.72	0.73	0.76	0.69	8
	(0.94)	(0.86)	(0.81)	(0.79)	(0.74)	(0.72)	(0.76)	(0.86)	(0.92)	(0.88)	(0.89)	(0.85)	(12)
Elnet	**0.81**	0.74	0.71	0.79	0.80	0.81	0.78	0.71	0.75	0.77	0.81	0.71	6
	(0.87)	(0.85)	(0.81)	(0.80)	(0.76)	(0.75)	(0.77)	(0.90)	(0.93)	(0.91)	(0.93)	(0.88)	(12)
adaLASSO	0.82	0.75	0.73	0.78	0.78	0.80	0.78	0.74	0.76	0.76	0.79	0.71	9
	(0.88)	(0.86)	(0.83)	(0.82)	(0.80)	(0.76)	(0.79)	(0.89)	(0.93)	(0.93)	(0.93)	(0.88)	(12)
adaElnet	0.83	0.75	0.72	0.78	0.78	0.80	0.77	0.73	0.77	0.77	0.80	0.71	8
	(0.88)	(0.89)	(0.83)	(0.82)	(0.80)	(0.77)	(0.80)	(0.89)	(0.93)	(0.92)	(0.93)	(0.87)	(12)
Fact.	0.87	0.82	0.80	0.83	0.83	0.86	0.83	0.78	0.82	0.83	0.85	0.81	1
	(0.93)	(0.89)	(0.87)	(0.86)	(0.82)	(0.80)	(0.83)	(0.92)	(0.97)	(0.94)	(0.96)	(0.94)	(12)
T. Fact.	0.91	0.83	0.80	0.79	0.81	0.83	0.81	0.75	0.79	0.80	0.81	0.78	1
	(0.89)	(0.83)	(0.83)	(0.84)	(0.81)	(0.78)	(0.79)	(0.89)	(0.93)	(0.91)	(0.93)	(0.92)	(9)
CSR	0.82	0.74	0.72	0.78	0.79	0.80	0.80	0.74	0.78	0.81	0.85	0.79	6
	(0.92)	(0.87)	(0.84)	(0.82)	(0.78)	(0.76)	(0.78)	(0.85)	(0.91)	(0.89)	(0.91)	(0.86)	(11)
Bagging	0.87	0.77	0.78	0.87	0.90	0.88	0.86	0.78	0.78	0.76	0.81	0.70	3
	(0.89)	**(0.80)**	**(0.78)**	(0.78)	(0.72)	(0.72)	(0.77)	**(0.85)**	(0.93)	(0.91)	(0.92)	(0.89)	(12)
Boosting	0.95	0.81	0.83	0.89	0.90	0.93	0.89	0.83	0.85	0.85	0.87	0.77	0
	(1.08)	(0.87)	(0.80)	(0.77)	(0.71)	(0.72)	(0.75)	(0.86)	(0.91)	(0.88)	(0.91)	(0.90)	(12)
Jackknife	0.92	0.88	0.85	0.92	0.98	0.97	0.93	0.84	0.94	0.87	0.92	0.81	0
	(1.03)	(0.86)	(0.82)	(0.85)	(0.72)	**(0.67)**	(0.79)	(0.89)	**(0.88)**	(0.88)	(0.90)	(0.84)	(12)
R. Forest	0.81	**0.71**	**0.71**	**0.75**	**0.75**	**0.75**	**0.71**	**0.65**	**0.66**	**0.68**	**0.72**	**0.66**	12
	(0.98)	(0.86)	(0.79)	**(0.77)**	**(0.71)**	(0.70)	**(0.73)**	(0.86)	(0.92)	**(0.87)**	**(0.88)**	**(0.84)**	(12)
Mean	0.81	0.74	0.72	0.76	0.77	0.78	0.75	0.69	0.72	0.72	0.74	0.69	7
	(0.90)	(0.84)	(0.82)	(0.81)	(0.77)	(0.75)	(0.78)	(0.87)	(0.92)	(0.89)	(0.91)	(0.87)	(12)
25T. Mean	0.81	0.73	0.72	0.77	0.77	0.78	0.75	0.69	0.72	0.73	0.76	0.69	6
	(0.90)	(0.85)	(0.82)	(0.80)	(0.77)	(0.75)	(0.78)	(0.88)	(0.92)	(0.90)	(0.92)	(0.87)	(12)
Median	0.81	0.73	0.72	0.77	0.77	0.78	0.75	0.69	0.72	0.73	0.76	0.70	6
	(0.89)	(0.85)	(0.82)	(0.80)	(0.77)	(0.75)	(0.78)	(0.88)	(0.92)	(0.90)	(0.91)	(0.86)	(12)
RMSE count	11	3	10	13	11	7	10	7	7	9	7	1	
MAE count	(18)	(18)	(18)	(16)	(17)	(17)	(17)	(17)	(17)	(18)	(18)	(18)	

