"Google it!" Forecasting the US unemployment rate with a Google job search index

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Abstract

In this paper we suggest the use of an internet job-search indicator (Google Index, GI) as the best leading indicator to predict the US unemployment rate. We perform a deep out-of-sample comparison of many forecasting models. With respect to the previous literature we concentrate on the monthly series extending the out-of-sample forecast comparison with models that adopt both our preferred leading indicator (GI), the more standard initial claims or combinations of both. Our results show that the GI indeed helps in predicting the US unemployment rate even after controlling for the effects of data snooping. Robustness checks show that models augmented with the GI perform better than traditional ones even in most state-level forecasts and in comparison with the Survey of Professional Forecasters' federal level predictions.

Keywords: Google econometrics, Forecast comparison, Keyword search, US unemployment, Time series models.
JEL Classification: C22, C53, E27, E37, J60, J64.

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1 Introduction

The need of reliable and updated unemployment forecasts has increased with the recent economic downturn. In this article we test the predictive power of a new indicator based on Google job-search-related query data, comparing the out-of-sample forecast accuracy of time series models including it as an exogenous variable with otherwise identical models normally used in the unemployment forecasting literature.

We suggest the use of the Google indicator (GI) as the best leading indicator to predict the US unemployment rate.[1] Our approach is very much in the same spirit of Montgomery et al. (1998) and Proietti (2003). In fact, we perform a deep out-of-sample comparison among 520 forecasting models (with a special emphasis on short-term forecasting) aimed at providing a better understanding of the strengths and weaknesses of each model. With respect to the above articles we follow Proietti (2003) concentrating on the monthly series rather than on quarterly data as in Montgomery et al. (1998), extending the out-of-sample forecast comparison with more linear models that adopt our preferred leading indicator. Furthermore, not only we select the best models out-of-sample in terms of the lowest mean squared error (MSE), but we also test both for equal forecast accuracy and forecast encompassing to assess their out-of-sample forecast ability. We also test our best models in terms of their superior predictive ability, which allows us to control for the effects of data-snooping biases. To do this we employ the Reality Check test suggested by White (2000). As an additional robustness check we test the predictive power of the GI estimating the same set of models on the most commonly used transformations for the time series of the unemployment rate: logit (as in Koop and Potter, 1999 or Wallis, 1987), first differences (as in Montgomery et al, 1998), logarithm, log-linear detrended or HP-filtered in logs (as in Rothman, 1998). As a further check, we forecast the unemployment rate in each of the 51 US states (including District of Columbia) with the same set of models, finding that in more than 70% of them, models including the GI outperform all the others. Finally, we construct a group of quarterly forecasts of the unemployment rate using the best models from

[1]The time series of US unemployment rate is certainly one of the most studied in the literature. Proietti (2003) defines this series as the 'testbed' or the 'case study' for many (if not most) non-linear time series models. In fact, many papers have documented its asymmetric behavior. Neftci (1984), DeLong and Summers (1986) and Rothman (1998) document that type of asymmetry called *steepness* for which unemployment rates rise faster than they decrease. Sichel (1993) finds evidence for another type of asymmetry called *deepness* in which contractions are deeper than expansions. McQueen and Thorley (1993) find *sharpness* for which peaks tend to be sharp while troughs are usually more rounded.

our horse-race and we compare them with the quarterly predictions released by the Survey of Professional Forecasters (SPF), conducted by the Federal Reserve Bank of Philadelphia. Even in this case we find that models using GI do outperform the professionals' forecasts.

The first article using Google data (Ginsberg et al., 2009) estimated the weekly influenza activity in the US using an index of the health seeking behavior equal to the incidence of influenza-related internet queries. To the best of our knowledge this is the first paper using this kind of internet indicator to forecast the unemployment rate in the US. However, there have already been some works for other countries, in particular for Germany (Askitas and Zimmermann, 2009), Italy (D'Amuri, 2009) and Israel (Suhoy, 2009), while Choi and Varian (2009) use the GI to predict initial unemployment claims for the US.

The paper is organized as follows. In Section 2 we describe the data used to predict the US unemployment rate, with a particular emphasis on the Google index. In Section 3 we discuss the 520 forecasting models employed to predict the US unemployment rate, while in Section 4 we compare the out-of-sample performance of such models. Finally, in Section 5 we perform some robustness tests, checking the predictive ability of models augmented with the GI at the state level, comparing the results of the federal estimates both with the quarterly estimates of the SPF and some nonlinear models typically deemed as the best forecasting models in the literature. Section 6 concludes.

2 Data

The data used in this article come from different sources. The seasonally adjusted monthly unemployment rate is the one released by the Bureau of Labor Statistics and comes from the Current Employment Statistics and the Local Area Unemployment Statistics for the national and the state level, respectively. Unemployment rates for month t refer to individuals who do not have a job, but are available for work, in the week including the 12th day of month t and who have looked for a job in the prior 4 weeks ending with the reference week. For the federal level the available sample is 1948.1-2009.6, while for the state level the data on unemployment are available from 1976.1 to 2009.6. We complement these data with the weekly seasonally adjusted Initial Claims (IC) released by the U.S. Department of Labor[2], a well-known leading indicator for the unemployment rate (see for example Montgomery et

[2]Since seasonally adjusted data are issued only at the national level, we have performed our own seasonal adjustment for the state-level data using Tramo-Seats.

al. 1998). The weekly IC for the US are available from 1967.1 until 2009.6, while for the single states they are available only from 1986.12.

The exogenous variable specific to this study is the weekly Google Index (GI) which summarizes the job searches performed through the Google website. The data are available almost in real time starting with the week ending on January 10 2004, and report the incidence of queries using the keyword *"jobs"* on total queries performed through Google in the relevant week.[3] The values of the index, available free of charge[4], are normalized with a value equal to 100 for the week in which the incidence was the highest. Absolute search volumes are not available. We chose to use the keyword *"jobs"* as an indicator of job search activities for two reasons.

Comparing relative incidences across different job-search-related keywords we found that the keyword "jobs" was the one showing the highest incidence. Even if we do not know the absolute search volumes, we can compare relative incidences of searches for the keyword "jobs" with other keywords searches which are assumed to be really popular. In particular, in Figure 1, we plot the monthly averages for the values of the GI for the keywords: *"facebook"*, *"youtube"*, *"jobs"* and *"job offer"*. It can be seen that, when the incidence of keyword searches for *"facebook"* was at its highest level in the interval considered here, the GI was slightly below the value of 80, while the GI for the keyword *"jobs"* was slightly above 20. This means that in that period there was more than one keyword search for *"jobs"* for each four searches for *"facebook"*. The results are similar when conducing the comparison with the keyword *"youtube"*, another popular search. Finally, the alternative job-search related keyword *"job offers"* reaches really low values of the GI (basically zero) in the interval.

Apart from its popularity, we choose the keyword *"jobs"* since we believe that it is a keyword widely used across the broadest range of job seekers. We could have augmented it with other job-search-related keywords, such as, for example *"unemployment benefits"* or *"state jobs"*. This would have increased the volume of searches underlying the value of the GI. But, at the same time, the information conveyed by these keywords is related to particular subgroups of the population, and the presence of demand or supply shocks specific to these subgroups could bias the values of the GI and its ability to predict the overall unemployment rate.

However, the variable has its limitations: individuals looking for a job through internet (jobs available through internet) may well be not randomly

[3]We have adjusted both the weekly and the monthly indicators for seasonality using Tramo-Seats.

[4]www.google.com/insights/search/#. The data used in this article were downloaded on July 29, 2009.

selected among job seekers (jobs) or may actually be employed while searching for a better job. Moreover, the indicator captures overall job search activities, that is the sum of unemployed and employed searches. This limitation is made more severe by the fact that, while unemployed job search is believed to follow the anti-cyclical variation of job separation rates, on-the-job search is normally assumed to be cyclical. We acknowledge that this can induce some bias in our preferred leading indicator GI.

In the empirical analysis we align the GI and IC data with the relevant weeks for the unemployment survey. In other words, when constructing the GI or the IC for month t, we take into consideration the week including the 12th of the month and the three preceding weeks. When there are more than four weeks between the reference week of month t and the following one in month $t+1$, we do not use either the GI or the IC for the week that is not used by the official statistics in order to calculate the unemployment rate (see Figure 2).

Tables 10, 11 and 12 in the appendix show the descriptive statistics of the IC and the GI both for the United States as a whole and for each single state. The IC for the US are public available through the Department of Labor website starting with January 1967, while those for the single states are available since December 1986. The monthly averages of the initial claims have almost always right-skewed distributions and are highly non-normal (we always reject the null of normality with the Jarque-Bera test). The monthly averages of the Google indicator (which starts in January 2004) are also right-skewed with non-normal distribution, except for Alaska and Maine. The weekly IC and GI (those with the subscript $wj, j = 1, ..., 4$) show similar features. From Table 9 in the appendix we can infer that also the unemployment rate has a right-skewed distribution and a high kurtosis which make the series non-normal as suggested by the Jarque-Bera test that almost always rejects the null hypothesis of normality. The same happens for the unemployment rate of each single state except for Colorado (state number 6).

In Figure 3 and 4 we plot separately the national unemployment rate and our exogenous variables adopted as leading indicators over the relevant sample periods. In Figure 3 we plot the unemployment rate and the initial claims over the sample period 1967:1-2009:6, according to the availability of IC. Figure 4 depicts instead the unemployment rate along with the IC as well as the Google 'job' search index over the sample 2004:1-2009:6. These latter indexes are rescaled with respect to the maximum value of each series over the sample. In both cases the two series show similar patterns, with both IC and GI seeming to be leading indicators for the unemployment rate. This behavior is confirmed by the correlations. Focusing on the 2004:1-2009:6

period (our short sample), we can see that both the GI and the IC are highly correlated with the level and with the first differences of the unemployment rate (see Table 2). In particular, the correlations of the GI with the first differences are higher than those of the IC, suggesting that this new indicator can be rather helpful for predicting not only the unemployment rate but also its changes.

Before proceeding with our forecasting exercise and the in-sample estimation of our set of models, we have checked for non-stationarity of the US unemployment rate by computing a robust univariate unit root test for the integration of the series. We have performed the Augmented Dickey-Fuller test with GLS de-trending (ADF-GLS) suggested by Elliott et al. (1996). This test is similar to the more standard Dickey-Fuller t test but it applies GLS de-trending before the series is tested with the ADF test. Compared with the standard ADF test, ADF-GLS test has the best overall performance in terms of small-sample size and power. Table 3 reports the results of this unit root test both considering a constant (superscript μ) and a constant and trend (superscript τ) as exogenous regressors. We have run these tests both for the full sample, i.e. 1967.1-2009.6, and for the short sample, i.e. 2004.1-2009.6. We report the unit root test results for the unemployment rate in levels u_t, and for other transformations typically used in the literature on forecasting the US unemployment rate, such as the log-level ($\log(u_t)$), the logistic transformation ($u_t^{logit} = \log(\frac{u_t}{1-u_t})$) suggested by Koop and Potter (1999) following Wallis (1987) to make the series unbounded, the log-linear de-trended ($u_t^{LLD} = \log(u_t) - \hat{a} - \hat{b}t$) and the HP-filtered series in log (u_t^{LHP}) both suggested by Rothman (1998).

Looking at u_t, the ADF-GLS$^\mu$ test fails to reject the null of a unit root for the full sample, but strongly rejects (at 1%) the null for the short sample. Similarly, the ADF-GLS$^\tau$ test fails to reject the null of a unit root on the full sample but it does reject the null on the short sample, indicating that the series of unemployment is stationary over this shorter sample. For all the other transformations, the ADF-GLS tests suggest an overall rejection of the null of a unit root only when the null is non-stationarity around the mean over the short sample. The test fails to reject over the full sample, except for the transformation u_t^{LHP}. We should also notice that over the short sample the ADF-GLS$^\tau$ tests are very close to the 10% critical value.

However, in the literature most works impose the presence of a unit root using the first differences of the unemployment rate for forecasting purposes. For example, Montgomery et al. (1998) argue that unit-root non-stationarity might be hard to justify for the US unemployment rate series, but nevertheless adopt an ARIMA(1,1,0)(4,0,4) as their benchmark model for short-term forecasting. In what follows we adopt a more general approach modeling both the level and the first differences of the unemployment rate series because we are interested in finding the best model for short-term forecasting and not in modeling the long-term dynamics of the series.

3 Forecasting models

In our forecasting exercise we compare a total of 520 linear ARMA models for the variable u_t, which denotes the US unemployment rate. As a robustness check we also estimate the same set of models on the most commonly used transformations for u_t: logarithm, logit, first differences, log-linear detrended or HP-filtered in logs. For the sake of brevity, and since all main results are confirmed when using these transformations, we will comment only the estimates obtained on the first differences of the unemployment rate. A full list of the models estimated on this series and their forecasting performance can be found in Table 16 of the appendix.

We estimate 384 AR, ARMA and ARMAX models that can be grouped in three broad categories:

- *Group A:* models not including the Google index as an exogenous variable and estimated on the full sample (in sample 1967:1-2007:2; out of sample 2007:3-2009.6)
- *Group B:* models not including the Google index as an exogenous variable but estimated on the short sample, for which Google data are available (in sample 2004:1-2007:2; out of sample 2007:3-2009.6)
- *Group C:* models including the Google index as an exogenous variable and estimated on the short sample (in sample 2004:1-2007:2; out of sample 2007:3-2009.6).

Within these three broad groups we estimate exactly the same set of models, both in terms of lag specification and of exogenous variables included, with the Google index indicator added as an additional independent variable in the last, otherwise identical, set of models.

We also estimate, on the short sample, an additional set of 136 models including different combinations of lag structures and exogenous variables. The rationale of repeating our forecasting exercise along three dimensions is straightforward. The inclusion of the GI among the exogenous variables limits the length of the estimation interval, given that the indicator is available since 2004.1 only. An exercise comparing the forecasting performance of models estimated on samples starting in 2004:1 could be able to assess the predictive power of the Google index, but it would be of little practical relevance if models estimated on the longer sample *(Group A)* were better at predicting unemployment rate dynamics.

Within the three groups we estimate pure time series AR(p) and ARMA(p, q) models, with at most 2 lags for p and q, for a total of four models (AR(1), AR(2), ARMA(1,1) and ARMA(2,2)).

In addition, we augment these basic specifications with exogenous leading indicators, i.e. ARMAX(p, q):

$$\phi(L)u_t = \mu + x_t'\beta + \theta(L)\varepsilon_t \tag{1}$$

where x_t' is a vector with a first column of one's and one or more columns of leading indicators. These indicators should help improving the predictions of the US unemployment rate. Thus, for example, an ARMAX(1,1) model is the following

$$u_t = \mu + \phi u_{t-1} + x_t'\beta + \varepsilon_t - \theta\varepsilon_{t-1} \tag{2}$$

In particular, we use as exogenous variables (both on the short and the long sample) the monthly IC, i.e. IC_t, their weekly levels ($IC_{w1,t}$, $IC_{w2,t}$, $IC_{w3,t}$, and $IC_{w4,t}$) and their lags up to the second. We then estimated the same models for the short sample using the monthly average of the GI G_t, its weekly values ($G_{w1,t}$, $G_{w2,t}$, $G_{w3,t}$, and $G_{w4,t}$) and their lags up to the second. Additionally, we augmented the four models with both leading indicators combined at the same frequency either monthly or weekly, at the same month t and for the previous months up to the second. Finally, the four models are estimated with both indicators IC and G both monthly and for each week. Additionally, all these models are estimated adding seasonal multiplicative factors.[5] In Table 4, we summarize all the groups of models within the short and the full sample. However, additional details on the models can be found in the not-for-publication appendix available from the authors upon request.

In all our forecasting exercises we use a rolling window. However we have also performed our forecasting horse-race using a recursive scheme. The results are similar to those with a rolling scheme and are not reported for the sake of brevity, but they are available upon request.

In our pseudo-out-of-sample exercise we consider the situation that the real forecasters face when they produce their forecasts and the future values of the exogenous variables (x_t) need to be forecast. At any given date, we have run our forecasting horse-race using only the information that was really

[5] In particular we used a seasonal multiplicative autoregressive factor $SAR(12)$ for AR models and both an AR and MA seasonal $SMA(12)$ for ARMA models.

available at that time. Therefore, we have adopted simple ARMA models to predict x_t, so that we could use such predictions as inputs in our forecasting models. For robustness, we have considered different models[6] but we present only those using an AR(1). The alternative would be to assume that x_t are known in the forecast period, but this assumption is not met in reality.

4 Out-of-Sample Forecasting Comparison

When we perform an out-of-sample forecasting horse-race comparing numerous models it is extremely important to assess which model does have the highest forecast accuracy with respect to a given benchmark or overall.

In Table 5 we present the mean squared errors (MSE), the Diebold and Mariano (DM) (1995) test of equal forecast accuracy and the Harvey et al. (HLN) (1998) test of forecast encompassing for the 15 best forecasting models of $u_t - u_{t-1}$, with forecast horizon from 1 to 3 months.[7] For each forecast horizon the column labeled "Rank" gives the rank of each model in terms of lowest MSE. The first column labeled 'n.' denotes the number of the model. For the complete list of models see Table 16 in the appendix. We can notice that for all forecast horizons the best model (i.e. the model with the lowest MSE out-of-sample) always includes the GI as the exogenous variable. In particular, the $ARX(1) - G_t$ (model #261), a standard AR(1) model with the average monthly GI, is the best model when forecasting both one and two months ahead. By the same token, the $ARMAX(1,1) - G_t - SA$ (model #398), a standard ARMA(1,1) model with the average monthly GI plus a multiplicative seasonal factor, has the best performance among the three-month-ahead forecasts. It is important to notice that, at all forecast horizons, the best fifteen models always include GI as an independent variable, in some cases in combination with the IC, a widely accepted leading indicator for the unemployment rate. Anyway, at one step ahead, the best 3 models include the GI only as an exogenous variable (thus not including IC). The same is also true for the two-step-ahead horizon (the best 5 models include only GI) and, even more, at the three-step-ahead horizon where the best 11 models include only our preferred leading indicator. Table 5 also reports the best model estimated over the full sample without the Google indicator and the best model without GI estimated over the short sample. The reader can notice that for 1-month-ahead forecasts the best model without GI over the

[6]We have adopted an AR(1), AR(2), ARMA(1,1) and ARMA(2,2) and the results for u_t are quite similar.

[7]Additional estimates for u_t and $\log(u_t)$ can be found in tables 14 and 15 of the appendix.

full sample ranks 73^{rd}, while the same model over the short sample ranks 197^{th}. For 2- and 3-month-ahead forecasts these models without GI rank higher than 173^{rd}.

The literature on US unemployment forecasting has so far considered only the ratios of the mean squared errors between a competitor model and a benchmark model to evaluate each model forecast ability. Nevertheless, after the seminal papers by Diebold and Mariano (1995) and West (1996) the community of forecasters has increasingly understood the importance of correctly testing for out-of-sample equal forecast accuracy. West (2006) provides a recent survey of the tests of equal forecast accuracy, while Busetti et al. (2009) provide extensive Monte Carlo evidence on the best tests of equal forecast accuracy or forecast encompassing to be used in any specific framework (nested or non-nested models). To provide a more formal assessment of the forecasting properties of each model in our horse-race, we use the best model in terms of lowest MSE as the benchmark model and we perform two tests. A two-sided DM test for the null of equal forecast accuracy between the benchmark and the competitor and a two-sided HLN test, to test if the benchmark model forecast encompasses the competitor[8]. We have to recall that a benchmark model forecast encompasses the k-th competitor model if the former cannot be significantly improved upon by a convex forecast combination of the two. In other words, the benchmark forecast encompasses the competitor if this latter model does not provide any additional information for predicting. We use the two-sided version of these tests because some models are nested and others are non-nested making the direction of the alternative hypothesis uncertain. Using the two-sided version of the tests we can thus compare both nested and non-nested models, as is our case where the exogenous variable often differs from one model to another and only a subset of models are really nested. Furthermore, we use both the DM and the HLN because they can be compared to standard critical values of the Gaussian distribution and, moreover, Busetti et al. (2009) show that the HLN test is rather powerful both in a nested and non-nested framework when compared to other more complicated tests with non-standard distributions.

[8]The DM test is based on the loss differential between the benchmark (model 0) and the k-th competitor, i.e. $d_t = e^2_{0,t} - e^2_{k,t}$. To test the null of equal forecast accuracy $H_0 : E(d_t) = 0$, we employ the DM statistic $DM = P^{1/2}\bar{d}/\hat{\sigma}_{DM}$, where $\bar{d}$ is the average loss differential, P is the out-of-sample size, and $\hat{\sigma}_{DM}$ is the square-root of the long-run variance of d_t. The HLN test analyzes the null $H_0 : E(f_t) = 0$, where $f_t = e_{0,t}(e_{0,t} - e_{k,t})$. The HLN test statistic is $HLN = P^{1/2}\bar{f}/\hat{\sigma}_{HLN}$, where $\bar{f}$ is the average of the forecast error differential multiplied by the forecast error of the benchmark model, P is the out-of-sample size and $\hat{\sigma}_{HLN}$ is the square root of the long-run variance of f_t. Both tests are distributed as a Gaussian under the null.

From Table 16 in the appendix we can see that the best model in terms of the lowest MSE always beats the competitors estimated on the full sample in predicting the unemployment rate in first differences. According to the standard DM test we can reject the null of equal forecast accuracy at 10% for 1- and 2-month-ahead forecast horizons. The same happens with the HLN test. At 10% we reject the null at the forecast horizons of 1 and 2 months. This means that our best model outperforms all those models that use the whole time series of unemployment and IC for the longest available time span, even though the former is estimated over a very short time window (38 months). When the benchmark is compared to models estimated on the short sample, both the DM and the HLN tests reject the null of equal forecast accuracy at 1-month ahead. However, they fail to reject the null for forecast horizons longer than 1-month.

In order to formally test the out-of-sample forecasting performance of the models using our suggested new leading indicator, we apply White's (2000) "Reality Check" (RC) test. This test builds on Diebold and Mariano (1995) and West (1996) and involves examining whether the expected value of the forecast loss (e.g. the squared forecast error in case of MSE) of one or several models is significantly greater than the forecast loss of a benchmark model. We adopt this test because in contrast to the previous ones, it tests for superior predictive ability rather than only for equal predictive ability. Furthermore, the RC test also allows us to account for the dependence among forecasting models that can arise when several models using the same data are compared in terms of predictive ability. Failing to do so can result in data-snooping problems, which occurs when one searches extensively a model until a good match with the given data is found. White (2000) develops a test of superior unconditional predictive ability among multiple models accounting for this specification search. With this test we compare all the competitor models together against a benchmark. The null hypothesis is that all the models are no better than the benchmark, i.e., $H_0 : \max_{1\leq k\leq L} E(f_k) \leq 0$, where $f_k = e^2_{0,t} - e^2_{k,t}$ for MSE losses. This is a multiple hypothesis, the intersection of the one-sided individual hypotheses $E(f_k) \leq 0$, $k = 1, ..., L$. The alternative is that H_0 is false, that is, there exists a model which is superior to the benchmark. If the null hypothesis is rejected, there must be at least one model for which $E(f_k)$ is positive.[9] Hansen (2005) shows that

[9]Suppose that $\sqrt{P}(\bar{f} - E(f)) \xrightarrow{d} N(0, \Omega)$ as $P(T) \to \infty$ when $T \to \infty$, for Ω positive semi-definite. White's (2000) RC test statistic for H_0 is formed as $\bar{V} = \max_{1\leq k\leq L} \sqrt{P}\bar{f}_k$, where $\bar{f}_k = P^{-1/2} \sum_{t=R+1}^{T} \hat{f}_{k,t}$. However, as the null limiting distribution of $\bar{V}$ is unknown, White (2000) showed that the distribution of $\sqrt{P}(\bar{f}^* - \bar{f})$ converges to that of $\sqrt{P}(\bar{f} - E(f))$, where $\bar{f}^*$ is obtained from the stationary bootstrap of Politis and Romano (1994).

White's reality check is conservative when a poor model is included in the set of L competing models. Hansen (2005) suggests using a studentized version of the RC test, suggesting the SPA test. We tried also the SPA test, but the two p-values are similar to the RC p-values and are not reported.