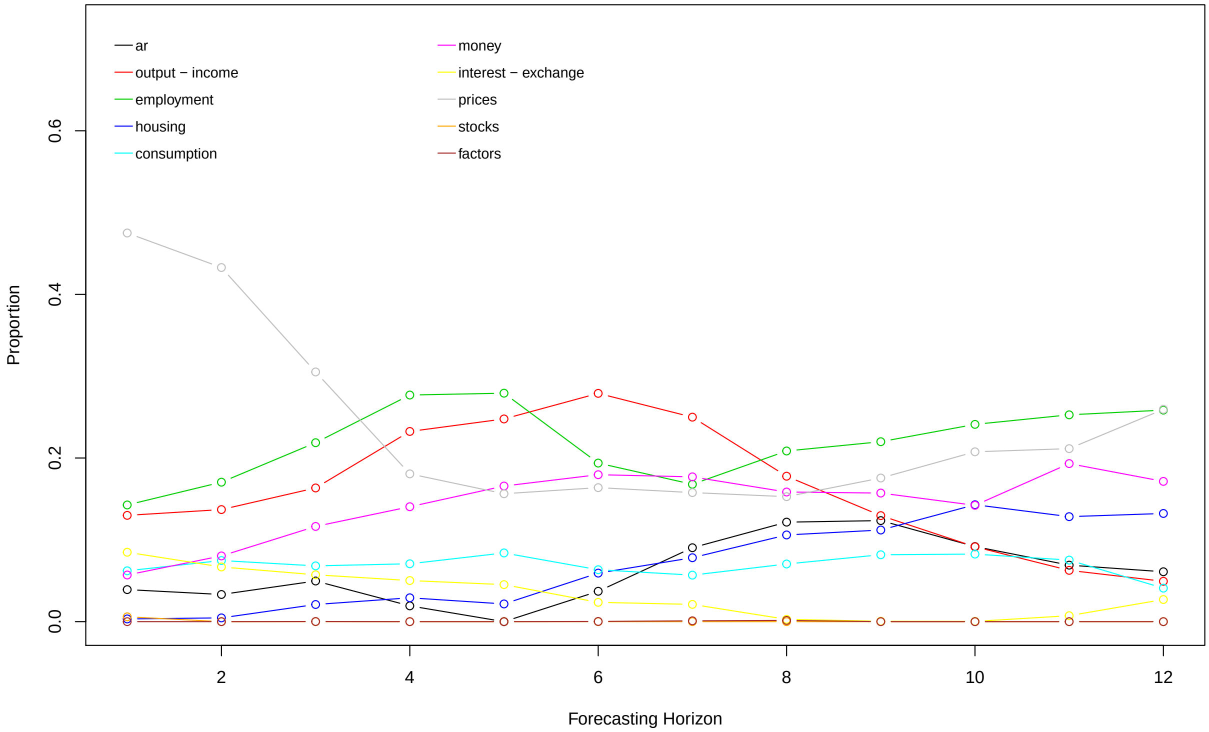
[a] This table shows the forecasting RMSE during expansion (recession) for all models relative to the Random Walk. The error measures were calculated from 300 rolling windows (1990-2000 and 2001-2015).
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the squared error as loss function.

Table 19. Forecasts Mean Absolute Errors for the PCE on NBER Expansion and Recession periods.