Table 6 reports the RC p-values for the best models against all the other models at each forecast horizon and for all the different transformations of the unemployment rate. In the Table we show the RC p-values for two different values of the probability parameter $q = (0.10, 0.50)$ and two different numbers of bootstrap replications $B = (2000, 5000)$. In boldface we report those RC p-values that are greater than the 5% significance level. We can notice that at this significance level we fail to reject the null hypothesis that none of the 519 competing models is better than our benchmark. Thus our best models with the Google index have (almost always) superior predictive ability when compared to all the other models in our horse-race. However, we should say that these results must be interpreted with caution. In the set of competing models we have other models that adopt the GI as a leading indicator but are less accurate than our benchmark and this could bias our results towards a rejection. We also have a very short out-of-sample period and it is well known that the RC is undersized and has low power in small samples (see Hubrich and West, 2009).

5 Robustness checks

5.1 Nonlinear models

Most of the previous literature on unemployment forecasting in the US suggests using non-linear models to better approximate the long-term dynamic structure of its time series (see Montgomery et al., 1998 and Rothman, 1998). In particular, Montgomery et al. (1998) argue that Threshold Autoregressive (TAR) models can better approximate the unemployment rate dynamics especially during economic contractions, while linear ARMA models generally give a better representation of its short-term dynamics. To check the robustness of our best models which use the Google indicator, we have also adopted some of non-linear models that are typically used with the unemployment rate. We have estimated three non-linear time series models. The first is a self-exciting threshold autoregression (SETAR) model which takes

By the continuous mapping theorem this result extends to the maximal element of the vector $\sqrt{P}(\bar{f}^* - \bar{f})$, so that the empirical distribution of $\bar{V}^* = \max_{1 \leq k \leq L} \sqrt{P}(\bar{f}^*_k - \bar{f}_k)$ may be used to compute the p-value of the test. This p-value is called the 'reality check p-value'.

the following form

$$u_t = [\phi_{01} + \phi_{11} u_{t-1} + \phi_{21} u_{t-2}]\, I(u_{t-1} \leq c) \\ + [\phi_{02} + \phi_{12} u_{t-1} + \phi_{22} u_{t-2}]\, I(u_{t-1} > c) + \varepsilon_t \quad (3)$$

where $I(.)$ is the indicator function and c is the value of the threshold.

The SETAR models endogenously identify two different regimes given by the threshold variable u_{t-1}. In particular, following Rothman (1998) we adopted a SETAR model with two lags for each regime.

The second non-linear model used to forecast the unemployment rate is a logistic smooth transition autoregressive (LSTAR) model which is a generalization of the SETAR. The LSTAR model takes the form

$$u_t = [\phi_{01} + \phi_{11} u_{t-1} + \phi_{21} u_{t-2}]\, [1 - G(\gamma, c, u_{t-1})] \\ + [\phi_{02} + \phi_{12} u_{t-1} + \phi_{22} u_{t-2}]\, G(\gamma, c, u_{t-1}) + \varepsilon_t \quad (4)$$

where $G(\gamma, c, u_{t-1}) = [1 + \exp(-\gamma \prod_{k=1}^{K} (u_t - c_k))]^{-1}$ is the logistic transition function, $\gamma > 0$ is the slope parameter set to zero for identification and c is the location parameter. In this model the change from one regime to the other is much smoother than in the SETAR model.

The third non-linear model employed to predict the US unemployment rate is an additive autoregressive model (AAR) of the following form

$$u_t = \mu + \sum_{i=1}^{m} s_i(u_{t-(i-1)d}) \quad (5)$$

where s_i are smooth functions represented by penalized cubic regression splines. The AAR model is a generalized additive model that combines additive models and generalized linear models. These models maximize the quality of prediction of a target variable from various distributions, by estimating a non-parametric function of the predictor variables which are connected to the dependent variable via a link function (see Hastie and Tibshirani, 1990). We have included this additional model to enlarge our out-of-sample comparison to non-parametric models which are found superior in predicting the US unemployment by Golan and Perloff (2004).

Table 5 reports the MSE, the DM test and the HLN test for 1- to 3-month-ahead forecasts from these three non-linear models estimated only up to the second lag for the first differences of the US unemployment. At 1-month ahead the best non-linear model is the SETAR which ranks 258^{th}, then the AAR (276) and the LSTAR (362). Thus, as previously found in the literature, non-linear models do not seem to be suitable for short-term forecasting. These non-linear models tend to fair better as soon as we forecast the unemployment at two and, in particular, at three months ahead, where their rank ranges between the 24^{th} and the 35^{th}. We can thus conclude that our simple linear model using our preferred leading indicator (GI) outperforms also non-linear models, even though the gain tends to shrink as the forecast horizon increases.[10]

5.2 State level forecasts

As a further robustness check for the predictive properties of the Google Index, we estimated the same 520 models introduced in the previous section for each of the 51 states (including District of Columbia), assessing the percentage of states for which the best model in terms of lower MSE is the one using the GI.

For the first-differenced series ($u_t - u_{t-1}$), the baseline in our forecast comparison, the percentage of the best models adopting the GI as a leading indicator ranges from 75% to 84% for the 1-step-ahead and the 3-step-ahead, respectively. When we use US unemployment rate in levels (u_t) as the dependent variable, the percentage of GI models with the lowest MSE out-of-sample ranges between 69% for the 2-step-ahead forecasts and 82% for the 3-step-ahead.

Finally, we test whether the aggregation of the 51 state models could improve the forecasting performance over the federal level benchmark. In particular, for each state we selected the model with the lowest MSE and then aggregated the single state best forecasts using different weights. In Table 7 we compare the out-of-sample results of this aggregation with the benchmark model estimated at the federal (US) level, reported in the first row of each sub-panel as 'best' model. This model is characterized by the lowest MSE for the unemployment rate in first differences and in levels.

In particular, in the second row of Table 7 we report the federal level forecasts obtained aggregating the state level estimates without weighting (simple average). In the following row we weight the state level forecasts using the share of the labor force (employed plus unemployed) in state i on the total federal labor force. In the following row, this share is further weighted by the state i diffusion of the internet (See Table 13 of the appendix for descriptive statistics on internet diffusion among the entire population, among the active

[10]When we forecast the level u_t or the log-level $\log(u_t)$ of unemployment (see Tables 14 and 15 in the appendix), these results hold only partially. In fact, non-linear models tend to rank poorly even at longer forecast horizon, thus showing that the linear models with Google clearly outperform nonlinear models even at longer horizons.

population aged 15-64, and among the 15-64 unemployed). The last row of each sub-panel is weighted by the share of unemployed combined with the 15-64 share of unemployed using internet. We define as internet diffusion in state i the share of individuals (active 15-64 individuals or unemployed 15-64 individuals according to the definition used) living in a household where at least an individual uses the internet.[11]

Forecasts obtained aggregating estimates of single state forecasts are inferior to the federal ones at all forecast horizons. Nevertheless it is interesting to note that the gap between the best federal model and the aggregation of the 51 state models reduces as the forecast horizon increases, with MSEs being very close to the best federal-level forecasts in the three-step-ahead predictions. A more in-depth investigation of these patterns could be an interesting starting point for further research, but is beyond the scope of the present article.

5.3 Comparison with the Survey of Professional Forecasters

As an additional robustness check we compare the forecasts of our best model with the results of the Survey of Professional Forecasters (SPF), a quarterly survey of about 30 professionals, conducted by the Federal Reserve Bank of Philadelphia.[12] The survey releases, approximately in the middle of the quarter, estimates of the quarterly evolution of a set of macroeconomic variables.[13]

In Figure 5 we compare simple forecast errors for the median (SPF^{median}), the mean (SPF^{mean}) and the best individual forecast[14] (SPF^{best}) of the SPF with those relative to the forecasts for each quarter obtained from a group of six best models. We define these best models as i) our best model overall (the one using GI); ii) the best model among those not using GI (IC) over the full sample; and iii) the best model among those not using GI over the short sample (IC_s). To these three groups of best models we add three additional groups of non-linear models based on iv) the SETAR(2), v) the

[11] We calculate the weights using the results of the October 2007 supplement of the Current Population Survey (CPS). The exact question used for calculating the weights asks: *Do you (Does anyone) in this household use the Internet at any location? The possible answers are simply Yes/Not.*

[12] http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/.

[13] The SPF is issued around the 15^{th} of February, May, August and November.

[14] The best individual forecast is calculated ex-post once the real values for $u_t - u_{t-1}$ are known.

LSTAR(2) and vi) the AAR(2) model. We do this to compare our best model with the Google indicator to a set of non-linear models which are known in the literature to be particularly suitable for long-term forecasting the US unemployment rate.

From each group we compute three series of quarterly forecasts. 1) $x^{1st-month}$ are the 1-month-ahead forecasts computed in the last month of each quarter before the one we want to forecast.[15] The prediction for the whole quarter is equal to the forecast for the first month of the quarter. 2) $x^{2nd-month}$ are the 2-month-ahead forecasts computed in the last month of the quarter before, with the estimate for the whole quarter being equal to the estimate for the second, central, month. Both these forecasts are very conservative with respect to those of SPF, since the SPF is issued on the 15^{th} of the second month of each reference quarter, thus around 45 days after our estimates are produced. Finally, 3) x^{Comb} are the quarterly forecasts computed as the average of the realized unemployment rate for the first month and the 1- and 2-month-ahead forecasts generated at the end of the first month of the reference quarter. These latter forecasts are less conservative because they use all the information available when the SPF is released. We thus expect that such forecasts should be at least as accurate as the SPF.

Does our model with Google outperform the professionals? It does, by a considerable margin, if we consider that it only uses a very short sample. In Table 8 we report the MSE for the nine best models and the three SPF forecasts over the period 2007Q2-2009Q2 along with the DM and the HLN tests where the benchmark is the model G^{Comb}, that is the model with the lowest MSE (in boldface). It is evident that the model including the GI outperforms all the three SPF forecasts. The DM test shows that the benchmark model is significantly better than all the other competitors using the first and second month forecasts, except for the less conservative forecasts x^{Comb} for which we reject the null hypothesis of equal forecast accuracy. Instead, the HLN test rejects the null that the benchmark model forecast encompasses the competitors, except for IC_s^{Comb} and $IC^{2nd-month}$. Figure 5 depicts the forecast errors from the best six models (those with the lowest MSE in Table 8) in addition to the mean and median SPF forecasts. It is rather clear that the model including the GI has the best performance in most periods, and in particular when the current recession worsened after the Lehman collapse in 2008Q4. We can see that the SPF and all the non-linear time series models tend to under-predict, whereas the linear models using either the initial claims or the Google index tend to over-predict. While the models includ-

[15]For example, if we want to forecast the quarterly unemployment rate for 2008Q2, at 2008.3 we compute the 1-month-ahead forecast from one of our three best models.

ing GI tend to give forecast errors that are close to zero, both the mean and median of SPF tend to under-predict the real unemployment rate. This means that our simple linear ARMA models with the Google index as a leading indicator outperform the predictions of the professional forecasters also during contractions, when the social impact of a high unemployment rate is even greater and the loss attached to high and positive forecast errors is maximal.[16]

6 Conclusions

In this paper we have tested the predictive power of a new leading indicator based on internet job-search performed through Google (Google Index, GI) in predicting the monthly unemployment rate in the US.

Popular time series specifications augmented with this indicator definitely improve their out-of-sample forecasting performance both at one-, two- and three-month horizons. To assess the forecast accuracy of our models out of sample, we also performed formal tests of equal forecast accuracy such as the Diebold Mariano test and the Harvey, Leybourne and Newbold test. We also performed White's (2000) Reality Check test for superior predictive ability. Our results from the out-of-sample horse-race with 520 linear models show that the best models in terms of lowest MSE are always those using GI as the leading indicator. These models fare better also when compared to other similar models using the initial claims as a leading indicator for a longer time span. Furthermore, these models outperform all the others both in terms of equal forecast accuracy and in terms of superior predictive ability. Our results are robust to various transformations of the dependent variable and are confirmed when assessing the predictive power of the GI in state-level forecasting. The best model including the GI also outperforms a set of non-linear models and the forecasts released in the Survey of Professional Forecasters conducted by the Philadelphia Fed.

Notwithstanding its limited availability (Google data start in January 2004) we believe that the GI should routinely be included in time series models to predict the unemployment dynamics. In fact, our results show that, even over a shorter sample period, simple regression models with ARMA errors using the GI as the leading indicator already outperform models estimated on a much longer sample both in terms of equal forecast accuracy

[16]We have also performed the same robustness check for the forecasts using the level of the unemployment rate finding even more striking results that are unreported. In this case, all the model using GI outperform the SPF and, in particular, the best model is the $GI^{2-month}$.

and superior predictive ability.

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Table 1: Descriptive statistics: sample 2004:1-2009:6

	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Jarque-Bera	Obs.
u_t	5.449	5.053	9.507	4.380	1.189	2.009	6.487	77.832***	66
$u_t - u_{t-1}$	0.058	0.026	0.539	-0.215	0.185	1.016	3.305	11.600***	66
$\log(u_t)$	1.676	1.620	2.252	1.477	0.187	1.610	5.029	39.819***	66
u_t^{logit}	-2.873	-2.933	-2.253	-3.083	0.200	1.637	5.121	41.838***	66
u_t^{LHP}	-0.019	-0.037	0.382	-0.191	0.139	1.087	3.905	15.239***	66
u_t^{LLD}	-0.140	-0.195	0.424	-0.340	0.184	1.550	4.900	36.372***	66
IC_t	1475.3	1337.5	2600.0	1152.0	365.3	2.035	5.983	70.037***	66
IC_{t-1}	1459.8	1337.5	2600.0	1152.0	343.7	2.209	6.948	96.539***	66
IC_{t-2}	1444.1	1337.5	2600.0	1152.0	317.2	2.382	8.093	133.767***	66
$IC_{w1,t}$	368.0	338.5	674.0	282.0	91.6	2.103	6.478	81.893***	66
$IC_{w1,t-1}$	363.9	338.5	674.0	282.0	85.8	2.287	7.588	115.427***	66
$IC_{w1,t-2}$	360.1	338.5	674.0	282.0	78.9	2.465	8.925	163.352***	66
$IC_{w2,t}$	367.4	333.5	660.0	288.0	90.2	2.061	6.243	75.629***	66
$IC_{w2,t-1}$	363.3	333.5	660.0	288.0	84.3	2.231	7.253	104.463***	66
$IC_{w2,t-2}$	359.7	333.5	660.0	288.0	78.7	2.433	8.601	151.386***	66
$IC_{w3,t}$	370.2	334.0	657.0	296.0	91.0	1.969	5.737	63.244***	66
$IC_{w3,t-1}$	366.6	334.0	657.0	296.0	86.2	2.134	6.633	86.396***	66
$IC_{w3,t-2}$	362.4	334.0	657.0	296.0	78.9	2.267	7.526	112.895***	66
$IC_{w4,t}$	369.7	330.5	645.0	284.0	95.8	1.891	5.340	54.400***	66
$IC_{w4,t-1}$	365.9	330.5	645.0	284.0	90.9	2.047	6.134	73.083***	66
$IC_{w4,t-2}$	361.9	330.5	645.0	284.0	84.4	2.193	7.021	97.361***	66
G_t	63.4	60.9	84.8	54.9	8.0	1.305	3.649	19.876***	66
G_{t-1}	63.2	60.6	84.8	54.9	7.8	1.388	3.968	23.402***	65
G_{t-2}	63.0	60.6	84.8	54.9	7.7	1.475	4.293	27.678***	64
$G_{w1,t}$	62.2	60.1	88.7	52.7	8.0	1.535	4.690	33.760***	66
$G_{w1,t-1}$	62.0	60.1	88.7	52.7	7.8	1.644	5.251	43.664***	66
$G_{w1,t-2}$	61.7	60.1	88.7	52.7	7.6	1.757	5.825	55.059***	65
$G_{w2,t}$	63.6	61.2	99.5	56.2	8.4	2.172	8.278	128.529***	66
$G_{w2,t-1}$	63.4	61.2	99.5	56.2	8.2	2.321	9.151	163.301***	66
$G_{w2,t-2}$	63.2	61.2	99.5	56.2	8.0	2.485	10.158	205.682***	65
$G_{w3,t}$	64.1	61.3	91.8	54.6	8.5	1.655	5.376	45.645***	66
$G_{w3,t-1}$	63.9	61.3	91.8	54.6	8.3	1.750	5.867	56.289***	66
$G_{w3,t-2}$	63.7	61.3	91.8	54.6	8.2	1.847	6.287	66.229***	65
$G_{w4,t}$	63.9	61.1	89.0	55.4	8.4	1.471	4.182	27.654***	66
$G_{w4,t-1}$	63.6	60.8	89.0	55.4	8.2	1.567	4.574	33.322***	65
$G_{w4,t-2}$	63.4	60.8	89.0	55.4	8.1	1.665	4.957	39.785***	64

Notes: u_t is the US unemployment rate in levels, $u_t - u_{t-1}$ are the first differences, $\log(u_t)$ is the unemployment rate in logs, $u_t^{logit} = \log(u_t/(1-u_t))$ is the logistic transformation suggested by Koop and Potter (1999), u_t^{LLD} is the log-linear de-trended unemployment rate and u_t^{LHP} is the HP-filtered series in log, both suggested by Rothman (1998). IC and G are the monthly initial claims and the monthly Google job web search index used as leading indicators. The subscripts wj indicate the j^{th} week and $t-k, k=(0,1,2)$ is the time lag. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 2: Correlations: sample 2004:1-2009:6

	u_t	$d(u_t)$	$\log(u_t)$	u_t^{logit}	u_t^{LHP}	u_t^{LLD}	IC	IC_{-1}	IC_{-2}	IC_{w1}	IC_{-1}^{w1}	IC_{-2}^{w1}	IC^{w2}	IC_{-1}^{w2}	IC_{-2}^{w2}	IC^{w3}	IC_{-1}^{w3}	IC_{-2}^{w3}
u_t	1	0.667	0.994	0.995	0.940	0.992	0.962	0.973	0.973	0.962	0.970	0.964	0.954	0.963	0.960	0.950	0.957	0.955
$u_t - u_{t-1}$	0.667	1	0.674	0.674	0.542	0.662	0.711	0.673	0.632	0.700	0.664	0.604	0.699	0.681	0.596	0.706	0.640	0.632
$\log(u_t)$	0.994	0.674	1	1.000	0.953	0.999	0.951	0.956	0.951	0.948	0.951	0.941	0.941	0.947	0.938	0.939	0.940	0.933
u_t^{logit}	0.995	0.674	1.000	1	0.953	0.999	0.952	0.957	0.953	0.949	0.953	0.943	0.942	0.948	0.940	0.940	0.942	0.935
u_t^{LHP}	0.940	0.542	0.953	0.953	1	0.962	0.844	0.864	0.873	0.842	0.859	0.860	0.832	0.854	0.856	0.842	0.858	0.866
u_t^{LLD}	0.992	0.662	0.999	0.999	0.962	1	0.942	0.949	0.946	0.940	0.945	0.936	0.933	0.940	0.932	0.931	0.934	0.929
IC_t	0.962	0.711	0.951	0.952	0.844	0.942	1	0.977	0.954	0.990	0.965	0.940	0.992	0.965	0.938	0.992	0.961	0.938
IC_{t-1}	0.973	0.673	0.956	0.957	0.864	0.949	0.977	1	0.975	0.982	0.988	0.961	0.972	0.991	0.960	0.961	0.991	0.957
IC_{t-2}	0.973	0.632	0.951	0.953	0.873	0.946	0.954	0.975	1	0.956	0.980	0.986	0.947	0.967	0.990	0.941	0.958	0.989
$IC_{w1,t}$	0.962	0.700	0.948	0.949	0.842	0.940	0.990	0.982	0.956	1	0.969	0.946	0.989	0.971	0.941	0.968	0.968	0.937
$IC_{w1,t-1}$	0.97	0.664	0.951	0.953	0.859	0.945	0.965	0.988	0.980	0.969	1	0.965	0.957	0.987	0.967	0.949	0.964	0.964
$IC_{w1,t-2}$	0.964	0.604	0.941	0.943	0.860	0.936	0.940	0.961	0.986	0.946	0.965	1	0.936	0.950	0.985	0.922	0.944	0.957
$IC_{w2,t}$	0.954	0.699	0.941	0.942	0.832	0.933	0.992	0.972	0.947	0.989	0.957	0.936	1	0.957	0.932	0.975	0.958	0.927
$IC_{w2,t-1}$	0.963	0.681	0.947	0.948	0.854	0.940	0.965	0.991	0.967	0.971	0.987	0.950	0.957	1	0.950	0.950	0.972	0.952
$IC_{w2,t-2}$	0.960	0.596	0.938	0.940	0.856	0.932	0.938	0.960	0.990	0.941	0.967	0.985	0.932	0.950	1	0.922	0.944	0.969
$IC_{w3,t}$	0.950	0.706	0.939	0.940	0.842	0.931	0.992	0.961	0.941	0.968	0.949	0.922	0.975	0.950	0.922	1	0.942	0.930
$IC_{w3,t-1}$	0.957	0.640	0.940	0.942	0.858	0.934	0.961	0.991	0.958	0.968	0.964	0.944	0.958	0.972	0.944	0.942	1	0.937
$IC_{w3,t-2}$	0.955	0.632	0.933	0.935	0.866	0.929	0.938	0.957	0.989	0.937	0.964	0.957	0.927	0.952	0.969	0.930	0.937	1
$IC_{w4,t}$	0.949	0.713	0.940	0.941	0.831	0.932	0.991	0.961	0.940	0.968	0.951	0.921	0.971	0.947	0.924	0.989	0.943	0.927
$IC_{w4,t-1}$	0.962	0.679	0.947	0.948	0.852	0.940	0.980	0.990	0.958	0.981	0.965	0.948	0.975	0.967	0.942	0.965	0.987	0.939
$IC_{w4,t-2}$	0.968	0.665	0.949	0.951	0.870	0.944	0.957	0.977	0.989	0.957	0.979	0.960	0.948	0.972	0.962	0.945	0.961	0.986
G_t	0.851	0.745	0.866	0.865	0.706	0.854	0.902	0.862	0.823	0.885	0.847	0.818	0.890	0.848	0.809	0.886	0.840	0.794
G_{t-1}	0.885	0.734	0.897	0.896	0.752	0.886	0.929	0.898	0.859	0.920	0.881	0.844	0.920	0.887	0.842	0.909	0.880	0.837
G_{t-2}	0.919	0.743	0.927	0.927	0.812	0.920	0.932	0.919	0.892	0.933	0.908	0.873	0.922	0.915	0.875	0.911	0.899	0.873
$G_{w1,t}$	0.852	0.735	0.861	0.861	0.709	0.850	0.903	0.860	0.835	0.899	0.849	0.837	0.900	0.849	0.824	0.884	0.833	0.806
$G_{w1,t-1}$	0.873	0.677	0.880	0.880	0.743	0.871	0.889	0.897	0.852	0.886	0.893	0.841	0.869	0.895	0.839	0.871	0.876	0.824
$G_{w1,t-2}$	0.900	0.707	0.904	0.904	0.785	0.896	0.904	0.883	0.896	0.898	0.880	0.892	0.896	0.861	0.891	0.880	0.863	0.874
$G_{w2,t}$	0.842	0.709	0.848	0.848	0.708	0.837	0.876	0.852	0.824	0.864	0.839	0.805	0.861	0.835	0.800	0.857	0.838	0.807
$G_{w2,t-1}$	0.881	0.717	0.879	0.879	0.756	0.870	0.921	0.875	0.855	0.919	0.863	0.841	0.929	0.860	0.832	0.898	0.853	0.842
$G_{w2,t-2}$	0.904	0.654	0.896	0.897	0.789	0.889	0.916	0.921	0.875	0.932	0.919	0.862	0.915	0.931	0.856	0.891	0.894	0.852
$G_{w3,t}$	0.819	0.718	0.838	0.837	0.696	0.828	0.862	0.824	0.787	0.841	0.805	0.782	0.842	0.808	0.772	0.853	0.809	0.759
$G_{w3,t-1}$	0.854	0.707	0.869	0.868	0.744	0.861	0.890	0.859	0.824	0.879	0.838	0.803	0.882	0.839	0.802	0.871	0.849	0.809
$G_{w3,t-2}$	0.898	0.710	0.904	0.904	0.799	0.897	0.928	0.894	0.868	0.927	0.882	0.846	0.921	0.888	0.841	0.907	0.872	0.858
$G_{w4,t}$	0.809	0.722	0.824	0.823	0.649	0.810	0.872	0.836	0.791	0.852	0.824	0.783	0.857	0.824	0.781	0.858	0.814	0.760
$G_{w4,t-1}$	0.843	0.733	0.854	0.854	0.694	0.842	0.905	0.867	0.832	0.895	0.846	0.820	0.895	0.852	0.816	0.887	0.850	0.809
$G_{w4,t-2}$	0.885	0.730	0.889	0.889	0.745	0.878	0.924	0.907	0.872	0.918	0.898	0.851	0.911	0.898	0.852	0.906	0.886	0.856