exp (*rec*)	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12	count
	Personal Consumption Expenditures MAE - Expansion and Recession												
					Forecasting Horizon								
AR	0.87	0.77	0.76	0.80	0.82	0.81	0.76	0.71	0.79	0.83	0.87	0.80	3
	(0.89)	(0.97)	(0.88)	(0.92)	(0.80)	(0.79)	(0.87)	(0.94)	(0.93)	(0.91)	(0.94)	(0.90)	(8)
UCSV	0.91	0.84	0.82	0.84	0.84	0.85	0.84	0.81	0.81	0.82	0.89	0.81	1
	(0.99)	(0.93)	(0.86)	(0.89)	(0.82)	(0.78)	(0.83)	(0.90)	(0.94)	(0.92)	(0.93)	(0.91)	(9)
BVAR	0.88	0.74	0.78	0.83	0.85	0.86	0.82	0.80	0.90	0.90	0.96	0.87	1
	(0.95)	(0.94)	(0.81)	(0.84)	(0.76)	(0.76)	(0.85)	(0.87)	(0.86)	(0.83)	(0.87)	(0.89)	(12)
LASSO	0.81	0.74	0.71	0.80	0.82	0.80	0.77	0.70	0.79	0.80	0.85	0.75	5
	(0.77)	(0.89)	(0.79)	(0.81)	(0.75)	(0.74)	(0.82)	(0.90)	(0.85)	(0.87)	(0.90)	(0.87)	(12)
Ridge	0.82	0.71	**0.71**	0.78	0.81	0.81	0.74	0.69	0.77	0.78	0.82	0.73	7
	(0.87)	(0.89)	(0.79)	(0.80)	(0.72)	(0.71)	(0.80)	**(0.86)**	**(0.84)**	**(0.82)**	(0.86)	(0.85)	(12)
Elnet	**0.81**	0.75	0.72	0.81	0.83	0.82	0.77	0.70	0.79	0.80	0.86	0.76	2
	(0.77)	(0.87)	(0.77)	(0.81)	(0.74)	(0.73)	(0.80)	(0.90)	(0.86)	(0.87)	(0.91)	(0.86)	(12)
adaLASSO	0.82	0.76	0.73	0.79	0.80	0.78	0.76	0.71	0.78	0.78	0.84	0.75	5
	(0.78)	(0.89)	(0.78)	(0.83)	(0.78)	(0.75)	(0.83)	(0.89)	(0.86)	(0.89)	(0.90)	(0.87)	(11)
adaElnet	0.83	0.76	0.72	0.80	0.80	0.79	0.76	0.70	0.79	0.79	0.85	0.75	2
	(0.81)	(0.91)	(0.79)	(0.82)	(0.78)	(0.75)	(0.83)	(0.89)	(0.86)	(0.88)	(0.91)	(0.87)	(11)
Fact.	0.88	0.83	0.83	0.84	0.86	0.87	0.83	0.78	0.88	0.87	0.89	0.87	0
	(0.84)	(0.90)	(0.81)	(0.86)	(0.81)	(0.79)	(0.88)	(0.93)	(0.92)	(0.90)	(0.96)	(0.94)	(11)
T. Fact.	0.93	0.84	0.82	0.78	0.83	0.85	0.80	0.75	0.84	0.85	0.86	0.82	2
	(0.84)	(0.86)	(0.79)	(0.87)	(0.82)	(0.78)	(0.83)	(0.87)	(0.88)	(0.88)	(0.91)	(0.92)	(11)
CSR	0.82	0.75	0.72	0.79	0.81	0.79	0.75	0.70	0.78	0.81	0.86	0.80	6
	(0.81)	(0.87)	(0.79)	(0.84)	(0.75)	(0.76)	(0.83)	(0.86)	(0.86)	(0.86)	(0.89)	(0.84)	(12)
Bagging	0.86	0.75	0.77	0.88	0.95	0.90	0.83	0.79	0.86	0.81	0.87	0.75	2
	(0.86)	**(0.82)**	**(0.72)**	(0.79)	(0.72)	(0.74)	(0.83)	(0.87)	(0.88)	(0.90)	(0.91)	(0.91)	(12)
Boosting	0.99	0.82	0.85	0.91	0.94	0.94	0.89	0.84	0.92	0.89	0.92	0.81	0
	(1.03)	(0.88)	(0.77)	(0.81)	(0.72)	(0.74)	(0.83)	(0.88)	(0.86)	(0.84)	(0.90)	(0.94)	(11)
Jackknife	0.95	0.92	0.88	0.97	1.05	0.96	0.91	0.84	1.00	0.94	0.97	0.88	0
	(0.89)	(0.85)	(0.76)	(0.95)	(0.73)	(0.73)	(0.89)	(0.95)	(0.87)	(0.85)	(0.87)	(0.89)	(11)
R. Forest	0.81	**0.71**	0.72	0.77	0.79	**0.77**	**0.71**	**0.64**	**0.70**	**0.72**	**0.76**	**0.67**	12
	(0.84)	(0.88)	(0.75)	**(0.77)**	**(0.69)**	**(0.70)**	**(0.78)**	(0.87)	(0.86)	(0.83)	**(0.85)**	**(0.83)**	(12)
Mean	0.82	0.74	0.72	0.77	**0.79**	0.77	0.74	0.68	0.75	0.75	0.79	0.72	6
	(0.81)	(0.86)	(0.78)	(0.82)	(0.75)	(0.75)	(0.82)	(0.86)	(0.85)	(0.85)	(0.89)	(0.85)	(12)
25T. Mean	0.81	0.74	0.71	**0.77**	0.79	0.77	0.73	0.67	0.75	0.75	0.80	0.73	6
	(0.80)	(0.87)	(0.77)	(0.81)	(0.75)	(0.74)	(0.81)	(0.87)	(0.85)	(0.86)	(0.89)	(0.85)	(12)
Median	0.81	0.74	0.71	0.77	0.79	0.77	0.73	0.67	0.75	0.75	0.80	0.73	6
	(0.80)	(0.87)	(0.77)	(0.81)	(0.75)	(0.75)	(0.82)	(0.88)	(0.85)	(0.86)	(0.89)	(0.84)	(12)
RMSE count	11	5	10	9	12	7	5	3	1	1	1	1	
MAE count	(14)	(18)	(16)	(16)	(14)	(18)	(18)	(18)	(17)	(18)	(18)	(18)	