Continued

Table 2: Correlations: sample 2004:1-2009:6 (Continued)

	IC^{w4}	IC^{w4}_{-1}	IC^{w4}_{-2}	G	G_{-1}	G_{-2}	G^{w1}	G^{w1}_{-1}	G^{w1}_{-2}	G^{w2}	G^{w2}_{-1}	G^{w2}_{-2}	G^{w3}	G^{w3}_{-1}	G^{w3}_{-2}	G^{w4}	G^{w4}_{-1}	G^{w4}_{-2}
u_t	0.949	0.962	0.968	0.851	0.885	0.919	0.852	0.873	0.900	0.842	0.881	0.904	0.819	0.854	0.898	0.809	0.843	0.885
$u_t - u_{t-1}$	0.713	0.679	0.665	0.745	0.734	0.743	0.735	0.677	0.707	0.709	0.717	0.654	0.718	0.707	0.710	0.722	0.733	0.730
$\log(u_t)$	0.940	0.947	0.949	0.866	0.897	0.927	0.861	0.880	0.904	0.848	0.879	0.896	0.838	0.869	0.904	0.824	0.854	0.889
u_t^{logit}	0.941	0.948	0.951	0.865	0.896	0.927	0.861	0.880	0.904	0.848	0.879	0.897	0.837	0.868	0.904	0.823	0.854	0.889
u_t^{LHP}	0.831	0.852	0.870	0.706	0.752	0.812	0.709	0.743	0.785	0.708	0.756	0.789	0.696	0.744	0.799	0.649	0.694	0.745
u_t^{LLD}	0.932	0.940	0.944	0.854	0.886	0.920	0.850	0.871	0.896	0.837	0.870	0.889	0.828	0.861	0.897	0.810	0.842	0.878
IC_t	0.991	0.980	0.957	0.902	0.929	0.932	0.903	0.889	0.904	0.876	0.921	0.916	0.862	0.890	0.928	0.872	0.905	0.924
IC_{t-1}	0.961	0.990	0.977	0.862	0.898	0.919	0.860	0.897	0.883	0.852	0.875	0.921	0.824	0.859	0.894	0.836	0.867	0.907
IC_{t-2}	0.940	0.958	0.989	0.823	0.859	0.892	0.835	0.852	0.896	0.824	0.855	0.875	0.787	0.824	0.868	0.791	0.832	0.872
$IC_{w1,t}$	0.968	0.981	0.957	0.885	0.920	0.933	0.899	0.886	0.898	0.864	0.919	0.932	0.841	0.879	0.927	0.852	0.895	0.918
$IC_{w1,t-1}$	0.951	0.965	0.979	0.847	0.881	0.908	0.849	0.893	0.880	0.839	0.863	0.919	0.805	0.838	0.882	0.824	0.846	0.898
$IC_{w1,t-2}$	0.921	0.948	0.960	0.818	0.844	0.873	0.837	0.841	0.892	0.805	0.841	0.862	0.782	0.803	0.846	0.783	0.820	0.851
$IC_{w2,t}$	0.971	0.975	0.948	0.890	0.920	0.922	0.900	0.869	0.896	0.861	0.929	0.915	0.842	0.882	0.921	0.857	0.895	0.911
$IC_{w2,t-1}$	0.947	0.967	0.972	0.848	0.887	0.915	0.849	0.895	0.861	0.835	0.860	0.931	0.808	0.839	0.888	0.824	0.852	0.898
$IC_{w2,t-2}$	0.924	0.942	0.962	0.809	0.842	0.875	0.824	0.839	0.891	0.800	0.832	0.856	0.772	0.802	0.841	0.781	0.816	0.852
$IC_{w3,t}$	0.989	0.965	0.945	0.886	0.909	0.911	0.884	0.871	0.880	0.857	0.898	0.891	0.853	0.871	0.907	0.858	0.887	0.906
$IC_{w3,t-1}$	0.943	0.987	0.961	0.840	0.880	0.899	0.833	0.876	0.863	0.838	0.853	0.894	0.809	0.849	0.872	0.814	0.850	0.886
$IC_{w3,t-2}$	0.927	0.939	0.986	0.794	0.837	0.873	0.806	0.824	0.874	0.807	0.842	0.852	0.759	0.809	0.858	0.760	0.809	0.856
$IC_{w4,t}$	1	0.963	0.944	0.913	0.933	0.930	0.897	0.899	0.907	0.890	0.908	0.894	0.879	0.897	0.924	0.888	0.909	0.930
$IC_{w4,t-1}$	0.963	1	0.960	0.876	0.909	0.919	0.872	0.890	0.892	0.863	0.888	0.904	0.843	0.876	0.898	0.847	0.883	0.910
$IC_{w4,t-2}$	0.944	0.960	1	0.832	0.874	0.903	0.835	0.866	0.886	0.842	0.865	0.887	0.799	0.842	0.883	0.802	0.842	0.888
G_t	0.913	0.876	0.832	1	0.982	0.936	0.957	0.935	0.913	0.930	0.896	0.837	0.978	0.955	0.908	0.984	0.978	0.959
G_{t-1}	0.933	0.909	0.874	0.982	1	0.967	0.951	0.954	0.931	0.944	0.927	0.890	0.954	0.977	0.953	0.953	0.983	0.978
G_{t-2}	0.930	0.919	0.903	0.936	0.967	1	0.919	0.938	0.942	0.923	0.929	0.912	0.912	0.937	0.968	0.900	0.935	0.967
$G_{w1,t}$	0.897	0.872	0.835	0.957	0.951	0.919	1	0.888	0.899	0.833	0.898	0.851	0.924	0.894	0.907	0.933	0.964	0.912
$G_{w1,t-1}$	0.899	0.890	0.866	0.935	0.954	0.938	0.888	1	0.880	0.918	0.824	0.892	0.912	0.921	0.891	0.923	0.929	0.963
$G_{w1,t-2}$	0.907	0.892	0.886	0.913	0.931	0.942	0.899	0.880	1	0.913	0.914	0.814	0.905	0.908	0.919	0.869	0.918	0.926
$G_{w2,t}$	0.890	0.863	0.842	0.930	0.944	0.923	0.833	0.918	0.913	1	0.893	0.823	0.918	0.965	0.909	0.896	0.915	0.962
$G_{w2,t-1}$	0.908	0.888	0.865	0.896	0.927	0.929	0.898	0.824	0.914	0.893	1	0.888	0.854	0.914	0.963	0.845	0.891	0.911
$G_{w2,t-2}$	0.894	0.904	0.887	0.837	0.890	0.912	0.851	0.892	0.814	0.823	0.888	1	0.774	0.847	0.911	0.798	0.836	0.885
$G_{w3,t}$	0.879	0.843	0.799	0.978	0.954	0.912	0.924	0.912	0.905	0.918	0.854	0.774	1	0.935	0.877	0.955	0.965	0.935
$G_{w3,t-1}$	0.897	0.876	0.842	0.955	0.977	0.937	0.894	0.921	0.908	0.965	0.914	0.847	0.935	1	0.931	0.920	0.952	0.964
$G_{w3,t-2}$	0.924	0.898	0.883	0.908	0.953	0.968	0.907	0.891	0.919	0.909	0.963	0.911	0.877	0.931	1	0.859	0.916	0.950
$G_{w4,t}$	0.888	0.847	0.802	0.984	0.953	0.900	0.933	0.923	0.869	0.896	0.845	0.798	0.955	0.920	0.859	1	0.957	0.939
$G_{w4,t-1}$	0.909	0.883	0.842	0.978	0.983	0.935	0.964	0.929	0.918	0.915	0.891	0.836	0.965	0.952	0.916	0.957	1	0.955
$G_{w4,t-2}$	0.930	0.910	0.888	0.959	0.978	0.967	0.912	0.963	0.926	0.962	0.911	0.885	0.935	0.964	0.950	0.939	0.955	1

Notes: u_t is the US unemployment rate in levels, $u_t - u_{t-1}$ are the first differences, $\log(u_t)$ is the unemployment rate in logs, $u_t^{logit} = \log(u_t/(1-u_t))$ is the logistic transformation suggested by Koop and Potter (1999), u_t^{LLD} is the log-linear de-trended unemployment rate and u_t^{LHP} is the HP-filtered series in log, both suggested by Rothman (1998). IC and G are the monthly initial claims and the monthly Google job web search index used as leading indicators. Both the subscripts and superscripts wj indicate the j^{th} week and the subscripts $t-k$, $k=(0,1,2)$ is the time lag. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 3: Unit Root tests for the US unemployment rate

Sample: 1967:1-2009:6			Sample: 2004:1-2009:6		
Variable	Test	Test stat.	Variable	Test	
u_t	$DF-GLS^{\mu}$	-1.054	u_t	$DF-GLS^{\mu}$	-2.881***
	$DF-GLS^{\tau}$	-2.282		$DF-GLS^{\tau}$	-2.902*
$\log(u_t)$	$DF-GLS^{\mu}$	-0.901	$\log(u_t)$	$DF-GLS^{\mu}$	-2.792***
	$DF-GLS^{\tau}$	-2.190		$DF-GLS^{\tau}$	-2.797
u_t^{logit}	$DF-GLS^{\mu}$	-0.912	u_t^{logit}	$DF-GLS^{\mu}$	-2.801***
	$DF-GLS^{\tau}$	-2.203		$DF-GLS^{\tau}$	-2.804
u_t^{HPlog}	$DF-GLS^{\mu}$	-3.752***	u_t^{HPlog}	$DF-GLS^{\mu}$	-2.659***
	$DF-GLS^{\tau}$	-4.414***		$DF-GLS^{\tau}$	-2.523
u_t^{LLD}	$DF-GLS^{\mu}$	-1.344	u_t^{LLD}	$DF-GLS^{\mu}$	-2.823***
	$DF-GLS^{\tau}$	-2.190		$DF-GLS^{\tau}$	-2.797

Notes: The $DF-GLS^{\mu}$ test indicates the test where a constant is included as the exogenous regressor, while $DF-GLS^{\tau}$ is the test with a constant and trend included. The critical values at 1, 5, and 10% for the $DF-GLS^{\mu}$ test are -2.569 (-2.600), -1.941 (-1.946) and -1.616 (-1.614), respectively, for the full sample 1967.1-2009.6 (short sample 2004.1-2009.6). Instead, the critical values at 1, 5, and 10% for the $DF-GLS^{\tau}$ test are -3.48 (-3.709), -2.89 (-3.138) and -2.57 (-2.842), respectively, for the full sample 1967.1-2009.6 (short sample 2004.1-2009.6). ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 4: Forecasting Models: $\phi(L)y_t = \mu + x_t'\beta + \theta(L)\varepsilon_t$ for the unemployment rate

	Full Sample: 1967.1-2007.2								Short Sample: 2004.1-2007.2							
	AR(1)	#	AR(2)	#	ARMA(1,1)	#	ARMA(2,2)	#	AR(1)	#	AR(2)	#	ARMA(1,1)	#	ARMA(2,2)	#
w/o LI																
	u_{t-1}	1	u_{t-k}	1	$u_{t-1}, \varepsilon_{t-1}$	1	$u_{t-k}, \varepsilon_{t-k}$	1	u_{t-1}	1	u_{t-k}	1	$u_{t-1}, \varepsilon_{t-1}$	1	$u_{t-k}, \varepsilon_{t-k}$	1
w/ LI x_t																
(t)																
IC	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1
IC_{wj}	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4
G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
G_{wj}	-		-		-		-		✓	4	✓	4	✓	4	✓	4
IC, G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
IC_{wj}, G_{wj}	-		-		-		-		✓	5	✓	5	✓	5	✓	5
$(t-1)$																
IC	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1
IC_{wj}	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4
G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
G_{wj}	-		-		-		-		✓	4	✓	4	✓	4	✓	4
IC, G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
IC_{wj}, G_{wj}	-		-		-		-		✓	5	✓	5	✓	5	✓	5
$(t-2)$																
IC	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1	✓	1
IC_{wj}	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4	✓	4
G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
G_{wj}	-		-		-		-		✓	4	✓	4	✓	4	✓	4
IC, G	-		-		-		-		✓	1	✓	1	✓	1	✓	1
IC_{wj}, G_{wj}	-		-		-		-		✓	5	✓	5	✓	5	✓	5
$j = 1, , 4; k = 1, 2$ - w/ or w/o SAR/SMA																

Notes: # indicates the number of models in each group. The subscript $wj, j = 1, ..., 4$ denotes the weekly leading indicators. A ✓ denotes that the model in that group adopts the row variable as a leading indicator.

Table 5: Forecasting US unemployment rate ($u_t - u_{t-1}$) in first differences. Best 15 models, best models without GI and non-linear models.

1-step ahead

n.	Model	MSE	Rank	DM	HLN
	Best models with Google				
261	$ARX(1) - G_t$	0.0166	1	-	-
398	$ARMAX(1,1) - G_t - SA$	0.0167	2	0.060	2.145**
327	$ARX(2) - G_t$	0.0172	3	0.448	1.063
491	$ARMAX(2,2) - IC_{t-1} - G_{t-1}$	0.0177	4	0.328	1.912*
305	$ARX(1) - G_{t-2}$	0.0179	5	0.616	1.289
464	$ARMAX(2,2) - G_t - SA$	0.0179	6	0.312	1.370
371	$ARX(2) - G_{t-2}$	0.0181	7	0.614	1.642
283	$ARX(1) - G_{t-1}$	0.0182	8	1.516	1.701*
463	$ARMAX(2,2) - G_{w4,t} - SA$	0.0184	9	0.442	2.116**
277	$ARX(1) - IC_t - G_t - SA$	0.0186	10	0.852	1.326
271	$ARX(1) - IC_t - G_t$	0.0186	11	0.709	1.605
266	$ARX(1) - G_t - SA$	0.0188	12	0.998	1.122
337	$ARX(2) - IC_t - G_t$	0.0191	13	0.799	1.875*
343	$ARX(2) - IC_t - G_t - SA$	0.0192	14	0.870	1.550
270	$ARX(1) - IC_{w4,t} - G_{w4,t}$	0.0192	15	0.778	1.807*
	Best models without Google				
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.0234	73	2.491**	3.074***
133	$ARMA(1,1)$	0.0301	197	2.152**	2.485**
	Non-linear models				
521	$SETAR(2)$	0.0332	258	2.434**	2.925***
522	$LSTAR(2)$	0.0368	362	2.497**	3.015***
523	$AAR(2)$	0.0342	276	2.337**	2.903***

2-step ahead

n.	Model	MSE	Rank	DM	HLN
	Best models with Google				
261	$ARX(1) - G_t$	0.0157	1	-	-
464	$ARMAX(2,2) - G_t - SA$	0.0163	2	0.136	1.291
398	$ARMAX(1,1) - G_t - SA$	0.0166	3	0.177	1.219
327	$ARX(2) - G_t$	0.0172	4	0.633	0.864
266	$ARX(1) - G_t - SA$	0.0175	5	0.700	0.869
277	$ARX(1) - IC_t - G_t - SA$	0.0186	6	0.952	1.142
332	$ARX(2) - G_t - SA$	0.0194	7	0.955	1.192
343	$ARX(2) - IC_t - G_t - SA$	0.0206	8	1.150	1.285
283	$ARX(1) - G_{t-1}$	0.0208	9	1.514	1.543
420	$ARMAX(1,1) - G_{t-1} - SA$	0.0217	10	0.981	1.373
288	$ARX(1) - G_{t-1} - SA$	0.0220	11	1.402	1.551
305	$ARX(1) - G_{t-2}$	0.0220	12	1.551	1.718*
349	$ARX(2) - G_{t-1}$	0.0222	13	1.915*	2.024**
293	$ARX(1) - IC_{t-1} - G_{t-1}$	0.0233	14	1.989**	1.994**
299	$ARX(1) - IC_{t-1} - G_{t-1} - SA$	0.0234	15	1.392	1.468
	Best models without Google				
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.0514	180	1.814*	1.618
234	$ARMAX(2,2) - IC_{w3,t} - SA$	0.0565	191	1.389	1.131
	Non-linear models				
521	$SETAR(2)$	0.0388	97	1.053	1.720*
522	$LSTAR(2)$	0.0447	140	1.190	1.779*
523	$AAR(2)$	0.0436	134	1.183	1.721*

3-step ahead

n.	Model	MSE	Rank	DM	HLN
	Best models with Google				
398	$ARMAX(1,1) - G_t - SA$	0.0350	1	-	-
327	$ARX(2) - G_t$	0.0372	2	0.230	0.793
332	$ARX(2) - G_t - SA$	0.0379	3	0.244	0.671
261	$ARX(1) - G_t$	0.0382	4	0.308	0.852
464	$ARMAX(2,2) - G_t - SA$	0.0382	5	0.295	0.579
266	$ARX(1) - G_t - SA$	0.0383	6	0.299	0.777
349	$ARX(2) - G_{t-1}$	0.0488	7	1.164	1.300
354	$ARX(2) - G_{t-1} - SA$	0.0495	8	1.115	1.440
393	$ARMAX(1,1) - G_t$	0.0508	9	0.722	1.060
288	$ARX(1) - G_{t-1} - SA$	0.0510	10	1.142	1.501
283	$ARX(1) - G_{t-1}$	0.0513	11	1.217	1.383
343	$ARX(2) - IC_t - G_t - SA$	0.0528	12	0.659	0.811
277	$ARX(1) - IC_t - G_t - SA$	0.0531	13	0.681	0.852
365	$ARX(2) - IC_{t-1} - G_{t-1} - SA$	0.0548	14	1.275	1.658*
265	$ARX(1) - G_{w4,t} - SA$	0.0555	15	0.938	1.219
	Best models without Google				
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.1406	191	1.309	1.249
215	$ARMAX(1,1) - IC_{w4,t-1} - SA$	0.1294	173	1.748*	1.752*
	Non-linear models				
521	$SETAR(2)$	0.0589	24	0.758	1.447
522	$LSTAR(2)$	0.0620	30	0.790	1.411
523	$AAR(2)$	0.0652	35	0.814	1.389

Notes: ***, ** and * indicate rejection at 1, 5 and 10%, respectively. This table reports the best 15 models in terms of MSE among the 523 estimated ones. The complete list of models and their forecasting performance is available in the appendix (table 16). SA indicates the model augmented with a multiplicative seasonal factor.

Table 6: Reality-Check p-values for testing the superior predictive ability of our best model (with Google Index) against all the other 519 models

	u_t		$u_t - u_{t-1}$		$\log(u_t)$		u_t^{LLD}		u_t^{logit}		u_t^{HPlog}	
B	2000	5000	2000	5000	2000	5000	2000	5000	2000	5000	2000	5000
1-step	Benchmark=403		Benchmark=261		Benchmark=327		Benchmark=327		Benchmark=327		Benchmark=327	
q=0.50	**0.073**	**0.070**	**0.107**	**0.098**	**0.099**	**0.100**	**0.076**	**0.076**	**0.083**	**0.083**	**0.073**	**0.083**
q=0.10	**0.053**	**0.057**	**0.055**	**0.057**	**0.050**	0.045	**0.053**	**0.060**	**0.073**	**0.068**	**0.057**	**0.060**
2-step	Benchmark=332		Benchmark=261		Benchmark=327		Benchmark=327		Benchmark=327		Benchmark=327	
q=0.50	0.037	0.039	**0.098**	**0.097**	**0.080**	**0.080**	0.043	0.040	0.027	0.033	**0.065**	**0.062**
q=0.10	**0.053**	**0.052**	**0.053**	0.045	**0.058**	**0.058**	**0.061**	**0.057**	**0.054**	**0.056**	**0.057**	**0.057**
3-step	Benchmark=332		Benchmark=398		Benchmark=266		Benchmark=266		Benchmark=266		Benchmark=266	
q=0.50	0.037	0.045	**0.073**	**0.073**	**0.114**	**0.114**	0.029	0.025	0.028	0.027	0.041	0.038
q=0.10	0.046	**0.052**	0.048	0.048	**0.058**	**0.066**	**0.050**	**0.052**	**0.052**	**0.054**	**0.061**	**0.052**

Notes: The null hypothesis of the Reality Check test is that none of the models beat the benchmark (i.e. our best model with Google index with the lowest MSE overall). B indicates the number of bootstrap replications and q is the probability parameter of the stationary bootstrap implemented to compute the Reality Check p-values. In boldface we indicate all the Reality Check p-values significant at 5% or more.

Table 7: Forecasts of the US unemployment rate aggregating single state level forecasts.

	1-Step					2-Step					3-Step				
Variable: $(u_t - u_{t-1})$	**MSE**	**Rk1**	**Rk2**	**DM**	**HLN**	**MSE**	**Rk1**	**Rk2**	**DM**	**HLN**	**MSE**	**Rk1**	**Rk2**	**DM**	**HLN**
Model															
Best federal level model	0.0166	1	1	-	-	0.0157	1	1	-	-	0.0350	1	4	-	-
Aggregation of state level models															
Simple average	0.2845	7	525	5.30***	4.92***	0.3391	7	524	2.77***	2.31**	0.3966	7	510	1.99**	2.31**
Weighted avg (labor force)	0.0292	2	181	-0.13	2.68***	0.0310	2	48	-0.30	1.31	0.0411	2	7	-1.17	1.31
- labor force*(internet use among labor force)	0.0299	5	196	-0.06	2.75***	0.0314	3	51	-0.28	1.32	0.0413	3	8	-1.16	1.32
- labor force*(internet use among active)	0.0296	3	190	-0.09	2.69***	0.0318	4	56	-0.26	1.30	0.0423	4	9	-1.14	1.30
- labor force*(internet use among unemployed)	0.0298	4	194	-0.07	2.71***	0.0322	5	57	-0.25	1.31	0.0425	5	10	-1.13	1.31
- unemployed*(internet use among unemployed)	0.0917	6	519	2.33**	3.33***	0.0690	6	239	0.65	1.66*	0.0618	6	32	-0.53	1.66*
Variable: u_t	**MSE**	**Rk1**	**Rk2**	**DM**	**HLN**	**MSE**	**Rk1**	**Rk2**	**DM**	**HLN**	**MSE**	**Rk1**	**Rk2**	**DM**	**HLN**
Model and weighting															
Best federal level model	0.0167	1	1	-	-	0.0169	1	7	-	-	0.0482	6	15	-	-
Aggregation of state level models															
Simple average	0.3000	7	526	5.29***	4.70***	0.3700	7	522	2.48**	2.15**	0.4560	7	514	1.83*	1.73*
Weighted avg (labor force)	0.0280	2	120	0.24	2.95***	0.0293	2	29	-1.23	0.37	0.0459	3	3	-1.06	0.54
- labor force*(internet use among labor force)	0.0283	3	131	0.26	2.98***	0.0294	3	30	-1.24	0.36	0.0454	2	2	-1.07	0.54
- labor force*(internet use among active)	0.0286	4	137	0.29	2.94***	0.0303	5	33	-1.21	0.38	0.0474	5	5	-1.04	0.55
- labor force*(internet use among unemployed)	0.0287	5	140	0.30	2.96***	0.0302	4	32	-1.21	0.38	0.0469	4	4	-1.05	0.56
- unemployed*(internet use among unemployed)	0.0709	6	513	2.06**	3.31***	0.0519	6	152	-0.65	1.41	0.0373	1	1	-1.16	0.70

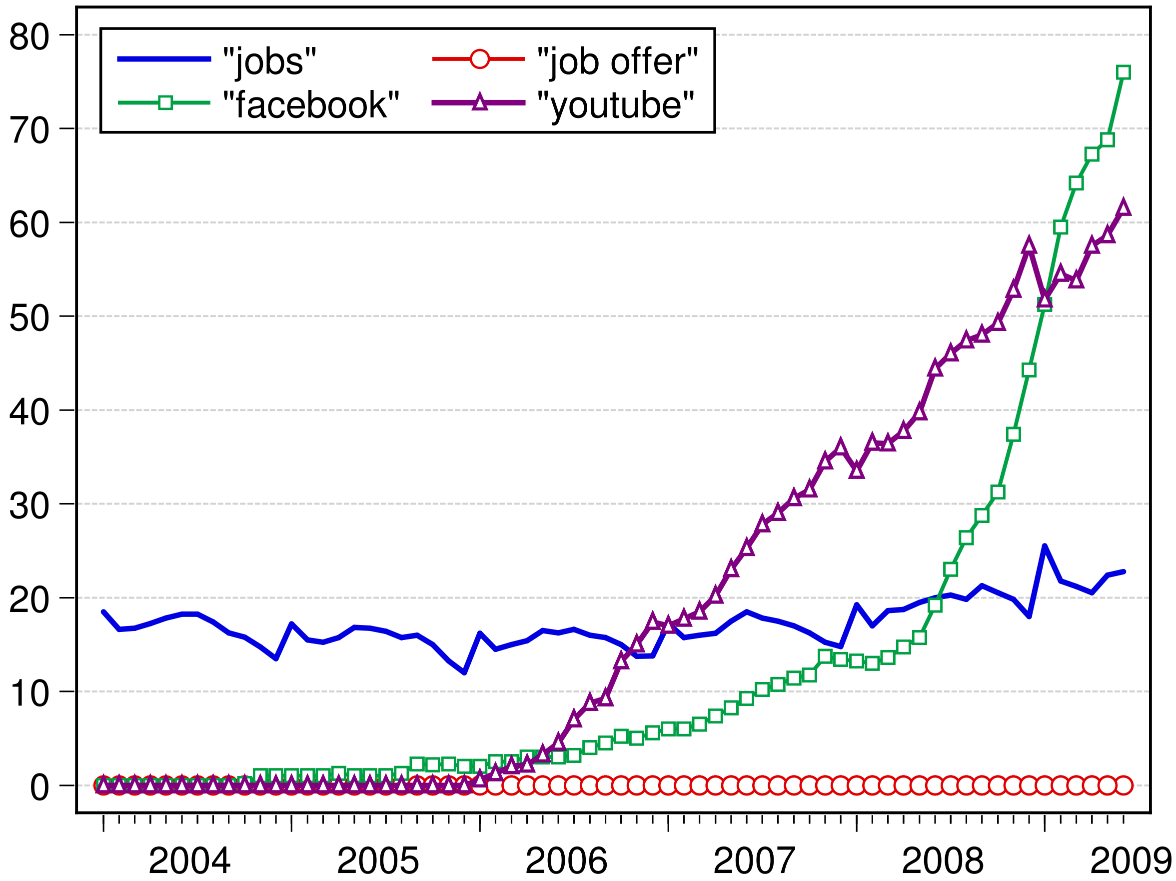
Notes: ***, ** and * indicate rejection at 1, 5 and 10%, respectively. The best federal level model is the model ranked first in the horse-race of table 5. Aggregation of state level models is made by taking the model with the lowest MSE for each state and than aggregating in a federal level forecast using a simple or weighed average as described in the table. Rk1 is the rank of each model within the table, while Rk2 is the rank of the model among all the models.

Table 8: Forecasts of the quarterly US unemployment: comparison of the best models with the Survey of Professional Forecasters.

	MSE	Rank	DM	HLN
SPF^{best}	1.373	21	1.911*	2.177**
SPF^{mean}	0.415	11	1.545	2.784***
SPF^{med}	0.360	7	1.317	2.892***
$G^{1st-month}$	0.530	15	-1.522	2.401**
$G^{2nd-month}$	0.419	12	1.724*	1.925*
G^{Comb}	**0.082**	1	-	-
$IC^{1st-month}$	0.893	17	-0.337	2.621***
$IC^{2nd-month}$	0.361	8	-0.919	1.457
IC^{Comb}	0.208	5	-2.012**	-1.875*
$IC_s^{1st-month}$	0.612	16	0.048	2.386**
$IC_s^{2nd-month}$	0.413	10	1.810*	1.759*
IC_s^{Comb}	0.218	6	1.306	1.239
$SETAR^{1st-month}$	1.123	19	2.881***	2.596***
$SETAR^{2nd-month}$	0.373	9	1.098	2.902***
$SETAR^{Comb}$	*0.098*	2	-1.401	2.587***
$LSTAR^{1st-month}$	1.228	20	2.558**	2.407**
$LSTAR^{2nd-month}$	0.433	14	1.550	2.723***
$LSTAR^{Comb}$	0.127	4	-1.265	2.315**
$AAR^{1st-month}$	1.060	18	2.630***	2.418**
$AAR^{2nd-month}$	0.432	13	1.768*	2.900***
AAR^{Comb}	0.102	3	-1.37	2.662***

Notes: In this table we compare the SPF one-quarter-ahead unemployment forecasts with similar forecasts generated from our best models for $u_t - u_{t-1}$, i.e. models n. 261, 261 and 398 for 1-, 2- and 3-month-ahead forecasts, respectively. The out-of-sample period is 2007.2-2009.6. SPF^{best} is the best individual forecaster in the survey, SPF^{mean} is the mean of the forecasts, while SPF^{median} is the median. Models $x^{1st-month}$ are 1-month-ahead forecasts computed in the last month of the quarter before. Models $x^{2nd-month}$ are 2-month-ahead forecasts computed in the last month of the quarter before. Both these forecasts are very conservative since the SPF is issued on the 15^{th} of the second month of each reference quarter. Models x^{Comb} compute the quarterly forecast as the average of the realized unemployment rate for the first month and the 1- and 2-month-ahead forecasts generated at the end of the first month of the reference quarter. The model with Google is the best model overall, the model with IC is the best model without Google, while the models with subscript IC_s is the best model without Google in the short sample. SETAR, LSTAR and AAR are the corresponding non-linear models estimated over the full sample up to the second lag. In boldface we indicate the model with the minimum MSE, while in italics the next to the minimum MSE. The benchmark model for the DM and HLN tests is G^{Comb}. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Figure 1: Relative incidence of keyword searches through Google



Notes: The figure depicts the relative incidence of the keyword searches 'jobs' adopted to construct our Google index along with the almost nil 'job offer', and the recently more popular 'facebook' and 'you tube' over the relevant sample 2004.1-2009.6.

Figure 2: Exact timing of monthly US Unemployment rate calculation

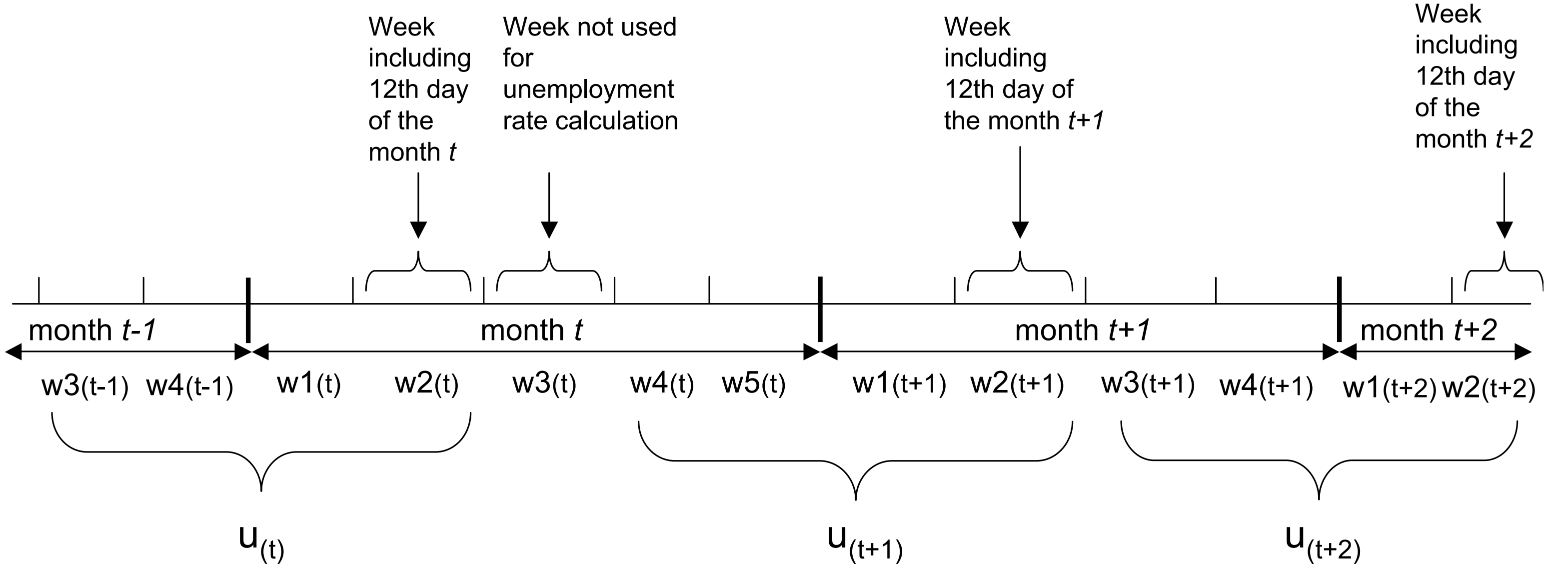
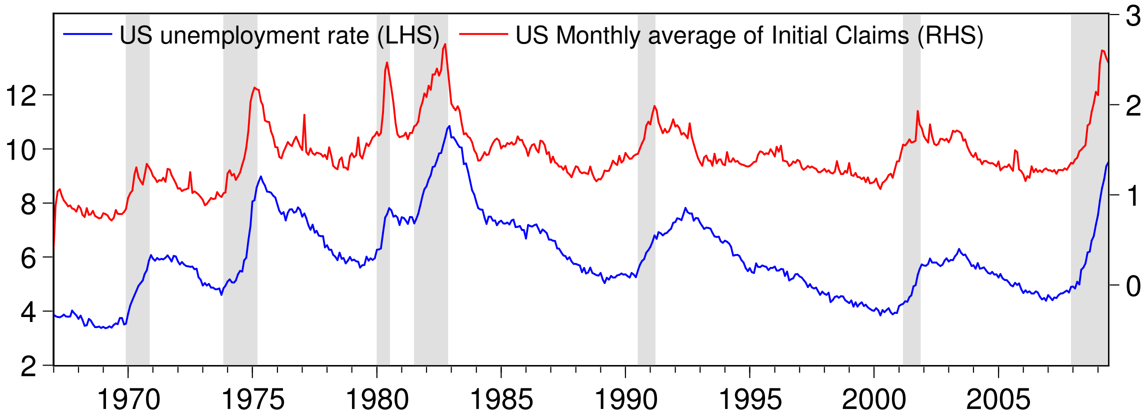
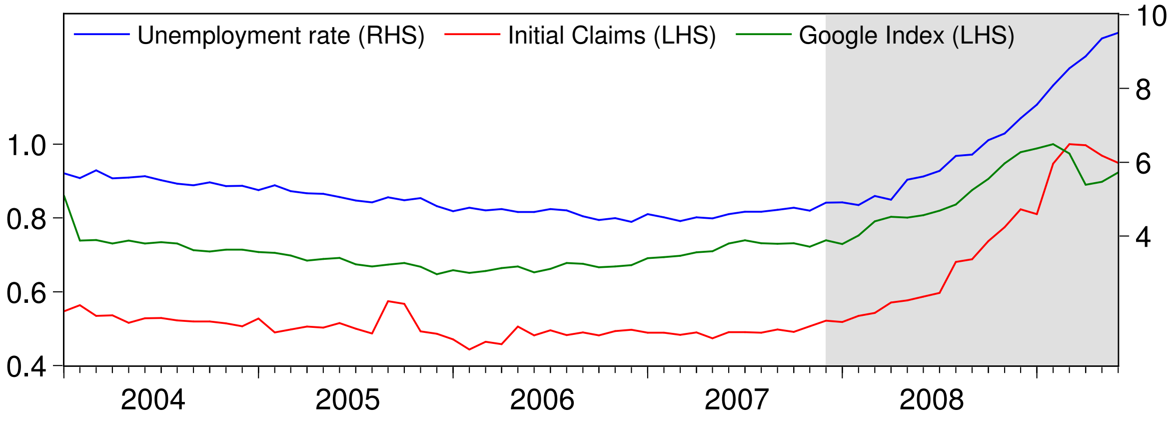


Figure 3: US Unemployment rate and Initial claims: Sample 1967:1-2009:6



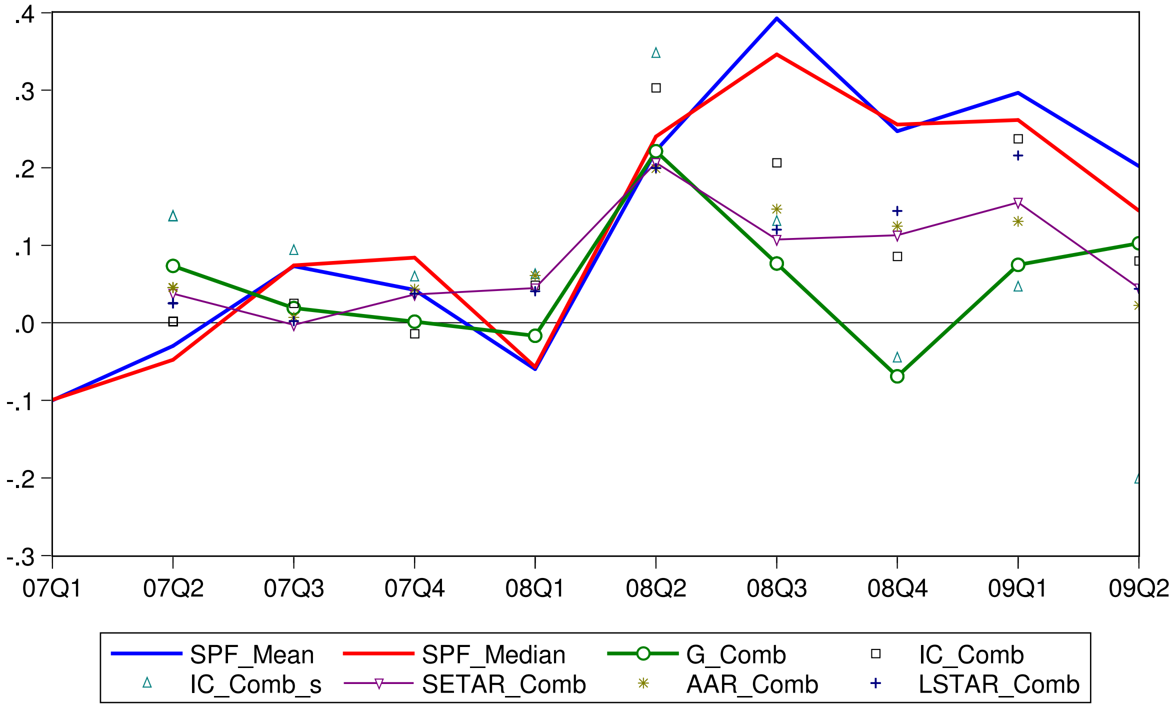
Notes: Shaded areas identify official NBER recessions.

Figure 4: US Unemployment rate, Initial claims and Google index: Sample 2004:1-2009:6



Notes: Shaded areas identify NBER recessions. The Initial claims are monthly averages rebased on their maximum over the sample 2004:1-2009:6. The Google index is the monthly average of Google 'job' searches rebased on their maximum value over the sample 2004:1-2009:6.

Figure 5: Forecast errors from quarterly forecasts of the US unemployment rate: comparison of the best models with the Survey of Professional Forecasters



Notes: In this table we compare the SPF one-quarter-ahead unemployment forecasts with similar forecasts generated from our best models for $u_t - u_{t-1}$, i.e. models n. 261, 261 and 398 for 1-, 2- and 3-month-ahead forecasts, respectively. The out-of-sample period is 2007.2-2009.6. SPF^{best} is the best individual forecaster in the survey, SPF^{mean} is the mean of the forecasts, while SPF^{median} is the median. Models $x^{1st-month}$ are 1-month-ahead forecasts computed in the last month of the quarter before. Models $x^{2nd-month}$ are 2-month-ahead forecasts computed in the last month of the quarter before. Both these forecasts are very conservative because the SPF is issued on the 15^{th} of the second month of each reference quarter. Models x^{Comb} compute the quarterly forecast as the average of the realized unemployment rate for the first month and the 1- and 2-month-ahead forecasts generated at the end of the first month of the reference quarter. The model with Google (G) is the best model overall, the model with the Initial Claims (IC) is the best model without Google, while the models with subscript IC_s is the best model without Google in the short sample. SETAR, LSTAR and AAR are the corresponding non-linear models estimated over the full sample up to the second lag.

Appendix:
Further Tables and Figures

Table 9: Descriptive statistics of the unemployment rate for the US and each single state

	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Jarque-Bera	Obs.
ur_{0t}	5.621	5.523	10.849	2.548	1.512	0.599	3.467	50.792***	738
ur_{1t}	6.522	6.218	14.429	3.256	2.437	1.150	4.115	109.442***	402
ur_{2t}	8.041	7.611	11.494	5.894	1.485	0.405	1.939	29.866***	402
ur_{3t}	5.979	5.774	11.480	3.592	1.635	1.278	4.597	152.176***	402
ur_{4t}	6.426	6.111	10.241	4.096	1.513	0.546	2.265	29.037***	402
ur_{5t}	7.034	6.833	11.611	4.726	1.594	0.621	2.667	27.710***	402
ur_{6t}	5.303	5.390	9.081	2.460	1.364	0.209	2.958	2.954	402
ur_{7t}	5.059	5.098	10.005	2.056	1.521	0.371	3.231	10.088***	402
ur_{8t}	5.021	4.351	8.428	2.891	1.737	0.616	1.881	46.440***	402
ur_{9t}	7.517	7.516	11.383	4.833	1.487	0.363	2.788	9.571***	402
ur_{10t}	6.039	5.869	10.553	3.325	1.582	0.459	2.673	15.893***	402
ur_{11t}	5.527	5.295	10.135	3.379	1.224	0.805	3.553	48.490***	402
ur_{12t}	4.671	4.748	10.170	2.192	1.589	0.657	3.642	35.805***	402
ur_{13t}	5.821	5.494	9.412	2.778	1.453	0.384	2.972	9.894***	402
ur_{14t}	6.731	6.370	12.864	4.100	1.837	1.128	4.234	110.741***	402
ur_{15t}	5.879	5.343	12.849	2.577	2.248	1.139	3.883	99.980***	402
ur_{16t}	4.695	4.300	8.538	2.552	1.541	1.094	3.239	81.087***	402
ur_{17t}	4.587	4.473	7.404	2.938	0.812	0.608	3.968	40.470***	402
ur_{18t}	6.682	5.950	12.111	4.041	1.821	1.007	3.228	68.755***	402
ur_{19t}	7.220	6.591	12.856	3.176	2.391	0.797	2.682	44.269***	402
ur_{20t}	5.713	5.370	9.001	2.987	1.516	0.401	2.170	22.303***	402
ur_{21t}	5.114	4.757	8.333	3.330	1.242	0.714	2.680	35.915***	402
ur_{22t}	5.511	5.276	10.941	2.655	1.811	0.652	2.729	29.707***	402
ur_{23t}	7.999	7.348	16.905	3.227	2.917	0.858	3.563	54.667***	402
ur_{24t}	4.855	4.711	9.021	2.475	1.300	0.883	4.125	73.453***	402
ur_{25t}	7.742	7.077	13.707	4.871	2.035	0.972	3.102	63.430***	402
ur_{26t}	5.740	5.600	10.476	2.593	1.468	0.868	4.256	76.932***	402
ur_{27t}	5.754	5.660	8.685	3.216	1.330	0.183	2.559	5.508*	402
ur_{28t}	3.469	3.143	6.849	2.159	0.951	1.055	3.638	81.454***	402
ur_{29t}	6.049	5.596	11.954	4.209	1.639	1.138	3.777	96.868***	402
ur_{30t}	4.332	3.953	7.743	1.870	1.480	0.704	2.540	36.762***	402
ur_{31t}	6.077	5.874	10.644	3.502	1.736	0.640	2.737	28.593***	402
ur_{32t}	6.779	6.767	9.927	3.481	1.522	-0.100	2.491	5.004*	402
ur_{33t}	6.514	6.388	10.490	4.047	1.520	0.454	2.530	17.525***	402
ur_{34t}	5.449	5.269	11.101	3.099	1.590	1.187	4.662	140.655***	402
ur_{35t}	4.098	4.012	6.867	2.511	0.965	0.523	2.392	24.482***	402
ur_{36t}	6.678	6.057	13.816	3.880	2.124	1.344	4.606	164.168***	402
ur_{37t}	5.239	5.030	9.400	2.714	1.503	0.605	2.745	25.641***	402
ur_{38t}	7.041	6.490	12.207	4.684	1.841	0.988	3.130	65.701***	402
ur_{39t}	6.444	5.857	12.902	4.039	1.869	1.217	4.535	138.732***	402
ur_{40t}	6.041	5.403	12.404	2.937	1.798	0.558	2.754	21.902***	402
ur_{41t}	6.161	6.024	12.078	3.083	1.664	1.130	5.033	154.748***	402
ur_{42t}	3.732	3.549	5.895	2.432	0.748	0.828	2.933	45.958***	402
ur_{43t}	6.382	5.789	12.361	3.791	1.899	1.478	4.740	197.094***	402
ur_{44t}	6.076	5.999	9.307	4.313	1.215	0.560	2.730	22.261***	402
ur_{45t}	4.891	4.698	9.735	2.423	1.471	0.887	3.765	62.510***	402
ur_{46t}	4.796	4.455	8.991	2.224	1.456	0.737	2.832	36.898***	402
ur_{47t}	4.539	4.473	7.846	2.188	1.215	0.273	2.754	6.022**	402
ur_{48t}	6.907	6.647	12.192	4.392	1.790	0.910	3.499	59.631***	402
ur_{49t}	8.424	7.695	18.197	4.090	3.288	0.927	3.311	59.150***	402
ur_{50t}	5.334	4.819	11.774	2.863	1.782	1.325	4.507	155.710***	402
ur_{51t}	4.944	4.693	10.090	1.898	1.631	0.930	3.647	64.999***	402

Notes: For the US (subscript 0), the sample is 1948:1-2009:6, while for the single states the sample is 1976:1-2009:6. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 10: Descriptive statistics of Initial Claims for the US and each single state - Full sample