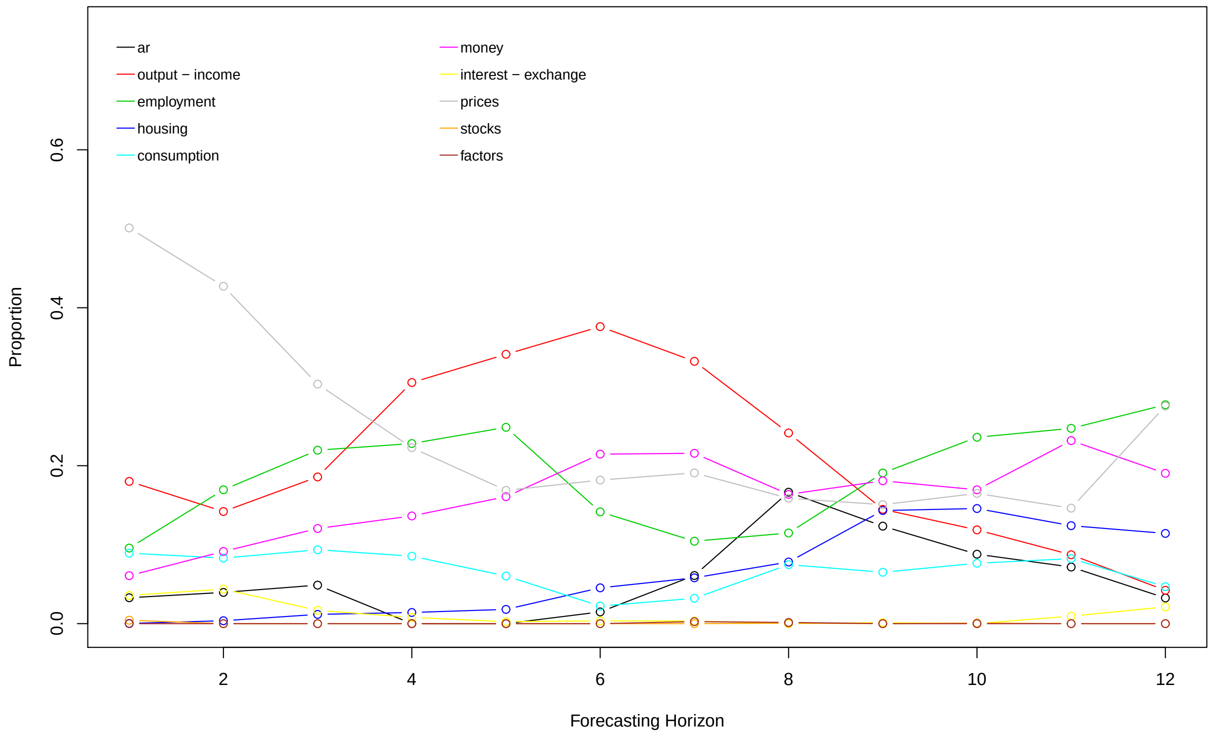
[a] This table shows the forecasting MAE during expansion (recession) for all models relative to the Random Walk. The error measures were calculated from 300 rolling windows (1990-2000 and 2001-2015).
[b] Values in bold show the most accurate model in each horizon.
[c] Cells in gray (blue) show the models included in the 50% model confidence set using the absolute error as loss function.