	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Jarque-Bera	Obs.
IC_{0t}	1430.7	1386.0	2673.0	415.0	344.2	0.720	4.511	92.580***	510
IC_{1t}	25.9	25.7	44.5	15.7	5.0	0.705	4.077	35.530***	271
IC_{2t}	7.0	7.1	11.4	4.4	1.0	0.067	4.064	12.984***	271
IC_{3t}	17.0	16.6	32.7	11.7	3.1	1.764	8.728	510.952***	271
IC_{4t}	14.6	13.0	38.4	8.3	5.0	2.240	9.295	674.145***	271
IC_{5t}	224.0	224.9	329.1	9.7	43.3	-0.096	4.218	17.177***	271
IC_{6t}	11.4	11.1	23.9	7.0	2.7	1.544	7.658	352.690***	271
IC_{7t}	18.4	17.5	33.6	10.7	4.0	0.775	3.419	29.122***	271
IC_{8t}	4.1	4.0	9.5	1.7	1.2	0.664	3.721	25.792***	271
IC_{9t}	2.2	2.3	6.7	1.0	0.9	0.881	5.139	86.733***	271
IC_{10t}	40.8	37.5	121.8	24.0	14.9	2.679	12.069	1253.035***	271
IC_{11t}	36.6	33.9	96.5	21.3	11.4	2.439	10.786	953.068***	271
IC_{12t}	6.0	6.0	15.3	0.0	1.9	0.922	5.566	112.792***	271
IC_{13t}	8.7	8.3	17.1	5.9	1.6	2.329	10.999	967.554***	271
IC_{14t}	57.9	55.2	112.8	40.0	11.1	2.037	9.489	662.804***	271
IC_{15t}	27.3	26.9	74.9	14.6	9.6	2.078	9.228	633.094***	271
IC_{16t}	13.0	12.2	42.5	7.5	4.6	3.544	19.880	3784.412***	271
IC_{17t}	11.1	10.5	26.1	6.6	3.0	2.165	10.115	783.302***	271
IC_{18t}	23.1	22.0	91.3	13.3	7.6	3.898	29.423	8569.968***	271
IC_{19t}	17.2	14.9	215.0	8.6	15.9	9.793	111.022	136089.900***	271
IC_{20t}	7.5	6.7	21.7	4.5	2.5	1.590	6.735	271.631***	271
IC_{21t}	18.4	17.5	34.1	12.7	3.7	1.439	5.547	166.823***	271
IC_{22t}	32.5	30.4	55.1	22.1	7.1	0.925	3.118	38.788***	271
IC_{23t}	71.9	69.1	160.6	42.0	20.1	1.512	6.333	228.666***	271
IC_{24t}	19.9	18.8	41.9	12.1	4.6	1.607	7.050	301.850***	271
IC_{25t}	14.4	14.0	60.0	9.1	4.4	5.483	52.606	29144.100***	271
IC_{26t}	32.4	31.0	52.4	22.1	5.9	1.174	4.463	86.365***	271
IC_{27t}	4.3	4.2	9.0	3.0	0.8	2.898	14.836	1961.225***	271
IC_{28t}	61.6	56.8	120.5	27.9	17.3	0.921	3.541	41.615***	271
IC_{29t}	2.4	2.3	7.5	1.3	0.6	4.297	31.933	10286.820***	271
IC_{30t}	5.3	5.1	9.8	3.5	1.1	1.201	5.103	115.054***	271
IC_{31t}	4.0	3.8	8.5	1.8	1.3	0.982	3.877	52.242***	271
IC_{32t}	42.8	42.5	65.2	30.6	6.3	0.722	4.058	36.178***	271
IC_{33t}	4.9	4.8	9.8	0.1	1.0	1.070	13.165	1218.368***	271
IC_{34t}	10.6	9.9	30.8	0.8	4.2	2.094	9.230	636.389***	271
IC_{35t}	86.2	84.2	139.7	54.2	14.2	1.082	4.665	84.186***	271
IC_{36t}	53.3	50.7	110.4	31.4	13.6	1.576	6.525	252.464***	271
IC_{37t}	9.7	9.3	20.9	5.2	2.5	1.161	4.908	101.958***	271
IC_{38t}	28.1	26.6	57.5	17.6	6.4	1.716	7.104	323.298***	271
IC_{39t}	89.0	86.6	164.0	61.7	14.2	2.339	12.413	1247.480***	271
IC_{40t}	8.0	7.4	14.5	5.5	1.8	0.778	2.797	27.775***	271
IC_{41t}	26.8	25.1	50.7	15.2	6.1	1.470	5.423	163.943***	271
IC_{42t}	1.5	1.5	3.1	0.9	0.3	1.908	9.398	626.599***	271
IC_{43t}	33.3	32.7	59.8	21.7	6.7	1.063	5.044	98.198***	271
IC_{44t}	62.7	59.2	116.2	45.9	12.5	1.709	6.264	252.112***	271
IC_{45t}	5.5	4.9	15.3	3.7	1.8	2.568	11.257	1067.685***	271
IC_{46t}	3.3	3.2	6.7	-1.7	0.8	0.233	10.183	585.076***	271
IC_{47t}	25.8	23.8	51.2	14.9	6.6	1.375	4.883	125.456***	271
IC_{48t}	40.0	39.0	64.1	25.9	6.5	0.978	4.455	67.086***	271
IC_{49t}	6.9	6.8	11.3	4.5	1.1	0.839	4.428	54.861***	271
IC_{50t}	41.8	38.6	100.0	24.1	12.2	1.576	7.281	319.177***	271
IC_{51t}	2.0	2.0	4.2	-0.9	0.5	0.399	7.310	216.985***	271

Notes: For the US (subscript 0), the sample is 1967:1-2009:6, while for the single states the sample is 1986:12-2009:6. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 11: Descriptive statistics of Initial Claims for the US and each single state - Short sample

	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Jarque-Bera	Obs.
IC_{0t}	1475.3	1337.5	2600.0	1152.0	365.3	2.035	5.983	70.037***	66
IC_{1t}	22.7	19.7	44.5	15.7	7.1	1.868	5.349	53.552***	66
IC_{2t}	6.7	6.5	8.8	5.8	0.7	1.256	4.085	20.594***	66
IC_{3t}	17.1	15.5	32.7	12.1	4.8	1.841	5.720	57.626***	66
IC_{4t}	18.4	16.4	38.4	11.0	6.8	1.645	4.666	37.384***	66
IC_{5t}	194.1	180.7	310.7	144.8	44.0	1.516	4.170	29.042***	66
IC_{6t}	11.5	10.0	23.9	8.3	3.9	2.049	6.175	73.917***	66
IC_{7t}	18.1	16.8	28.6	15.2	3.5	1.959	5.642	61.433***	66
IC_{8t}	4.6	4.4	6.7	3.1	0.8	0.580	2.576	4.192	66
IC_{9t}	1.4	1.3	2.6	1.0	0.4	1.849	5.394	53.360***	66
IC_{10t}	53.0	43.7	121.8	32.7	22.4	1.527	4.342	30.588***	66
IC_{11t}	44.0	37.2	96.5	31.6	16.6	1.866	5.164	51.203***	66
IC_{12t}	5.5	4.8	10.6	3.4	1.9	1.478	3.973	26.631***	66
IC_{13t}	9.0	8.1	17.1	5.9	2.7	1.623	4.734	37.235***	66
IC_{14t}	61.1	56.1	112.8	49.1	15.3	2.334	7.508	115.798***	66
IC_{15t}	36.9	31.6	74.9	27.0	12.0	1.792	5.033	46.694***	66
IC_{16t}	16.3	13.6	42.5	10.7	7.3	2.328	7.620	118.347***	66
IC_{17t}	12.1	10.6	26.1	8.2	4.1	2.281	7.217	106.127***	66
IC_{18t}	26.4	22.9	54.1	16.0	9.1	1.785	5.460	51.681***	66
IC_{19t}	19.7	13.0	215.0	8.6	31.4	5.082	29.128	2161.375***	66
IC_{20t}	5.8	5.3	9.8	4.6	1.2	2.041	6.103	72.311***	66
IC_{21t}	18.7	16.8	34.1	13.5	4.9	1.859	5.383	53.641***	66
IC_{22t}	32.2	30.8	50.8	26.9	5.1	2.020	6.683	82.198***	66
IC_{23t}	78.0	71.1	160.6	59.4	20.8	2.260	7.784	119.106***	66
IC_{24t}	23.7	22.1	41.9	19.3	5.1	2.255	7.301	106.811***	66
IC_{25t}	13.4	11.2	60.0	9.1	7.5	4.708	27.244	1860.254***	66
IC_{26t}	32.4	30.5	52.4	24.4	6.8	1.732	5.348	48.170***	66
IC_{27t}	4.6	4.1	9.0	3.3	1.3	1.989	5.932	67.155***	66
IC_{28t}	58.5	52.6	120.5	41.9	17.7	2.080	6.451	80.330***	66
IC_{29t}	2.2	2.0	5.0	1.3	0.8	2.384	7.769	125.083***	66
IC_{30t}	6.0	5.8	9.8	4.6	1.2	1.491	4.912	34.516***	66
IC_{31t}	4.3	3.9	8.5	3.4	1.3	2.098	6.204	76.644***	66
IC_{32t}	44.9	42.7	65.2	36.6	6.6	1.744	5.310	48.119***	66
IC_{33t}	4.9	4.6	9.8	3.1	1.5	2.017	6.443	77.331***	66
IC_{34t}	14.1	11.5	30.8	8.8	5.7	1.596	4.282	32.528***	66
IC_{35t}	86.7	81.1	139.7	66.7	16.3	1.836	5.641	56.268***	66
IC_{36t}	58.0	52.5	110.4	43.7	16.8	2.053	6.135	73.378***	66
IC_{37t}	9.6	8.5	20.9	6.0	3.2	1.843	6.115	64.061***	66
IC_{38t}	30.3	26.9	57.5	20.9	8.9	1.702	4.855	41.311***	66
IC_{39t}	96.4	88.9	164.0	80.4	20.7	2.218	7.035	98.878***	66
IC_{40t}	6.7	6.3	14.5	5.5	1.4	3.617	19.232	868.440***	66
IC_{41t}	27.2	24.3	50.3	19.9	7.3	1.867	5.329	53.242***	66
IC_{42t}	1.6	1.5	3.1	1.2	0.4	1.981	6.665	80.090***	66
IC_{43t}	29.3	26.7	59.8	21.7	9.1	2.096	6.423	80.532***	66
IC_{44t}	65.5	59.5	116.2	48.0	18.1	1.395	4.023	24.283***	66
IC_{45t}	6.4	5.5	15.3	4.0	2.8	1.877	5.522	56.261***	66
IC_{46t}	3.5	3.3	6.1	2.6	0.7	1.869	6.116	65.137***	66
IC_{47t}	24.2	21.6	46.9	17.1	7.2	1.971	5.823	64.636***	66
IC_{48t}	38.1	35.4	64.1	28.6	9.0	1.657	5.020	41.427***	66
IC_{49t}	6.1	5.7	11.2	4.6	1.4	2.398	8.386	143.050***	66
IC_{50t}	52.9	48.3	100.0	41.8	13.0	2.388	7.953	130.174***	66
IC_{51t}	1.8	1.6	4.2	1.0	0.7	2.196	7.323	104.444***	66

Notes: The sample for the US (subscript 0) and the single states is 2004:1-2009:6. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 12: Descriptive statistics of Google indicator for the US and each single state

	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Jarque-Bera	Obs.
GI_{0t}	63.437	60.919	84.839	54.899	7.995	1.305	3.649	19.876***	66
GI_{1t}	61.650	59.597	80.778	50.670	7.585	1.148	3.599	15.490***	66
GI_{2t}	75.927	75.767	82.472	70.735	2.734	0.515	2.911	2.935	66
GI_{3t}	52.178	49.486	70.849	43.314	7.400	1.116	3.208	13.821***	66
GI_{4t}	64.332	61.877	83.549	55.609	6.801	1.216	3.701	17.615***	66
GI_{5t}	38.437	38.214	48.748	33.787	2.968	0.986	4.177	14.498***	66
GI_{6t}	58.817	57.312	75.194	48.793	6.098	1.133	3.634	15.230***	66
GI_{7t}	48.856	46.474	61.727	43.010	5.317	1.186	3.086	15.481***	66
GI_{8t}	56.603	52.752	79.817	44.556	10.225	0.939	2.696	9.949***	66
GI_{9t}	52.161	51.126	67.535	45.360	4.867	1.431	4.793	31.379***	66
GI_{10t}	44.919	42.818	60.330	37.512	7.074	0.888	2.474	9.439***	66
GI_{11t}	50.258	47.891	66.686	42.319	6.325	1.276	3.497	18.583***	66
GI_{12t}	47.899	45.476	62.027	40.306	5.941	1.123	2.992	13.880***	66
GI_{13t}	59.562	56.952	81.643	49.267	8.350	1.136	3.312	14.462***	66
GI_{14t}	44.734	43.044	56.921	38.325	5.015	1.006	3.011	11.122***	66
GI_{15t}	48.955	47.443	63.651	41.945	5.166	1.408	4.224	25.921***	66
GI_{16t}	56.357	55.746	68.457	48.286	4.428	0.881	3.464	9.128**	66
GI_{17t}	55.156	53.236	70.825	48.312	5.565	1.335	3.936	22.006***	66
GI_{18t}	55.735	53.918	72.940	46.096	6.828	1.035	3.196	11.889***	66
GI_{19t}	53.601	53.125	70.330	42.478	6.356	0.850	3.393	8.374**	66
GI_{20t}	61.455	59.966	75.739	51.763	5.893	0.555	2.495	4.087	66
GI_{21t}	53.972	51.493	72.681	45.472	6.794	1.453	4.131	26.733***	66
GI_{22t}	39.725	38.155	50.671	35.021	4.375	1.187	3.234	15.636***	66
GI_{23t}	48.104	46.028	60.602	44.911	4.175	1.702	4.677	39.596***	66
GI_{24t}	48.357	46.906	63.063	42.128	4.852	1.422	4.302	26.898***	66
GI_{25t}	62.866	60.376	84.746	52.298	8.316	1.144	3.339	14.712***	66
GI_{26t}	48.143	46.225	61.602	42.127	5.217	1.407	3.831	23.683***	66
GI_{27t}	58.251	55.900	82.424	45.868	8.527	1.375	4.277	25.266***	66
GI_{28t}	55.852	54.692	70.379	48.175	4.879	1.279	4.109	21.360***	66
GI_{29t}	57.613	53.876	76.088	45.674	8.306	0.847	2.527	8.503**	66
GI_{30t}	58.316	55.653	80.347	48.795	7.540	1.145	3.479	15.041***	66
GI_{31t}	45.386	43.264	60.192	39.252	5.654	1.372	3.618	21.745***	66
GI_{32t}	61.900	60.887	80.087	53.232	5.996	1.298	4.322	23.327***	66
GI_{33t}	39.346	38.168	48.891	34.967	3.992	1.086	3.113	12.999***	66
GI_{34t}	56.217	53.837	72.214	48.994	6.528	1.229	3.300	16.855***	66
GI_{35t}	60.669	61.089	69.816	50.779	4.085	0.049	2.712	0.255	66
GI_{36t}	49.950	47.640	64.258	42.536	5.391	1.331	3.733	20.964***	66
GI_{37t}	56.057	54.400	73.466	45.811	6.202	1.358	4.365	25.404***	66
GI_{38t}	48.891	48.318	58.723	42.633	4.501	0.653	2.543	5.264*	66
GI_{39t}	42.455	40.593	56.199	37.073	5.092	1.295	3.572	19.340***	66
GI_{40t}	53.536	49.963	69.884	45.062	7.272	0.907	2.413	9.995***	66
GI_{41t}	64.543	61.934	83.442	54.952	6.993	1.246	3.720	18.499***	66
GI_{42t}	62.359	60.382	84.677	50.115	8.074	1.147	3.817	16.295***	66
GI_{43t}	56.319	53.650	74.492	47.818	7.355	1.240	3.412	17.381***	66
GI_{44t}	47.254	46.202	63.223	39.614	6.267	1.140	3.415	14.771***	66
GI_{45t}	60.265	57.009	83.959	48.690	8.933	1.308	3.845	20.793***	66
GI_{46t}	57.103	56.193	72.158	48.735	5.157	0.982	3.713	12.009***	66
GI_{47t}	47.029	48.605	54.371	37.041	4.415	-0.912	2.739	9.330***	66
GI_{48t}	45.850	43.964	59.215	39.752	5.239	1.064	3.153	12.517***	66
GI_{49t}	59.866	58.874	77.394	47.424	5.855	0.840	3.928	10.127***	66
GI_{50t}	49.865	48.482	65.075	44.367	4.804	1.585	4.647	35.109***	66
GI_{51t}	60.580	58.442	80.550	51.443	6.646	1.468	4.479	29.731***	66

Notes: For the US (subscript 0) and all the states the sample is 2004:1-2009:6. ***, ** and * indicate rejection at 1, 5 and 10%, respectively.

Table 13: US states and internet diffusion among total population, active population, unemployed population

N.	State	All	Act.	Une.	N.	State	All	Act.	Une.
0	United States	1.000	1.000	1.000	26	Missouri	0.969	0.975	0.865
1	Alabama	0.872	0.904	0.655	27	Montana	1.012	1.023	1.061
2	Alaska	1.141	1.096	1.096	28	Nebraska	1.054	1.035	1.061
3	Arizona	0.981	0.995	1.097	29	Nevada	1.022	0.992	0.804
4	Arkansas	0.869	0.904	0.688	30	New Hampshire	1.143	1.110	1.056
5	California	1.000	0.998	1.008	31	New Jersey	1.045	1.022	0.935
6	Colorado	1.061	1.035	0.925	32	New Mexico	0.978	0.980	1.215
7	Connecticut	1.058	1.046	0.860	33	New York	0.978	0.988	1.099
8	Delaware	1.018	1.008	1.010	34	North Carolina	0.954	0.959	0.992
9	D. of Columbia	1.032	1.039	0.908	35	North Dakota	1.054	1.050	0.880
10	Florida	0.979	0.966	0.980	36	Ohio	1.002	1.006	1.005
11	Georgia	0.989	0.985	1.074	37	Oklahoma	0.908	0.928	0.905
12	Hawaii	1.035	1.016	1.097	38	Oregon	1.034	1.013	1.109
13	Idaho	0.965	0.948	1.052	39	Pennsylvania	1.007	1.006	1.021
14	Illinois	1.036	1.035	1.014	40	Rhode Island	1.041	1.029	0.948
15	Indiana	0.982	0.993	0.773	41	South Carolina	0.956	0.964	0.853
16	Iowa	1.038	1.012	0.869	42	South Dakota	1.072	1.043	1.055
17	Kansas	1.070	1.045	0.984	43	Tennessee	0.957	0.965	1.144
18	Kentucky	0.953	1.006	1.094	44	Texas	0.935	0.939	0.950
19	Louisiana	0.926	0.955	0.799	45	Utah	1.132	1.087	1.253
20	Maine	1.072	1.087	1.127	46	Vermont	1.107	1.075	1.143
21	Maryland	1.069	1.038	0.939	47	Virginia	1.045	1.015	1.172
22	Massachusetts	1.070	1.078	1.118	48	Washington	1.120	1.104	1.140
23	Michigan	1.014	1.025	1.008	49	West Virginia	0.872	0.941	1.010
24	Minnesota	1.114	1.079	1.156	50	Wisconsin	1.085	1.068	1.054
25	Mississippi	0.867	0.888	0.684	51	Wyoming	1.102	1.067	1.110

Notes: Authors calculations using the October 2007 CPS computer use supplement. State internet diffusion is expressed in relative terms with the the federal average normalized to one. The actual diffusion at the national level is equal to 76.2, 82.6 and 76.5 respectively for total, active and unemployed population.

Table 14: Forecasting US unemployment rate (u_t) in levels. Best 15 models in terms of lowest MSE, best models without GI and non-linear models.

1-step ahead

n.	Model	MSE	Rank	DM	HLN
Best models with Google					
403	$ARMAX(1,1)-IC_t-G_t$	0.0167	1	-	-
393	$ARMAX(1,1)-G_t$	0.0183	2	0.927	1.106
327	$ARX(2)-G_t$	0.0186	3	0.676	1.982**
425	$ARMAX(1,1)-IC_{t-1}-G_{t-1}$	0.0187	4	1.147	1.486
459	$ARMAX(2,2)-G_t$	0.0189	5	1.155	1.507
332	$ARX(2)-G_t-SA$	0.0191	6	1.097	2.368**
371	$ARX(2)-G_{t-2}$	0.0192	7	0.786	1.778*
437	$ARMAX(1,1)-G_{t-2}$	0.0193	8	0.819	1.201
481	$ARMAX(2,2)-G_{t-1}$	0.0194	9	1.450	2.113**
343	$ARX(2)-IC_t-G_t-SA$	0.0197	10	1.037	1.790*
469	$ARMAX(2,2)-IC_t-G_t$	0.0197	11	1.820*	1.867*
415	$ARMAX(1,1)-G_{t-1}$	0.0197	12	1.716*	2.414**
491	$ARMAX(2,2)-IC_{t-1}-G_{t-1}$	0.0197	13	1.332	1.713*
409	$ARMAX(1,1)-IC_t-G_t-SA$	0.0200	14	1.251	2.278**
420	$ARMAX(1,1)-G_{t-1}-SA$	0.0200	15	1.172	3.011***
Best models without Google					
127	$ARMAX(2,2)-IC_{w4,t-2}-SA$	0.0269	97	1.925*	3.270***
205	$ARMAX(1,1)-IC_{w4,t}-SA$	0.0303	172	1.969**	2.591***
Non-linear models					
521	$SETAR(2)$	0.0511	491	2.967***	3.541***
522	$LSTAR(2)$	0.0518	493	3.001***	3.540***
523	$AAR(2)$	0.0554	498	3.111***	3.618***

2-step ahead

n.	Model	MSE	Rank	DM	HLN
Best models with Google					
332	$ARX(2)-G_t-SA$	0.0169	1	-	-
327	$ARX(2)-G_t$	0.0184	2	0.487	0.636
459	$ARMAX(2,2)-G_t$	0.0214	3	0.500	0.931
349	$ARX(2)-G_{t-1}$	0.0215	4	1.456	1.598
371	$ARX(2)-G_{t-2}$	0.0218	5	1.559	1.525
491	$ARMAX(2,2)-IC_{t-1}-G_{t-1}$	0.0228	6	0.950	1.217
403	$ARMAX(1,1)-IC_t-G_t$	0.0233	7	0.697	1.113
354	$ARX(2)-G_{t-1}-SA$	0.0237	8	1.087	0.866
343	$ARX(2)-IC_t-G_t-SA$	0.0240	9	1.483	1.373
359	$ARX(2)-IC_{t-1}-G_{t-1}$	0.0244	10	1.894*	2.048**
393	$ARMAX(1,1)-G_t$	0.0246	11	0.750	1.171
469	$ARMAX(2,2)-IC_t-G_t$	0.0248	12	0.805	1.219
365	$ARX(2)-IC_{t-1}-G_{t-1}-SA$	0.0252	13	1.307	0.998
376	$ARX(2)-G_{t-2}-SA$	0.0253	14	1.260	1.050
261	$ARX(1)-G_t$	0.0253	15	0.941	1.312
Best models without Google					
122	$ARMAX(2,2)-IC_{w4,t-2}$	0.0581	170	1.927*	2.031**
160	$ARX(1)-IC_{w4,t-2}$	0.0694	208	2.038**	2.091**
Non-linear models					
521	$SETAR(2)$	0.1750	509	2.087**	1.994**
522	$LSTAR(2)$	0.1746	508	2.080**	1.990**
523	$AAR(2)$	0.1851	510	1.972**	1.893*

3-step ahead

n.	Model	MSE	Rank	DM	HLN
Best models with Google					
332	$ARX(2)-G_t-SA$	0.0482	1	-	-
354	$ARX(2)-G_{t-1}-SA$	0.0518	2	0.280	0.495
327	$ARX(2)-G_t$	0.0529	3	0.386	0.470
266	$ARX(1)-G_t-SA$	0.0535	4	0.226	0.706
459	$ARMAX(2,2)-G_t$	0.0547	5	0.356	0.769
491	$ARMAX(2,2)-IC_{t-1}-G_{t-1}$	0.0554	6	0.407	0.838
261	$ARX(1)-G_t$	0.0569	7	0.357	0.807
349	$ARX(2)-G_{t-1}$	0.0596	8	1.232	1.307
376	$ARX(2)-G_{t-2}-SA$	0.0599	9	0.827	0.991
403	$ARMAX(1,1)-IC_t-G_t$	0.0601	10	0.561	0.849
393	$ARMAX(1,1)-G_t$	0.0615	11	0.632	1.000
365	$ARX(2)-IC_{t-1}-G_{t-1}-SA$	0.0618	12	1.099	1.122
425	$ARMAX(1,1)-IC_{t-1}-G_{t-1}$	0.0624	13	0.840	1.036
481	$ARMAX(2,2)-G_{t-1}$	0.0626	14	0.718	0.947
398	$ARMAX(1,1)-G_t-SA$	0.0630	15	0.865	1.103
Best models without Google					
122	$ARMAX(2,2)-IC_{w4,t-2}$	0.1549	174	1.548	1.625
134	$ARMA(1,1)-SA$	0.1787	205	1.264	1.255
Non-linear models					
521	$SETAR(2)$	0.4154	502	1.701*	1.584
522	$LSTAR(2)$	0.4156	503	1.667*	1.569
523	$AAR(2)$	0.4341	505	1.609	1.519

Notes: ***, ** and * indicate rejection at 1, 5 and 10%, respectively. This table reports the best 15 models in terms of MSE among the 523 estimated ones. The complete list of models and their forecasting performance is available in the appendix (table 16). SA indicates the model augmented with a multiplicative seasonal factor.

Table 15: Forecasting US unemployment rate in logs ($\log(u_t)$). Best 15 models, best models without GI and non-linear models.

1-step ahead

n.	Model	MSE	Rank	DM	HLN
	Best models with Google				
327	$ARX(2) - G_t$	0.0191	1	-	-
337	$ARX(2) - IC_t - G_t$	0.0224	2	1.700*	1.882*
398	$ARMAX(1,1) - G_t - SA$	0.0224	3	1.026	2.406**
425	$ARMAX(1,1) - IC_{t-1} - G_{t-1}$	0.0232	4	0.988	1.847*
326	$ARX(2) - G_{w4,t}$	0.0234	5	1.186	1.734*
331	$ARX(2) - G_{w4,t} - SA$	0.0236	6	1.449	1.957*
338	$ARX(2) - IC_{w1,t} \dots IC_{w4,t}$ $-G_{w1,t} \dots G_{w4,t}$	0.0238	7	1.524	3.559***
332	$ARX(2) - G_t - SA$	0.0241	8	0.954	1.061
336	$ARX(2) - IC_{w4,t} - G_{w4,t}$	0.0244	9	1.406	1.806*
469	$ARMAX(2,2) - IC_t - G_t$	0.0246	10	1.701*	2.181**
349	$ARX(2) - G_{t-1}$	0.0248	11	1.081	1.130
371	$ARX(2) - G_{t-2}$	0.0248	12	2.025**	2.492**
343	$ARX(2) - IC_t - G_t - SA$	0.0248	13	1.490	1.740*
475	$ARMAX(2,2) - IC_t - G_t - SA$	0.0249	14	1.637	2.711***
260	$ARX(1) - G_{w4,t}$	0.0252	15	1.421	2.794***
	Best models without Google				
127	$ARMAX(2,2) - IC_{w4,t-2} - SA$	0.0255	17	1.560	2.848***
129	$AR(1)$	0.0430	258	2.203**	2.893***
	Non-linear models				
521	$SETAR(2)$	0.0513	308	2.768***	3.556***
522	$LSTAR(2)$	0.0514	309	2.759***	3.509***
523	$AAR(2)$	0.0616	390	3.023***	3.591***

2-step ahead

n.	Model	MSE	Rank	DM	HLN
	Best models with Google				
327	$ARX(2) - G_t$	0.0237	1	-	-
261	$ARX(1) - G_t$	0.0270	2	0.248	0.877
332	$ARX(2) - G_t - SA$	0.0276	3	0.563	0.680
343	$ARX(2) - IC_t - G_t - SA$	0.0278	4	0.687	0.950
265	$ARX(1) - G_{w4,t} - SA$	0.0334	5	0.655	1.684*
349	$ARX(2) - G_{t-1}$	0.0347	6	1.170	0.845
260	$ARX(1) - G_{w4,t}$	0.0353	7	0.650	1.462
371	$ARX(2) - G_{t-2}$	0.0376	8	1.336	0.933
331	$ARX(2) - G_{w4,t} - SA$	0.0377	9	0.605	0.814
359	$ARX(2) - IC_{t-1} - G_{t-1}$	0.0379	10	1.317	0.994
266	$ARX(1) - G_t - SA$	0.0380	11	0.451	0.633
338	$ARX(2) - IC_{w1,t} \dots IC_{w4,t}$ $-G_{w1,t} \dots G_{w4,t}$	0.0382	12	0.822	1.341
326	$ARX(2) - G_{w4,t}$	0.0398	13	0.665	0.848
337	$ARX(2) - IC_t - G_t$	0.0404	14	1.462	1.336
381	$ARX(2) - IC_{t-2} - G_{t-2}$	0.0431	15	1.246	0.915
	Best models without Google				
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.0502	30	1.365	1.768*
129	$AR(1)$	0.1018	228	1.599	1.658*
	Non-linear models				
521	$SETAR(2)$	0.1763	370	2.116**	1.964**
522	$LSTAR(2)$	0.1770	371	2.130**	1.971**
523	$AAR(2)$	0.2083	434	1.970**	1.832*

3-step ahead

n.	Model	MSE	Rank	DM	HLN
	Best models with Google				
266	$ARX(1) - G_t - SA$	0.0503	1	-	-
261	$ARX(1) - G_t$	0.0543	2	0.422	0.632
288	$ARX(1) - G_{t-1} - SA$	0.0627	3	1.028	0.994
310	$ARX(1) - G_{t-2} - SA$	0.0679	4	1.527	1.719*
283	$ARX(1) - G_{t-1}$	0.0732	5	1.243	1.313
332	$ARX(2) - G_t - SA$	0.0750	6	0.780	1.095
265	$ARX(1) - G_{w4,t} - SA$	0.0763	7	0.563	0.819
305	$ARX(1) - G_{t-2}$	0.0789	8	1.481	1.279
354	$ARX(2) - G_{t-1} - SA$	0.0804	9	0.994	1.202
327	$ARX(2) - G_t$	0.0828	10	0.848	1.023
260	$ARX(1) - G_{w4,t}$	0.0841	11	0.575	0.776
376	$ARX(2) - G_{t-2} - SA$	0.0908	12	1.108	1.300
408	$ARMAX(1,1) - IC_{w4,t} - G_{w4,t} - SA$	0.0911	13	1.043	1.281
365	$ARX(2) - IC_{t-1} - G_{t-1} - SA$	0.0932	14	1.170	1.248
349	$ARX(2) - G_{t-1}$	0.0989	15	1.293	1.306
	Best models without Google				
122	$ARMAX(2,2) - IC_{w4,t-2}$	0.1348	37	1.650*	1.417
129	$AR(1)$	0.2521	198	1.293	1.120
	Non-linear models				
521	$SETAR(2)$	0.4173	357	1.758*	1.529
522	$LSTAR(2)$	0.4214	360	1.769*	1.537
523	$AAR(2)$	0.4717	384	1.650*	1.452

Notes: ***, ** and * indicate rejection at 1, 5 and 10%, respectively. This table reports the best 15 models in terms of MSE among the 523 estimated ones. The complete list of models and their forecasting performance is available in the appendix (table 16). SA indicates the model augmented with a multiplicative seasonal factor.

Table 16: Forecasting US unemployment rate ($u_t - u_{t-1}$) in first differences.

	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-St	2-St	3-St	HLN 1-St	2-St	3-St
	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-Step	2-Step	3-Step	HLN 1-Step	2-Step	3-Step
1	$AR(1)$	0.0564	507	0.1842	521	0.4270	516	3.328***	2.108**	1.819*	3.629***	1.961**	1.582
2	$AR(1)-SA$	0.0577	508	0.1894	522	0.4391	519	3.310***	2.119**	1.824*	3.570***	1.973**	1.582
3	$AR(2)$	0.0388	404	0.1063	454	0.2826	459	2.993***	1.959*	1.737*	3.426***	1.871*	1.534
4	$AR(2)-SA$	0.0395	421	0.1094	461	0.2905	466	3.044***	1.998**	1.755*	3.423***	1.902*	1.544
5	$ARMA(1,1)$	0.0354	310	0.0834	326	0.2048	320	2.530**	1.800*	1.625	3.054***	1.765*	1.470
6	$ARMA(1,1)-SA$	0.0357	329	0.0954	406	0.2339	402	2.577***	1.985**	1.783*	3.096***	1.907*	1.550
7	$ARMA(2,2)$	0.0314	229	0.0718	252	0.1833	258	2.314**	1.684*	1.583	2.911***	1.689*	1.431
8	$ARMA(2,2)-SA$	0.0324	252	0.0886	370	0.2172	367	2.564**	1.852*	1.760*	3.095***	1.868*	1.548
9	$ARX(1)-IC_{w1,t}$	0.0458	471	0.1365	489	0.3286	480	2.895***	2.072**	1.869*	3.232***	1.942*	1.639
10	$ARX(1)-IC_{w2,t}$	0.0454	465	0.1357	488	0.3256	478	2.913***	2.040**	1.868*	3.248***	1.922*	1.634
11	$ARX(1)-IC_{w3,t}$	0.0452	461	0.1303	483	0.3145	474	2.933***	2.174**	1.957*	3.307***	2.044**	1.716*
12	$ARX(1)-IC_{w4,t}$	0.0418	441	0.1170	477	0.2843	461	2.805***	2.202**	1.999**	3.251***	2.079**	1.756*
13	$ARX(1)-IC_t$	0.0439	449	0.1263	482	0.3044	471	2.857***	2.110**	1.926*	3.233***	1.988**	1.689*
14	$ARX(1)-IC_{w1,t}-SA$	0.0470	476	0.1418	494	0.3423	485	2.961***	2.094**	1.882*	3.238***	1.957*	1.646*
15	$ARX(1)-IC_{w2,t}-SA$	0.0465	474	0.1407	493	0.3387	483	2.971***	2.063**	1.881*	3.251***	1.937*	1.642
16	$ARX(1)-IC_{w3,t}-SA$	0.0462	472	0.1348	487	0.3261	479	2.979***	2.183**	1.961**	3.301***	2.046**	1.715*
17	$ARX(1)-IC_{w4,t}-SA$	0.0424	444	0.1204	480	0.2937	468	2.836***	2.207**	2.002**	3.235***	2.076**	1.755*
18	$ARX(1)-IC_t-SA$	0.0448	459	0.1307	484	0.3160	475	2.902***	2.118**	1.929*	3.226***	1.992**	1.689*
19	$ARX(1)-IC_{w1,t-1}$	0.0487	485	0.1493	502	0.3568	493	3.038***	2.087**	1.847*	3.352***	1.948*	1.617
20	$ARX(1)-IC_{w2,t-1}$	0.0481	481	0.1471	501	0.3510	490	3.037***	2.067**	1.850*	3.354***	1.938*	1.618
21	$ARX(1)-IC_{w3,t-1}$	0.0484	483	0.1456	499	0.3476	489	3.066***	2.152**	1.899*	3.404***	2.012**	1.660*
22	$ARX(1)-IC_{w4,t-1}$	0.0453	463	0.1328	485	0.3193	476	2.971***	2.171**	1.934*	3.355***	2.033**	1.691*
23	$ARX(1)-IC_{t-1}$	0.0474	479	0.1422	496	0.3397	484	3.019***	2.113**	1.882*	3.356***	1.978**	1.647*
24	$ARX(1)-IC_{w1,t-1}-SA$	0.0504	496	0.1565	510	0.3740	501	3.111***	2.118**	1.861*	3.361***	1.971**	1.623
25	$ARX(1)-IC_{w2,t-1}-SA$	0.0498	490	0.1543	507	0.3683	499	3.112***	2.100**	1.867*	3.364***	1.962**	1.626
26	$ARX(1)-IC_{w3,t-1}-SA$	0.0501	493	0.1529	506	0.3649	498	3.131***	2.171**	1.905*	3.404***	2.025**	1.659*
27	$ARX(1)-IC_{w4,t-1}-SA$	0.0469	475	0.1398	492	0.3364	482	3.044***	2.186**	1.937*	3.353***	2.042**	1.688*
28	$ARX(1)-IC_{t-1}-SA$	0.0491	487	0.1494	503	0.3571	494	3.091***	2.136**	1.890*	3.361***	1.995**	1.648*
29	$ARX(1)-IC_{w1,t-2}$	0.0462	473	0.1559	509	0.3768	506	2.653***	1.954*	1.757*	2.889***	1.840*	1.554
30	$ARX(1)-IC_{w2,t-2}$	0.0446	455	0.1511	504	0.3648	497	2.671***	1.875*	1.770*	2.902***	1.783*	1.554
31	$ARX(1)-IC_{w3,t-2}$	0.0501	494	0.1517	505	0.3622	496	3.123***	2.094**	1.867*	3.439***	1.983**	1.631
32	$ARX(1)-IC_{w4,t-2}$	0.0446	456	0.1376	490	0.3342	481	3.066***	2.159**	1.917*	3.543***	2.038**	1.667*
33	$ARX(1)-IC_{t-2}$	0.0440	450	0.1421	495	0.3449	487	2.707***	1.922*	1.795*	2.974***	1.836*	1.577
34	$ARX(1)-IC_{w1,t-2}-SA$	0.0473	478	0.1605	513	0.3877	509	2.714***	1.977**	1.773*	2.928***	1.861*	1.564
35	$ARX(1)-IC_{w2,t-2}-SA$	0.0455	467	0.1558	508	0.3757	502	2.734***	1.899*	1.789*	2.931***	1.804*	1.567
36	$ARX(1)-IC_{w3,t-2}-SA$	0.0517	499	0.1592	512	0.3790	508	3.164***	2.114**	1.880*	3.440***	1.998**	1.635
37	$ARX(1)-IC_{w4,t-2}-SA$	0.0457	470	0.1432	497	0.3475	488	3.112***	2.171**	1.921*	3.524***	2.046**	1.667*
38	$ARX(1)-IC_{t-2}-SA$	0.0448	460	0.1466	500	0.3552	492	2.745***	1.939*	1.809*	2.992***	1.853*	1.586
39	$ARX(2)-IC_{w1,t}$	0.0357	328	0.0940	402	0.2516	426	2.675***	1.913*	1.767*	3.152***	1.833*	1.564
40	$ARX(2)-IC_{w2,t}$	0.0354	309	0.0931	397	0.2488	420	2.679***	1.893*	1.766*	3.154***	1.818*	1.560
41	$ARX(2)-IC_{w3,t}$	0.0354	312	0.0901	383	0.2420	413	2.689***	1.975**	1.832*	3.201***	1.899*	1.625
42	$ARX(2)-IC_{w4,t}$	0.0333	268	0.0826	318	0.2222	381	2.532**	1.988**	1.856*	3.119***	1.921*	1.653*
43	$ARX(2)-IC_t$	0.0347	289	0.0885	369	0.2368	407	2.621***	1.931*	1.806*	3.138***	1.858*	1.600
44	$ARX(2)-IC_{w1,t}-SA$	0.0364	359	0.0970	417	0.2603	437	2.763***	1.948*	1.786*	3.172***	1.858*	1.576
45	$ARX(2)-IC_{w2,t}-SA$	0.0361	345	0.0961	410	0.2574	433	2.764***	1.927*	1.785*	3.177***	1.843*	1.573
46	$ARX(2)-IC_{w3,t}-SA$	0.0361	343	0.0931	396	0.2503	424	2.766***	2.001**	1.844*	3.220***	1.916*	1.631
47	$ARX(2)-IC_{w4,t}-SA$	0.0339	274	0.0853	341	0.2300	397	2.603***	2.009**	1.869*	3.131***	1.932*	1.658*

(Continued on next page)

Table 16 − continued

	Model	MSE 1-Step	Rank	MSE 2-Step	Rank	MSE 3-Step	Rank	DM 1-St	DM 2-St	DM 3-St	HLN 1-St	HLN 2-St	HLN 3-St
48	$ARX(2)-IC_t-SA$	0.0353	307	0.0914	390	0.2452	417	2.700***	1.957*	1.818*	3.157***	1.877*	1.607
49	$ARX(2)-IC_{w1,t-1}$	0.0371	372	0.0995	428	0.2665	443	2.839***	1.930*	1.742*	3.286***	1.844*	1.542
50	$ARX(2)-IC_{w2,t-1}$	0.0368	368	0.0982	423	0.2629	440	2.823***	1.918*	1.743*	3.274***	1.837*	1.543
51	$ARX(2)-IC_{w3,t-1}$	0.0370	369	0.0976	418	0.2617	438	2.846***	1.956*	1.766*	3.308***	1.871*	1.564
52	$ARX(2)-IC_{w4,t-1}$	0.0355	313	0.0918	392	0.2464	418	2.741***	1.960*	1.785*	3.246***	1.879*	1.583
53	$ARX(2)-IC_{t-1}$	0.0365	362	0.0964	413	0.2582	434	2.807***	1.936*	1.757*	3.272***	1.853*	1.557
54	$ARX(2)-IC_{w1,t-1}-SA$	0.0380	388	0.1030	438	0.2758	454	2.923***	1.974**	1.763*	3.305***	1.878*	1.554
55	$ARX(2)-IC_{w2,t-1}-SA$	0.0376	382	0.1018	435	0.2723	451	2.912***	1.963**	1.767*	3.296***	1.871*	1.557
56	$ARX(2)-IC_{w3,t-1}-SA$	0.0378	383	0.1012	434	0.2710	448	2.928***	1.995**	1.784*	3.326***	1.902*	1.573
57	$ARX(2)-IC_{w4,t-1}-SA$	0.0363	356	0.0955	407	0.2565	432	2.833***	1.995**	1.801*	3.264***	1.905*	1.591
58	$ARX(2)-IC_{t-1}-SA$	0.0374	377	0.1001	431	0.2679	447	2.895***	1.977**	1.777*	3.292***	1.885*	1.567
59	$ARX(2)-IC_{w1,t-2}$	0.0356	319	0.1089	459	0.2900	465	2.446**	1.833*	1.664*	2.801***	1.752*	1.487
60	$ARX(2)-IC_{w2,t-2}$	0.0343	283	0.1052	450	0.2806	457	2.449**	1.775*	1.677*	2.789***	1.708*	1.486
61	$ARX(2)-IC_{w3,t-2}$	0.0387	400	0.1036	440	0.2760	455	2.986***	1.931*	1.753*	3.400***	1.865*	1.548
62	$ARX(2)-IC_{w4,t-2}$	0.0350	298	0.0961	409	0.2587	435	2.837***	1.960**	1.783*	3.404***	1.896*	1.568
63	$ARX(2)-IC_{t-2}$	0.0348	294	0.1027	437	0.2728	452	2.518**	1.801*	1.693*	2.874***	1.743*	1.500
64	$ARX(2)-IC_{w1,t-2}-SA$	0.0361	348	0.1112	467	0.2958	469	2.516**	1.863*	1.685*	2.848***	1.780*	1.501
65	$ARX(2)-IC_{w2,t-2}-SA$	0.0347	290	0.1076	457	0.2863	463	2.528**	1.805*	1.700*	2.831***	1.735*	1.502
66	$ARX(2)-IC_{w3,t-2}-SA$	0.0395	419	0.1073	456	0.2849	462	3.060***	1.971**	1.777*	3.448***	1.901*	1.563
67	$ARX(2)-IC_{w4,t-2}-SA$	0.0356	316	0.0990	426	0.2665	444	2.906***	1.990**	1.797*	3.420***	1.920*	1.576
68	$ARX(2)-IC_{t-2}-SA$	0.0352	305	0.1053	451	0.2789	456	2.580***	1.828*	1.714*	2.919***	1.769*	1.515
69	$ARMAX(1,1)-IC_{w1,t}$	0.0357	331	0.0851	340	0.2069	331	2.597***	1.781*	1.590	3.110***	1.749*	1.440
70	$ARMAX(1,1)-IC_{w2,t}$	0.0357	330	0.0849	336	0.2068	330	2.584***	1.786*	1.592	3.097***	1.752*	1.443
71	$ARMAX(1,1)-IC_{w3,t}$	0.0356	315	0.0844	331	0.2058	327	2.569**	1.767*	1.582	3.082***	1.734*	1.433
72	$ARMAX(1,1)-IC_{w4,t}$	0.0355	314	0.0838	329	0.2057	326	2.542**	1.774*	1.599	3.057***	1.739*	1.447
73	$ARMAX(1,1)-IC_t$	0.0357	323	0.0849	337	0.2072	333	2.577***	1.775*	1.588	3.089***	1.741*	1.438
74	$ARMAX(1,1)-IC_{w1,t}-SA$	0.0340	276	0.0938	400	0.2209	378	2.576***	1.883*	1.743*	3.116***	1.890*	1.537
75	$ARMAX(1,1)-IC_{w2,t}-SA$	0.0342	282	0.0953	405	0.2255	384	2.588***	1.903*	1.763*	3.117***	1.902*	1.551
76	$ARMAX(1,1)-IC_{w3,t}-SA$	0.0348	295	0.0985	424	0.2342	403	2.602***	1.926*	1.799*	3.120***	1.916*	1.578
77	$ARMAX(1,1)-IC_{w4,t}-SA$	0.0483	482	0.1630	515	0.3694	500	3.634***	2.746***	2.726***	4.364***	2.572**	2.263**
78	$ARMAX(1,1)-IC_t-SA$	0.0345	285	0.0969	414	0.2300	396	2.582***	1.899*	1.770*	3.111***	1.902*	1.558
79	$ARMAX(1,1)-IC_{w1,t-1}$	0.0360	342	0.0871	359	0.2109	349	2.635***	1.774*	1.573	3.140***	1.746*	1.425
80	$ARMAX(1,1)-IC_{w2,t-1}$	0.0360	338	0.0867	355	0.2104	348	2.628***	1.779*	1.574	3.131***	1.748*	1.428
81	$ARMAX(1,1)-IC_{w3,t-1}$	0.0359	335	0.0864	351	0.2094	340	2.629***	1.751*	1.553	3.134***	1.723*	1.409
82	$ARMAX(1,1)-IC_{w4,t-1}$	0.0361	347	0.0875	362	0.2128	356	2.628***	1.756*	1.562	3.126***	1.724*	1.415
83	$ARMAX(1,1)-IC_{t-1}$	0.0360	341	0.0871	358	0.2114	352	2.632***	1.765*	1.565	3.134***	1.735*	1.419
84	$ARMAX(1,1)-IC_{w1,t-1}-SA$	0.0328	256	0.0878	365	0.2053	325	2.527**	1.817*	1.664*	3.109***	1.856*	1.481
85	$ARMAX(1,1)-IC_{w2,t-1}-SA$	0.0330	258	0.0890	374	0.2087	337	2.537**	1.833*	1.680*	3.108***	1.865*	1.493
86	$ARMAX(1,1)-IC_{w3,t-1}-SA$	0.0333	267	0.0905	387	0.2125	355	2.545**	1.842*	1.693*	3.102***	1.861*	1.500
87	$ARMAX(1,1)-IC_{w4,t-1}-SA$	0.0337	273	0.0923	394	0.2172	366	2.564**	1.853*	1.704*	3.111***	1.867*	1.507
88	$ARMAX(1,1)-IC_{t-1}-SA$	0.0331	260	0.0895	379	0.2103	347	2.528**	1.823*	1.674*	3.102***	1.858*	1.489
89	$ARMAX(1,1)-IC_{w1,t-2}$	0.0311	220	0.0821	313	0.2089	338	2.023**	1.594	1.531	2.564**	1.596	1.397
90	$ARMAX(1,1)-IC_{w2,t-2}$	0.0295	188	0.0799	296	0.2034	315	1.875*	1.383	1.444	2.394**	1.399	1.307
91	$ARMAX(1,1)-IC_{w3,t-2}$	0.0342	281	0.0793	292	0.2053	324	2.237**	1.846*	1.874*	2.749***	1.920*	1.708*
92	$ARMAX(1,1)-IC_{w4,t-2}$	0.0289	173	0.0654	222	0.1730	232	1.839*	1.922*	1.947*	2.531**	2.100**	1.819*
93	$ARMAX(1,1)-IC_{t-2}$	0.0282	165	0.0663	226	0.1736	233	1.910*	1.581	1.651*	2.561**	1.632	1.491
94	$ARMAX(1,1)-IC_{w1,t-2}-SA$	0.0308	212	0.0890	373	0.2240	382	2.087**	1.713*	1.692*	2.602***	1.723*	1.487
95	$ARMAX(1,1)-IC_{w2,t-2}-SA$	0.0293	185	0.0851	339	0.2149	363	2.031**	1.591	1.604	2.491**	1.570	1.411
96	$ARMAX(1,1)-IC_{w3,t-2}-SA$	0.0311	218	0.0826	317	0.2090	339	2.582***	1.977**	1.930*	3.197***	2.010**	1.678*
97	$ARMAX(1,1)-IC_{w4,t-2}-SA$	0.0262	126	0.0689	241	0.1799	249	2.118**	1.958*	1.998**	3.105***	2.079**	1.733*

(Continued on next page)