FIGURE 8. Proportion each variable group was selected by the LASSO in the PCE forecasts



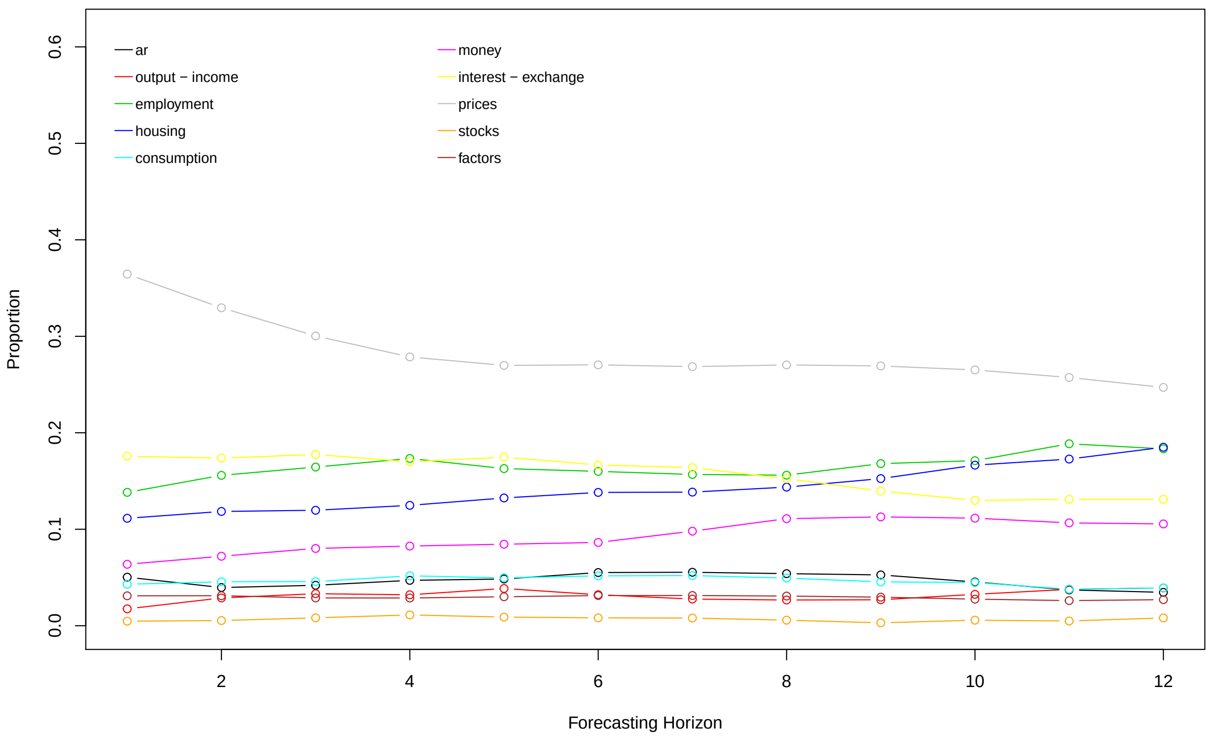
This figure shows the relative importance of each variable group for the LASSO for all the 12 forecasting horizons. The relative importance was calculated using the number of times each variable was selected across the rolling windows. The values were rescaled to sum one.

Figure 9. Proportion each variable group was selected by the adaLASSO in the PCE forecasts



This figure shows the relative importance of each variable group for the adaLASSO for all the 12 forecasting horizons. The relative importance was calculated using the number of times each variable was selected across the rolling windows. The values were rescaled to sum one.

FIGURE 10. Proportion each variable had on the Random Forest out-of-bag importance measure in the PCE forecast



This figure shows the relative importance of each variable group for the Random Forest for all the 12 forecasting horizons. The relative importance was calculated using the mean decrease in accuracy each variable had in the out-of-bag observations in each regression tree. The total importance is the sum of the importance on all rolling windows. The values were rescaled to sum one.