Table 16 – continued

	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-St	2-St	3-St	HLN 1-St	2-St	3-St
98	$ARMAX(1,1)-IC_{t-2}-SA$	0.0282	162	0.0762	284	0.1969	297	2.090**	1.703*	1.773*	2.743***	1.752*	1.547
99	$ARMAX(2,2)-IC_{w1,t}$	0.0316	233	0.0722	259	0.1830	256	2.340**	1.667*	1.559	2.927***	1.675*	1.411
100	$ARMAX(2,2)-IC_{w2,t}$	0.0315	232	0.0720	255	0.1830	255	2.325**	1.671*	1.565	2.915***	1.678*	1.416
101	$ARMAX(2,2)-IC_{w3,t}$	0.0313	225	0.0713	249	0.1822	253	2.302**	1.667*	1.571	2.896***	1.672*	1.419
102	$ARMAX(2,2)-IC_{w4,t}$	0.0306	209	0.0692	244	0.1798	248	2.234**	1.697*	1.617	2.864***	1.701*	1.458
103	$ARMAX(2,2)-IC_{t}$	0.0313	227	0.0715	250	0.1826	254	2.303**	1.667*	1.570	2.898***	1.673*	1.418
104	$ARMAX(2,2)-IC_{w1,t}-SA$	0.0323	249	0.0877	363	0.2134	359	2.563**	1.859*	1.772*	3.102***	1.874*	1.557
105	$ARMAX(2,2)-IC_{w2,t}-SA$	0.0327	255	0.0895	376	0.2189	373	2.593***	1.887*	1.801*	3.118***	1.891*	1.578
106	$ARMAX(2,2)-IC_{w3,t}-SA$	0.0336	271	0.0940	403	0.2328	401	2.659***	1.943*	1.874*	3.167***	1.931*	1.634
107	$ARMAX(2,2)-IC_{w4,t}-SA$	0.0357	322	0.1049	449	0.2671	446	2.876***	2.151**	2.110**	3.357***	2.087**	1.819*
108	$ARMAX(2,2)-IC_{t}-SA$	0.0331	261	0.0919	393	0.2270	386	2.608***	1.901*	1.830*	3.128***	1.903*	1.603
109	$ARMAX(2,2)-IC_{w1,t-1}$	0.0322	246	0.0752	281	0.1882	275	2.416**	1.666*	1.537	2.974***	1.675*	1.393
110	$ARMAX(2,2)-IC_{w2,t-1}$	0.0322	244	0.0747	277	0.1876	273	2.405**	1.672*	1.540	2.967***	1.679*	1.398
111	$ARMAX(2,2)-IC_{w3,t-1}$	0.0321	241	0.0747	276	0.1874	272	2.395**	1.643	1.517	2.953***	1.650*	1.377
112	$ARMAX(2,2)-IC_{w4,t-1}$	0.0322	243	0.0749	278	0.1888	279	2.385**	1.649*	1.531	2.941***	1.653*	1.387
113	$ARMAX(2,2)-IC_{t-1}$	0.0322	245	0.0751	280	0.1888	277	2.403**	1.656*	1.530	2.960***	1.663*	1.387
114	$ARMAX(2,2)-IC_{w1,t-1}-SA$	0.0308	213	0.0802	299	0.1918	286	2.463**	1.759*	1.653*	3.064***	1.822*	1.473
115	$ARMAX(2,2)-IC_{w2,t-1}-SA$	0.0311	217	0.0815	309	0.1956	295	2.482**	1.778*	1.674*	3.071***	1.834*	1.488
116	$ARMAX(2,2)-IC_{w3,t-1}-SA$	0.0314	228	0.0831	321	0.2004	301	2.495**	1.792*	1.692*	3.065***	1.832*	1.499
117	$ARMAX(2,2)-IC_{w4,t-1}-SA$	0.0319	238	0.0857	346	0.2073	334	2.532**	1.819*	1.723*	3.081***	1.847*	1.520
118	$ARMAX(2,2)-IC_{t-1}-SA$	0.0312	222	0.0821	314	0.1978	298	2.470**	1.769*	1.670*	3.059***	1.826*	1.486
119	$ARMAX(2,2)-IC_{w1,t-2}$	0.0286	171	0.0746	274	0.1908	282	1.833*	1.526	1.483	2.427**	1.545	1.354
120	$ARMAX(2,2)-IC_{w2,t-2}$	0.0269	136	0.0726	260	0.1862	267	1.610	1.313	1.392	2.163**	1.345	1.267
121	$ARMAX(2,2)-IC_{w3,t-2}$	0.0294	186	0.0643	219	0.1699	228	2.185**	1.670*	1.714*	2.761***	1.743*	1.545
122	$ARMAX(2,2)-IC_{w4,t-2}$	0.0234	73	0.0514	184	0.1406	196	1.535	1.745*	1.763*	2.437**	1.947*	1.633
123	$ARMAX(2,2)-IC_{t-2}$	0.0247	94	0.0582	204	0.1552	209	1.569	1.412	1.537	2.256**	1.490	1.394
124	$ARMAX(2,2)-IC_{w1,t-2}-SA$	0.0290	176	0.0807	304	0.2015	307	1.949*	1.601	1.590	2.519**	1.643	1.409
125	$ARMAX(2,2)-IC_{w2,t-2}-SA$	0.0275	147	0.0768	286	0.1933	289	1.841*	1.505	1.521	2.356**	1.505	1.347
126	$ARMAX(2,2)-IC_{w3,t-2}-SA$	0.0289	174	0.0729	267	0.1834	259	2.495**	1.815*	1.786*	3.116***	1.867*	1.553
127	$ARMAX(2,2)-IC_{w4,t-2}-SA$	0.0237	75	0.0604	209	0.1582	210	1.883*	1.761*	1.835*	3.001***	1.898*	1.595
128	$ARMAX(2,2)-IC_{t-2}-SA$	0.0260	120	0.0685	237	0.1772	238	1.860*	1.565	1.656*	2.521**	1.622	1.448
129	$AR(1)$	0.0531	503	0.1644	517	0.3895	510	3.621***	2.360**	2.097**	3.753***	2.157**	1.808*
130	$AR(1)-SA$	0.0559	506	0.1694	519	0.3942	512	3.701***	2.409**	2.166**	3.863***	2.205**	1.861*
131	$AR(2)$	0.0359	337	0.0847	334	0.2397	410	2.645***	2.220**	2.170**	3.464***	2.097**	1.883*
132	$AR(2)-SA$	0.0382	390	0.0835	328	0.2414	411	3.100***	2.252**	2.291**	3.805***	2.135**	2.022**
133	$ARMA(1,1)$	0.0301	201	0.0580	202	0.1353	190	2.059**	1.893*	1.567	2.830***	1.593	1.649*
134	$ARMA(1,1)-SA$	0.0388	402	0.0601	207	0.1683	226	2.378**	1.442	1.258	2.852***	1.331	1.162
135	$ARMA(2,2)$	0.0448	458	0.1157	476	0.2877	464	2.996***	2.413**	1.902*	3.446***	1.973**	1.596
136	$ARMA(2,2)-SA$	0.0455	466	0.0895	378	0.2628	439	3.141***	1.765*	1.418	3.361***	1.615	1.240
137	$ARX(1)-IC_{w1,t}$	0.0379	385	0.0903	386	0.2138	360	2.617***	1.596	1.152	3.042***	1.336	1.081
138	$ARX(1)-IC_{w2,t}$	0.0348	296	0.0864	352	0.2044	319	2.802***	1.766*	1.419	3.514***	1.516	1.387
139	$ARX(1)-IC_{w3,t}$	0.0374	379	0.0819	311	0.2213	379	2.368**	2.017**	1.518	3.011***	1.946*	1.481
140	$ARX(1)-IC_{w4,t}$	0.0319	235	0.0722	258	0.1836	260	2.230**	1.989**	1.800*	3.172***	1.843*	1.810*
141	$ARX(1)-IC_{t}$	0.0346	288	0.0789	291	0.2012	304	2.590***	1.716*	1.248	3.072***	1.429	1.144
142	$ARX(1)-IC_{w1,t}-SA$	0.0391	407	0.0931	398	0.2201	376	2.630***	1.652*	1.194	3.047***	1.391	1.118
143	$ARX(1)-IC_{w2,t}-SA$	0.0364	358	0.0907	388	0.2084	336	2.935***	1.736*	1.441	3.386***	1.471	1.407
144	$ARX(1)-IC_{w3,t}-SA$	0.0379	387	0.0813	308	0.2167	364	2.486**	1.927*	1.456	3.151***	1.777*	1.414
145	$ARX(1)-IC_{w4,t}-SA$	0.0331	259	0.0720	254	0.1774	240	2.533**	1.889*	1.710*	3.121***	1.604	1.700*
146	$ARX(1)-IC_{t}-SA$	0.0359	336	0.0810	307	0.2001	300	2.787***	1.627	1.214	3.055***	1.338	1.111
147	$ARX(1)-IC_{w1,t-1}$	0.0361	344	0.0856	345	0.2033	314	2.225**	1.386	0.933	2.497**	1.140	0.861

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Table 16 − continued

	Model	MSE 1-Step	Rank	MSE 2-Step	Rank	MSE 3-Step	Rank	DM 1-St	DM 2-St	DM 3-St	HLN 1-St	HLN 2-St	HLN 3-St
148	$ARX(1)-IC_{w2,t-1}$	0.0354	311	0.0901	384	0.2109	350	2.502**	1.640	1.239	3.020***	1.400	1.172
149	$ARX(1)-IC_{w3,t-1}$	0.0376	381	0.0822	315	0.2214	380	2.358**	2.020**	1.598	3.059***	2.016**	1.580
150	$ARX(1)-IC_{w4,t-1}$	0.0319	237	0.0707	245	0.1816	251	2.192**	1.940*	1.793*	3.121***	1.819*	1.797*
151	$ARX(1)-IC_{t-1}$	0.0346	287	0.0787	290	0.2019	309	2.416**	1.703*	1.236	2.980***	1.442	1.134
152	$ARX(1)-IC_{w1,t-1}-SA$	0.0375	380	0.0869	356	0.2032	313	2.301**	1.396	0.938	2.515**	1.147	0.865
153	$ARX(1)-IC_{w2,t-1}-SA$	0.0362	351	0.0938	401	0.2183	371	2.442**	1.667*	1.279	2.973***	1.442	1.209
154	$ARX(1)-IC_{w3,t-1}-SA$	0.0384	395	0.0856	344	0.2280	389	2.414**	2.038**	1.633	3.154***	2.047**	1.616
155	$ARX(1)-IC_{w4,t-1}-SA$	0.0329	257	0.0746	275	0.1880	274	2.285**	1.936*	1.828*	3.242***	1.823*	1.835*
156	$ARX(1)-IC_{t-1}-SA$	0.0357	321	0.0823	316	0.2078	335	2.462**	1.733*	1.278	3.015***	1.482	1.174
157	$ARX(1)-IC_{w1,t-2}$	0.0396	423	0.1047	446	0.2435	414	2.308**	1.539	1.105	2.691***	1.303	1.019
158	$ARX(1)-IC_{w2,t-2}$	0.0383	392	0.1048	448	0.2499	422	2.495**	1.746*	1.292	2.981***	1.549	1.230
159	$ARX(1)-IC_{w3,t-2}$	0.0387	401	0.0882	366	0.2297	394	2.415**	1.772*	1.366	2.991***	1.627	1.280
160	$ARX(1)-IC_{w4,t-2}$	0.0350	299	0.0720	253	0.1870	269	2.265**	1.795*	1.484	2.744***	1.517	1.378
161	$ARX(1)-IC_{t-2}$	0.0366	363	0.0865	353	0.2180	370	2.350**	1.638	1.204	2.700***	1.394	1.092
162	$ARX(1)-IC_{w1,t-2}-SA$	0.0409	434	0.1093	460	0.2500	423	2.310**	1.540	1.128	2.665***	1.313	1.040
163	$ARX(1)-IC_{w2,t-2}-SA$	0.0390	406	0.1119	470	0.2653	442	2.437**	1.760*	1.344	2.951***	1.605	1.278
164	$ARX(1)-IC_{w3,t-2}-SA$	0.0398	427	0.0930	395	0.2357	405	2.521**	1.757*	1.390	2.974***	1.604	1.303
165	$ARX(1)-IC_{w4,t-2}-SA$	0.0361	346	0.0752	282	0.1915	284	2.347**	1.791*	1.523	2.804***	1.519	1.417
166	$ARX(1)-IC_{t-2}-SA$	0.0379	386	0.0933	399	0.2300	395	2.427**	1.656*	1.261	2.749***	1.432	1.145
167	$ARX(2)-IC_{w1,t}$	0.0383	391	0.0895	377	0.2131	358	2.620***	1.607	1.154	3.060***	1.339	1.084
168	$ARX(2)-IC_{w2,t}$	0.0357	327	0.0872	361	0.2042	317	2.845***	1.753*	1.417	3.503***	1.487	1.385
169	$ARX(2)-IC_{w3,t}$	0.0365	361	0.0743	271	0.2102	346	2.292**	1.887*	1.433	2.837***	1.792*	1.387
170	$ARX(2)-IC_{w4,t}$	0.0319	236	0.0679	232	0.1780	242	2.208**	1.913*	1.748*	3.055***	1.746*	1.752*
171	$ARX(2)-IC_{t}$	0.0358	333	0.0796	294	0.2012	305	2.667***	1.707*	1.248	3.123***	1.413	1.145
172	$ARX(2)-IC_{w1,t}-SA$	0.0394	415	0.0911	389	0.2178	369	2.641***	1.709*	1.211	3.083***	1.428	1.137
173	$ARX(2)-IC_{w2,t}-SA$	0.0406	432	0.0998	430	0.2122	354	3.365***	1.614	1.458	2.994***	1.316	1.427
174	$ARX(2)-IC_{w3,t}-SA$	0.0396	422	0.0835	327	0.2173	368	2.683***	1.916*	1.468	3.220***	1.707*	1.432
175	$ARX(2)-IC_{w4,t}-SA$	0.0353	308	0.0767	285	0.1798	247	2.790***	1.874*	1.737*	3.066***	1.541	1.733*
176	$ARX(2)-IC_{t}-SA$	0.0395	418	0.0890	375	0.2027	311	3.178***	1.575	1.217	2.928***	1.261	1.117
177	$ARX(2)-IC_{w1,t-1}$	0.0357	324	0.0833	323	0.2029	312	2.226**	1.441	0.931	2.543**	1.183	0.861
178	$ARX(2)-IC_{w2,t-1}$	0.0358	332	0.0897	381	0.2116	353	2.504**	1.698*	1.244	3.097***	1.450	1.180
179	$ARX(2)-IC_{w3,t-1}$	0.0356	320	0.0739	269	0.2095	341	2.203**	1.944*	1.552	2.891***	1.939*	1.543
180	$ARX(2)-IC_{w4,t-1}$	0.0323	247	0.0678	231	0.1773	239	2.197**	1.902*	1.752*	3.066***	1.771*	1.750*
181	$ARX(2)-IC_{t-1}$	0.0353	306	0.0785	288	0.2023	310	2.483**	1.741*	1.245	3.079***	1.472	1.145
182	$ARX(2)-IC_{w1,t-1}-SA$	0.0363	355	0.0809	306	0.2008	302	2.152**	1.572	0.949	2.485**	1.288	0.875
183	$ARX(2)-IC_{w2,t-1}-SA$	0.0360	339	0.0900	382	0.2168	365	2.333**	1.780*	1.293	2.931***	1.567	1.227
184	$ARX(2)-IC_{w3,t-1}-SA$	0.0363	352	0.0728	263	0.2096	342	2.255**	1.935*	1.589	2.807***	2.022**	1.576
185	$ARX(2)-IC_{w4,t-1}-SA$	0.0339	275	0.0721	257	0.1830	257	2.392**	1.933*	1.808*	3.292***	1.801*	1.809*
186	$ARX(2)-IC_{t-1}-SA$	0.0362	349	0.0805	303	0.2061	328	2.486**	1.847*	1.305	3.061***	1.595	1.202
187	$ARX(2)-IC_{w1,t-2}$	0.0386	399	0.1036	441	0.2440	415	2.239**	1.591	1.111	2.704***	1.356	1.028
188	$ARX(2)-IC_{w2,t-2}$	0.0385	397	0.1058	452	0.2522	427	2.491**	1.814*	1.309	3.074***	1.618	1.249
189	$ARX(2)-IC_{w3,t-2}$	0.0373	373	0.0808	305	0.2207	377	2.303**	1.686*	1.320	2.899***	1.546	1.236
190	$ARX(2)-IC_{w4,t-2}$	0.0360	340	0.0720	256	0.1872	270	2.348**	1.797*	1.464	2.821***	1.514	1.357
191	$ARX(2)-IC_{t-2}$	0.0373	374	0.0869	357	0.2191	374	2.419**	1.668*	1.212	2.805***	1.416	1.102
192	$ARX(2)-IC_{w1,t-2}-SA$	0.0394	416	0.1099	464	0.2504	425	2.231**	1.671*	1.175	2.692***	1.429	1.091
193	$ARX(2)-IC_{w2,t-2}-SA$	0.0371	371	0.1046	445	0.2667	445	2.242**	1.809*	1.392	2.801***	1.744*	1.331
194	$ARX(2)-IC_{w3,t-2}-SA$	0.0385	398	0.0849	338	0.2286	391	2.441**	1.745*	1.380	3.004***	1.610	1.294
195	$ARX(2)-IC_{w4,t-2}-SA$	0.0384	393	0.0786	289	0.1935	290	2.616***	1.807*	1.522	2.937***	1.491	1.414
196	$ARX(2)-IC_{t-2}-SA$	0.0392	411	0.0964	412	0.2315	399	2.635***	1.691*	1.283	2.862***	1.436	1.168
197	$ARMAX(1,1)-IC_{w1,t}$	0.0430	445	0.1004	432	0.2248	383	2.704***	1.715*	1.115	3.268***	1.396	1.057

(Continued on next page)

Table 16 − continued

	Model	MSE						DM			HLN		
		1-Step	Rank	2-Step	Rank	3-Step	Rank	1-St	2-St	3-St	1-St	2-St	3-St
198	$ARMAX(1,1) - IC_{w2,t}$	0.0404	431	0.1035	439	0.2292	392	3.535***	2.070**	1.513	4.081***	1.698*	1.453
199	$ARMAX(1,1) - IC_{w3,t}$	0.0388	403	0.0865	354	0.2325	400	2.529**	2.301**	1.632	3.305***	2.186**	1.608
200	$ARMAX(1,1) - IC_{w4,t}$	0.0393	412	0.0833	324	0.1953	294	3.121***	2.630***	2.000**	4.162***	2.269**	1.986**
201	$ARMAX(1,1) - IC_{t}$	0.0373	376	0.0861	348	0.2145	361	2.978***	1.988**	1.364	3.526***	1.614	1.265
202	$ARMAX(1,1) - IC_{w1,t} - SA$	0.0446	454	0.1019	436	0.2042	318	3.002***	1.437	1.238	2.609***	1.157	1.150
203	$ARMAX(1,1) - IC_{w2,t} - SA$	0.0424	443	0.1047	447	0.2052	323	3.138***	1.389	1.327	2.431**	1.131	1.265
204	$ARMAX(1,1) - IC_{w3,t} - SA$	0.0397	425	0.0687	239	0.1621	218	2.984***	1.561	1.246	2.754***	1.273	1.190
205	$ARMAX(1,1) - IC_{w4,t} - SA$	0.0370	370	0.0631	217	0.1314	182	3.342***	1.290	1.532	2.697***	1.040	1.488
206	$ARMAX(1,1) - IC_{t} - SA$	0.0398	428	0.0855	343	0.1787	244	2.876***	1.423	1.244	2.407**	1.138	1.141
207	$ARMAX(1,1) - IC_{w1,t-1}$	0.0393	413	0.0895	380	0.2097	344	2.457**	1.478	0.965	2.739***	1.202	0.894
208	$ARMAX(1,1) - IC_{w2,t-1}$	0.0392	409	0.0998	429	0.2296	393	2.962***	1.881*	1.331	3.401***	1.574	1.268
209	$ARMAX(1,1) - IC_{w3,t-1}$	0.0475	480	0.1045	444	0.2718	450	3.143***	2.606***	1.929*	3.815***	2.481**	1.871*
210	$ARMAX(1,1) - IC_{w4,t-1}$	0.0395	417	0.0979	420	0.2281	390	3.094***	2.752***	2.256**	4.085***	2.415**	2.221**
211	$ARMAX(1,1) - IC_{t-1}$	0.0380	389	0.0884	367	0.2184	372	2.863***	1.976**	1.349	3.451***	1.625	1.251
212	$ARMAX(1,1) - IC_{w1,t-1} - SA$	0.0413	438	0.0956	408	0.1767	237	2.200**	1.194	0.886	2.195**	0.990	0.808
213	$ARMAX(1,1) - IC_{w2,t-1} - SA$	0.0442	452	0.1043	443	0.2009	303	2.821***	1.527	1.282	2.788***	1.269	1.230
214	$ARMAX(1,1) - IC_{w3,t-1} - SA$	0.0447	457	0.0839	330	0.1888	278	2.590***	1.838*	1.491	2.919***	1.633	1.413
215	$ARMAX(1,1) - IC_{w4,t-1} - SA$	0.0366	364	0.0617	212	0.1294	178	2.741***	1.388	1.607	2.873***	1.177	1.540
216	$ARMAX(1,1) - IC_{t-1} - SA$	0.0411	437	0.0981	422	0.2071	332	1.945*	1.329	1.029	2.222**	1.160	0.926
217	$ARMAX(1,1) - IC_{w1,t-2}$	0.0422	442	0.1139	473	0.2563	431	2.569**	1.688*	1.173	2.955***	1.401	1.091
218	$ARMAX(1,1) - IC_{w2,t-2}$	0.0433	446	0.1191	479	0.2757	453	3.044***	2.069**	1.452	3.605***	1.803*	1.387
219	$ARMAX(1,1) - IC_{w3,t-2}$	0.0494	489	0.1094	462	0.2825	458	2.767***	1.934*	1.633	3.265***	1.829*	1.555
220	$ARMAX(1,1) - IC_{w4,t-2}$	0.0399	429	0.0793	293	0.2051	322	2.877***	2.091**	1.649*	3.220***	1.720*	1.538
221	$ARMAX(1,1) - IC_{t-2}$	0.0453	462	0.1137	472	0.2714	449	3.017***	2.137**	1.514	3.441***	1.817*	1.408
222	$ARMAX(1,1) - IC_{w1,t-2} - SA$	0.0487	486	0.1118	469	0.2098	345	2.548**	1.298	1.066	2.386**	1.059	0.969
223	$ARMAX(1,1) - IC_{w2,t-2} - SA$	0.0484	484	0.1117	468	0.2366	406	2.654***	1.540	1.348	2.620***	1.281	1.292
224	$ARMAX(1,1) - IC_{w3,t-2} - SA$	0.0517	498	0.1060	453	0.2193	375	3.138***	1.794*	1.552	3.042***	1.554	1.447
225	$ARMAX(1,1) - IC_{w4,t-2} - SA$	0.0341	278	0.0688	240	0.1535	206	2.418**	1.560	1.467	2.782***	1.368	1.424
226	$ARMAX(1,1) - IC_{t-2} - SA$	0.0518	500	0.1180	478	0.2478	419	1.751*	1.388	1.223	1.936*	1.180	1.051
227	$ARMAX(2,2) - IC_{w1,t}$	0.0307	210	0.0628	215	0.1468	202	1.984**	1.383	1.085	2.430**	1.120	1.069
228	$ARMAX(2,2) - IC_{w2,t}$	0.0306	207	0.0728	264	0.1597	213	2.502**	1.674*	1.242	3.059***	1.323	1.263
229	$ARMAX(2,2) - IC_{w3,t}$	0.0367	365	0.0760	283	0.2113	351	2.212**	2.025**	1.519	2.864***	1.948*	1.494
230	$ARMAX(2,2) - IC_{w4,t}$	0.0357	326	0.0659	224	0.1635	220	1.981**	1.847*	1.520	2.663***	1.657*	1.540
231	$ARMAX(2,2) - IC_{t}$	0.0388	405	0.0803	300	0.2041	316	2.455**	1.691*	1.226	3.061***	1.440	1.181
232	$ARMAX(2,2) - IC_{w1,t} - SA$	0.0417	440	0.0945	404	0.1863	268	2.671***	1.272	1.300	2.404**	1.052	1.235
233	$ARMAX(2,2) - IC_{w2,t} - SA$	0.0410	435	0.0961	411	0.1848	263	2.461**	1.184	1.251	2.063**	0.987	1.180
234	$ARMAX(2,2) - IC_{w3,t} - SA$	0.0393	414	0.0565	195	0.1583	211	2.601***	1.505	1.167	2.877***	1.302	1.123
235	$ARMAX(2,2) - IC_{w4,t} - SA$	0.0410	436	0.0641	218	0.1305	180	2.932***	1.160	1.335	2.344**	0.949	1.315
236	$ARMAX(2,2) - IC_{t} - SA$	0.0436	447	0.0889	371	0.1846	261	2.951***	1.371	1.232	2.390**	1.121	1.148
237	$ARMAX(2,2) - IC_{w1,t-1}$	0.0398	426	0.0801	298	0.1862	266	2.533**	1.766*	1.331	3.191***	1.405	1.271
238	$ARMAX(2,2) - IC_{w2,t-1}$	0.0385	396	0.0872	360	0.1948	292	2.401**	1.897*	1.554	3.152***	1.600	1.559
239	$ARMAX(2,2) - IC_{w3,t-1}$	0.0323	248	0.0684	236	0.1680	225	2.002**	1.633	1.410	2.872***	1.499	1.440
240	$ARMAX(2,2) - IC_{w4,t-1}$	0.0347	292	0.0712	248	0.1712	230	2.419**	1.835*	1.640	2.977***	1.537	1.622
241	$ARMAX(2,2) - IC_{t-1}$	0.0384	394	0.0749	279	0.1859	265	2.384**	1.653*	1.562	3.006***	1.440	1.513
242	$ARMAX(2,2) - IC_{w1,t-1} - SA$	0.0313	224	0.0727	262	0.1614	217	1.875*	1.516	1.096	2.581***	1.265	1.043
243	$ARMAX(2,2) - IC_{w2,t-1} - SA$	0.0492	488	0.0859	347	0.1873	271	2.621***	1.726*	1.390	3.122***	1.452	1.346
244	$ARMAX(2,2) - IC_{w3,t-1} - SA$	0.0313	223	0.0732	268	0.2097	343	1.779*	1.501	1.329	2.534**	1.520	1.185
245	$ARMAX(2,2) - IC_{w4,t-1} - SA$	0.0396	424	0.0677	230	0.1614	216	2.818***	1.485	1.487	3.302***	1.388	1.389
246	$ARMAX(2,2) - IC_{t-1} - SA$	0.0399	430	0.0832	322	0.1782	243	1.664*	1.300	1.123	1.976**	1.130	1.013
247	$ARMAX(2,2) - IC_{w1,t-2}$	0.0363	354	0.0969	416	0.2148	362	2.496**	1.890*	1.474	3.329***	1.592	1.414

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Table 16 − continued

	Model	MSE						DM			HLN		
		1-Step	Rank	2-Step	Rank	3-Step	Rank	1-St	2-St	3-St	1-St	2-St	3-St
248	$ARMAX(2,2) - IC_{w2,t-2}$	0.0323	250	0.0864	349	0.2017	308	2.961***	1.792*	1.327	3.690***	1.523	1.291
249	$ARMAX(2,2) - IC_{w3,t-2}$	0.0368	367	0.0800	297	0.1906	281	2.534**	1.426	1.392	2.841***	1.186	1.291
250	$ARMAX(2,2) - IC_{w4,t-2}$	0.0350	300	0.0744	272	0.2013	306	2.062**	1.865*	1.523	2.770***	1.580	1.427
251	$ARMAX(2,2) - IC_{t-2}$	0.0395	420	0.0889	372	0.2354	404	2.114**	1.693*	1.060	2.207**	1.461	0.964
252	$ARMAX(2,2) - IC_{w1,t-2} - SA$	0.0356	317	0.0981	421	0.1915	283	2.378**	1.518	1.177	2.503**	1.225	1.121
253	$ARMAX(2,2) - IC_{w2,t-2} - SA$	0.0518	502	0.1066	455	0.2561	430	2.335**	1.817*	1.216	2.533**	1.516	1.144
254	$ARMAX(2,2) - IC_{w3,t-2} - SA$	0.0363	357	0.0884	368	0.2310	398	2.558**	1.545	1.453	2.623***	1.411	1.326
255	$ARMAX(2,2) - IC_{w4,t-2} - SA$	0.0454	464	0.0777	287	0.1599	214	3.100***	1.572	1.448	2.951***	1.362	1.385
256	$ARMAX(2,2) - IC_{t-2} - SA$	0.0518	501	0.1156	475	0.2278	387	1.720*	1.319	1.102	1.835*	1.139	0.962
257	$ARX(1) - G_{w1,t}$	0.0277	156	0.0479	163	0.1064	132	1.720*	0.906	1.037	1.722*	0.878	0.906
258	$ARX(1) - G_{w2,t}$	0.0212	43	0.0478	162	0.1686	227	1.379	0.810	0.592	1.582	0.749	0.616
259	$ARX(1) - G_{w3,t}$	0.0227	62	0.0325	58	0.0856	82	1.854*	1.863*	1.443	2.332**	1.971**	1.813*
260	$ARX(1) - G_{w4,t}$	0.0206	32	0.0279	33	0.0556	20	1.771*	1.418	1.025	2.305**	1.640	1.419
261	$ARX(1) - G_{t}$	0.0166	1	0.0157	1	0.0382	4	0.000	0.000	0.308	0.000	0.000	0.852
262	$ARX(1) - G_{w1,t} - SA$	0.0294	187	0.0503	175	0.1084	142	2.605***	1.002	1.247	2.474**	0.945	1.063
263	$ARX(1) - G_{w2,t} - SA$	0.0241	82	0.0509	180	0.1847	262	1.608	0.787	0.567	1.485	0.707	0.577
264	$ARX(1) - G_{w3,t} - SA$	0.0270	139	0.0393	102	0.0913	94	1.684*	1.837*	1.531	1.843*	1.784*	1.937*
265	$ARX(1) - G_{w4,t} - SA$	0.0222	53	0.0291	37	0.0555	19	1.639	1.319	0.938	2.021**	1.610	1.219
266	$ARX(1) - G_{t} - SA$	0.0188	12	0.0175	5	0.0383	6	0.998	0.700	0.299	1.122	0.869	0.777
267	$ARX(1) - IC_{w1,t} - G_{w1,t}$	0.0256	108	0.0443	143	0.1089	145	2.057**	1.591	1.048	2.962***	1.387	1.069
268	$ARX(1) - IC_{w2,t} - G_{w2,t}$	0.0201	26	0.0385	95	0.1056	128	1.087	1.285	1.079	2.874***	1.292	1.194
269	$ARX(1) - IC_{w3,t} - G_{w3,t}$	0.0240	79	0.0372	88	0.1150	157	1.669*	1.969**	1.502	2.272**	1.918*	1.542
270	$ARX(1) - IC_{w4,t} - G_{w4,t}$	0.0192	15	0.0296	38	0.0735	55	0.778	1.479	1.035	1.807*	1.296	1.145
271	$ARX(1) - IC_{t} - G_{t}$	0.0186	11	0.0242	20	0.0680	45	0.709	1.159	0.757	1.605	1.002	0.821
272	$ARX(1) - IC_{w1,t} \ldots IC_{w4,t} - G_{w1,t} \ldots G_{w4,t}$	0.0221	50	0.0282	34	0.1066	134	1.360	1.008	1.503	2.346**	1.457	1.609
273	$ARX(1) - IC_{w1,t} - G_{w1,t} - SA$	0.0266	133	0.0421	125	0.1043	125	2.231**	1.822*	1.257	2.792***	1.676*	1.288
274	$ARX(1) - IC_{w2,t} - G_{w2,t} - SA$	0.0206	33	0.0399	107	0.1090	146	1.205	1.364	1.097	2.939***	1.330	1.186
275	$ARX(1) - IC_{w3,t} - G_{w3,t} - SA$	0.0241	83	0.0353	77	0.1084	143	1.672*	1.953*	1.436	2.200**	1.946*	1.471
276	$ARX(1) - IC_{w4,t} - G_{w4,t} - SA$	0.0200	24	0.0312	50	0.0745	57	0.924	1.236	0.872	2.080**	1.162	0.918
277	$ARX(1) - IC_{t} - G_{t} - SA$	0.0186	10	0.0186	6	0.0531	17	0.852	0.952	0.681	1.326	1.142	0.852
278	$ARX(1) - IC_{w1,t} \ldots IC_{w4,t} - G_{w1,t} \ldots G_{w4,t} - SA$	0.0241	81	0.0297	39	0.1127	153	1.763*	0.951	1.602	2.617***	1.385	1.754*
279	$ARX(1) - G_{w1,t-1}$	0.0292	180	0.0491	168	0.1130	154	1.736*	1.001	1.140	1.753*	0.950	0.963
280	$ARX(1) - G_{w2,t-1}$	0.0313	226	0.0878	364	0.3210	477	1.189	0.661	0.538	1.222	0.605	0.513
281	$ARX(1) - G_{w3,t-1}$	0.0230	70	0.0314	52	0.0887	87	1.891*	1.287	1.080	1.973**	1.116	1.143
282	$ARX(1) - G_{w4,t-1}$	0.0231	71	0.0354	79	0.0778	67	2.692***	1.813*	1.482	3.061***	1.783*	1.792*
283	$ARX(1) - G_{t-1}$	0.0182	8	0.0208	9	0.0513	15	1.516	1.514	1.217	1.701*	1.543	1.383
284	$ARX(1) - G_{w1,t-1} - SA$	0.0310	215	0.0530	186	0.1198	167	2.482**	1.151	1.375	2.385**	1.054	1.164
285	$ARX(1) - G_{w2,t-1} - SA$	0.0392	410	0.0977	419	0.3762	504	1.181	0.637	0.521	1.148	0.579	0.490
286	$ARX(1) - G_{w3,t-1} - SA$	0.0276	151	0.0396	106	0.1018	117	2.057**	1.188	0.993	1.978**	0.998	0.981
287	$ARX(1) - G_{w4,t-1} - SA$	0.0254	105	0.0381	94	0.0802	71	2.291**	1.657*	1.360	2.429**	1.595	1.502
288	$ARX(1) - G_{t-1} - SA$	0.0197	20	0.0220	11	0.0510	14	1.647*	1.402	1.142	2.014**	1.551	1.501
289	$ARX(1) - IC_{w1,t-1} - G_{w1,t-1}$	0.0336	270	0.0711	247	0.1779	241	2.393**	1.632	0.979	2.827***	1.357	0.945
290	$ARX(1) - IC_{w2,t-1} - G_{w2,t-1}$	0.0255	106	0.0581	203	0.1763	236	1.921*	1.334	0.951	2.655***	1.211	0.912
291	$ARX(1) - IC_{w3,t-1} - G_{w3,t-1}$	0.0239	77	0.0312	49	0.0924	95	2.182**	1.251	1.145	2.222**	1.101	1.176
292	$ARX(1) - IC_{w4,t-1} - G_{w4,t-1}$	0.0227	63	0.0344	73	0.0850	80	2.182**	1.657*	1.751*	2.627***	1.585	1.816*
293	$ARX(1) - IC_{t-1} - G_{t-1}$	0.0200	25	0.0233	14	0.0623	36	2.201**	1.989**	1.439	2.419**	1.994**	1.638
294	$ARX(1) - IC_{w1,t-1} \ldots IC_{w4,t-1} - G_{w1,t-1} \ldots G_{w4,t-1}$	0.0293	184	0.0605	210	0.1654	223	2.074**	1.743*	1.579	2.694***	1.565	1.312
295	$ARX(1) - IC_{w1,t-1} - G_{w1,t-1} - SA$	0.0324	251	0.0631	216	0.1624	219	2.257**	2.043**	1.187	2.629***	1.768*	1.160
296	$ARX(1) - IC_{w2,t-1} - G_{w2,t-1} - SA$	0.0315	231	0.0727	261	0.2387	409	1.955*	1.194	0.793	2.039**	1.020	0.725
297	$ARX(1) - IC_{w3,t-1} - G_{w3,t-1} - SA$	0.0300	198	0.0411	120	0.1083	141	2.322**	1.244	1.073	2.263**	1.085	1.091

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Table 16 − continued

		MSE						DM			HLN		
	Model	**1-Step**	**Rank**	**2-Step**	**Rank**	**3-Step**	**Rank**	**1-St**	**2-St**	**3-St**	**1-St**	**2-St**	**3-St**
298	$ARX(1) - IC_{w4,t-1} - G_{w4,t-1} - SA$	0.0258	117	0.0360	83	0.0879	85	3.051***	1.522	1.668*	3.192***	1.467	1.543
299	$ARX(1) - IC_{t-1} - G_{t-1} - SA$	0.0224	57	0.0234	15	0.0556	22	2.054**	1.392	1.227	2.300**	1.468	1.615
300	$ARX(1) - IC_{w1,t-1} \dots IC_{w4,t-1} - G_{w1,t-1} \dots G_{w4,t-1} - SA$	0.0347	291	0.0627	214	0.1793	245	2.404**	1.594	1.560	2.785***	1.489	1.270
301	$ARX(1) - G_{w1,t-2}$	0.0253	104	0.0340	68	0.0832	75	1.733*	1.401	1.744*	2.323**	1.448	1.525
302	$ARX(1) - G_{w2,t-2}$	0.0408	433	0.0525	185	0.1466	200	1.688*	0.884	0.988	1.680*	0.922	1.000
303	$ARX(1) - G_{w3,t-2}$	0.0223	54	0.0381	93	0.1107	149	1.812*	1.706*	1.530	2.722***	1.530	1.521
304	$ARX(1) - G_{w4,t-2}$	0.0212	42	0.0343	71	0.0790	69	1.833*	1.684*	1.554	2.355**	1.646*	1.854*
305	$ARX(1) - G_{t-2}$	0.0179	5	0.0220	12	0.0588	27	0.616	1.551	1.690*	1.289	1.718*	1.737*
306	$ARX(1) - G_{w1,t-2} - SA$	0.0275	149	0.0331	63	0.0825	73	2.331**	1.421	1.653*	2.662***	1.358	1.626
307	$ARX(1) - G_{w2,t-2} - SA$	0.0345	284	0.0834	325	0.2592	436	1.283	0.945	0.725	1.316	0.870	0.677
308	$ARX(1) - G_{w3,t-2} - SA$	0.0275	148	0.0467	157	0.1302	179	2.626***	1.512	1.344	2.625***	1.289	1.270
309	$ARX(1) - G_{w4,t-2} - SA$	0.0237	76	0.0401	110	0.0888	88	2.617***	1.909*	1.677*	3.067***	1.843*	1.850*
310	$ARX(1) - G_{t-2} - SA$	0.0205	31	0.0269	27	0.0659	42	1.753*	1.527	2.182**	2.286**	1.595	2.398**
311	$ARX(1) - IC_{w1,t-2} - G_{w1,t-2}$	0.0292	183	0.0505	177	0.1355	191	1.581	1.337	0.954	2.321**	1.283	0.906
312	$ARX(1) - IC_{w2,t-2} - G_{w2,t-2}$	0.0317	234	0.0690	243	0.1968	296	1.648*	1.257	1.158	1.793*	1.291	1.115
313	$ARX(1) - IC_{w3,t-2} - G_{w3,t-2}$	0.0242	84	0.0412	121	0.1192	165	2.072**	1.700*	1.530	2.725***	1.570	1.511
314	$ARX(1) - IC_{w4,t-2} - G_{w4,t-2}$	0.0246	91	0.0387	100	0.1049	127	2.078**	1.680*	1.568	2.712***	1.527	1.507
315	$ARX(1) - IC_{t-2} - G_{t-2}$	0.0196	19	0.0253	22	0.0713	50	1.265	1.499	1.533	1.633	1.572	1.681*
316	$ARX(1) - IC_{w1,t-2} \dots IC_{w4,t-2} - G_{w1,t-2} \dots G_{w4,t-2}$	0.0742	516	0.1734	520	0.4743	520	2.918***	1.561	1.330	2.550**	1.369	1.135
317	$ARX(1) - IC_{w1,t-2} - G_{w1,t-2} - SA$	0.0304	204	0.0455	147	0.1282	175	1.813*	1.483	1.189	2.385**	1.594	1.199
318	$ARX(1) - IC_{w2,t-2} - G_{w2,t-2} - SA$	0.0638	512	0.1155	474	0.3766	505	1.594	1.002	0.734	1.574	0.911	0.657
319	$ARX(1) - IC_{w3,t-2} - G_{w3,t-2} - SA$	0.0311	221	0.0536	188	0.1399	195	2.637***	1.608	1.353	2.701***	1.462	1.349
320	$ARX(1) - IC_{w4,t-2} - G_{w4,t-2} - SA$	0.0263	129	0.0410	119	0.1059	130	2.922***	1.683*	1.965**	3.455***	1.544	1.865*
321	$ARX(1) - IC_{t-2} - G_{t-2} - SA$	0.0230	69	0.0305	45	0.0723	53	2.324**	1.403	1.994**	2.961***	1.469	2.492**
322	$ARX(1) - IC_{w1,t-2} \dots IC_{w4,t-2} - G_{w1,t-2} \dots G_{w4,t-2} - SA$	0.0724	515	0.1387	491	0.3758	503	3.415***	1.454	1.124	3.347***	1.393	1.028
323	$ARX(2) - G_{w1,t}$	0.0285	169	0.0493	170	0.1069	135	1.859*	0.974	1.062	1.959*	0.939	0.924
324	$ARX(2) - G_{w2,t}$	0.0209	37	0.0458	151	0.1596	212	1.336	0.924	0.614	1.863*	0.834	0.638
325	$ARX(2) - G_{w3,t}$	0.0225	59	0.0344	72	0.0895	90	1.664*	1.980**	1.528	2.215**	2.041**	1.856*
326	$ARX(2) - G_{w4,t}$	0.0199	23	0.0301	41	0.0579	26	1.282	1.498	1.145	2.131**	1.682*	1.487
327	$ARX(2) - G_t$	0.0172	3	0.0172	4	0.0372	2	0.448	0.633	0.230	1.063	0.864	0.793
328	$ARX(2) - G_{w1,t} - SA$	0.0298	193	0.0504	176	0.1065	133	2.871***	1.094	1.295	2.869***	1.019	1.101
329	$ARX(2) - G_{w2,t} - SA$	0.0247	93	0.0484	167	0.1810	250	1.754*	0.891	0.577	1.659*	0.772	0.584
330	$ARX(2) - G_{w3,t} - SA$	0.0257	112	0.0400	108	0.0945	101	2.087**	2.227**	1.621	2.574**	2.160**	2.002**
331	$ARX(2) - G_{w4,t} - SA$	0.0212	41	0.0299	40	0.0571	25	1.643	1.374	1.027	2.386**	1.621	1.271
332	$ARX(2) - G_t - SA$	0.0193	16	0.0194	7	0.0379	3	1.135	0.955	0.244	1.538	1.192	0.671
333	$ARX(2) - IC_{w1,t} - G_{w1,t}$	0.0276	152	0.0483	166	0.1120	152	2.265**	1.668*	1.096	3.211***	1.448	1.123
334	$ARX(2) - IC_{w2,t} - G_{w2,t}$	0.0207	34	0.0412	123	0.1040	123	1.201	1.346	1.061	2.970***	1.301	1.188
335	$ARX(2) - IC_{w3,t} - G_{w3,t}$	0.0251	99	0.0403	112	0.1183	162	1.762*	2.163**	1.564	2.415**	2.101**	1.619
336	$ARX(2) - IC_{w4,t} - G_{w4,t}$	0.0198	21	0.0327	61	0.0752	59	0.848	1.743*	1.059	1.985**	1.526	1.185
337	$ARX(2) - IC_t - G_t$	0.0191	13	0.0253	21	0.0646	38	0.799	1.301	0.727	1.875*	1.063	0.807
338	$ARX(2) - IC_{w1,t} \dots IC_{w4,t} - G_{w1,t} \dots G_{w4,t}$	0.0222	52	0.0318	55	0.1082	140	1.036	1.220	1.606	1.822*	1.652*	1.834*
339	$ARX(2) - IC_{w1,t} - G_{w1,t} - SA$	0.0285	167	0.0457	149	0.1071	137	2.404**	1.934*	1.297	3.018***	1.775*	1.335
340	$ARX(2) - IC_{w2,t} - G_{w2,t} - SA$	0.0224	56	0.0463	155	0.1061	131	1.719*	1.313	1.078	2.816***	1.180	1.188
341	$ARX(2) - IC_{w3,t} - G_{w3,t} - SA$	0.0256	109	0.0387	99	0.1086	144	1.834*	2.228**	1.468	2.386**	2.192**	1.545
342	$ARX(2) - IC_{w4,t} - G_{w4,t} - SA$	0.0210	38	0.0356	80	0.0759	60	1.077	1.338	0.877	2.280**	1.179	0.919
343	$ARX(2) - IC_t - G_t - SA$	0.0192	14	0.0206	8	0.0528	16	0.870	1.150	0.659	1.550	1.285	0.811
344	$ARX(2) - IC_{w1,t} \dots IC_{w4,t} - G_{w1,t} \dots G_{w4,t} - SA$	0.0248	96	0.0334	65	0.1160	159	1.420	1.162	1.697*	2.109**	1.631	1.999**
345	$ARX(2) - G_{w1,t-1}$	0.0301	200	0.0508	178	0.1147	156	1.902*	1.101	1.208	2.068**	1.029	0.985
346	$ARX(2) - G_{w2,t-1}$	0.0356	318	0.1006	433	0.3447	486	1.220	0.667	0.536	1.243	0.608	0.510
347	$ARX(2) - G_{w3,t-1}$	0.0251	100	0.0358	81	0.0949	102	1.928*	1.335	1.057	1.861*	1.119	1.088

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Table 16 − continued

	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-St	2-St	3-St	HLN 1-St	2-St	3-St
348	$ARX(2) - G_{w4,t-1}$	0.0243	86	0.0394	105	0.0772	65	2.542**	1.793*	1.406	2.970***	1.694*	1.674*
349	$ARX(2) - G_{t-1}$	0.0196	18	0.0222	13	0.0488	11	1.767*	1.915*	1.164	2.217**	2.024**	1.300
350	$ARX(2) - G_{w1,t-1} - SA$	0.0311	219	0.0531	187	0.1175	161	2.679***	1.275	1.479	2.791***	1.150	1.222
351	$ARX(2) - G_{w2,t-1} - SA$	0.0442	451	0.1102	466	0.3973	514	1.226	0.646	0.520	1.177	0.583	0.489
352	$ARX(2) - G_{w3,t-1} - SA$	0.0297	191	0.0434	135	0.1079	139	2.131**	1.268	0.997	1.943*	1.036	0.968
353	$ARX(2) - G_{w4,t-1} - SA$	0.0263	130	0.0417	124	0.0794	70	2.455**	1.656*	1.295	2.734***	1.542	1.427
354	$ARX(2) - G_{t-1} - SA$	0.0213	44	0.0242	18	0.0495	12	1.746*	1.859*	1.115	2.080**	1.994**	1.440
355	$ARX(2) - IC_{w1,t-1} - G_{w1,t-1}$	0.0349	297	0.0717	251	0.1794	246	2.422**	1.695*	0.978	2.925***	1.411	0.947
356	$ARX(2) - IC_{w2,t-1} - G_{w2,t-1}$	0.0280	160	0.0661	225	0.1916	285	2.024**	1.300	0.871	2.465**	1.126	0.824
357	$ARX(2) - IC_{w3,t-1} - G_{w3,t-1}$	0.0261	121	0.0353	76	0.0969	107	2.224**	1.309	1.097	2.064**	1.086	1.095
358	$ARX(2) - IC_{w4,t-1} - G_{w4,t-1}$	0.0239	78	0.0386	97	0.0838	77	2.154**	1.666*	1.652*	2.592***	1.533	1.703*
359	$ARX(2) - IC_{t-1} - G_{t-1}$	0.0213	45	0.0255	24	0.0615	32	2.089**	2.322**	1.515	2.556**	2.429**	1.671*
360	$ARX(2) - IC_{w1,t-1} \ldots IC_{w4,t-1} - G_{w1,t-1} \ldots G_{w4,t-1}$	0.0286	170	0.0551	192	0.1536	207	1.928*	1.715*	1.634	2.614***	1.572	1.331
361	$ARX(2) - IC_{w1,t-1} - G_{w1,t-1} - SA$	0.0332	265	0.0594	206	0.1515	204	2.295**	2.180**	1.252	2.581***	1.958*	1.244
362	$ARX(2) - IC_{w2,t-1} - G_{w2,t-1} - SA$	0.0348	293	0.0821	312	0.2496	421	2.004**	1.180	0.764	2.052**	0.993	0.699
363	$ARX(2) - IC_{w3,t-1} - G_{w3,t-1} - SA$	0.0325	253	0.0458	150	0.1144	155	2.442**	1.351	1.080	2.281**	1.141	1.088
364	$ARX(2) - IC_{w4,t-1} - G_{w4,t-1} - SA$	0.0272	142	0.0403	113	0.0874	84	3.030***	1.566	1.602	3.288***	1.448	1.490
365	$ARX(2) - IC_{t-1} - G_{t-1} - SA$	0.0241	80	0.0258	25	0.0548	18	2.210**	1.839*	1.275	2.568**	1.876*	1.658*
366	$ARX(2) - IC_{w1,t-1} \ldots IC_{w4,t-1} - G_{w1,t-1} \ldots G_{w4,t-1} - SA$	0.0358	334	0.0593	205	0.1656	224	2.450**	1.574	1.495	2.934***	1.486	1.234
367	$ARX(2) - G_{w1,t-2}$	0.0271	141	0.0379	91	0.0890	89	1.793*	1.518	1.691*	2.342**	1.528	1.498
368	$ARX(2) - G_{w2,t-2}$	0.0514	497	0.0569	197	0.1492	203	1.641	0.966	0.983	1.663*	0.991	1.000
369	$ARX(2) - G_{w3,t-2}$	0.0246	92	0.0431	133	0.1157	158	2.230**	1.776*	1.425	2.892***	1.490	1.391
370	$ARX(2) - G_{w4,t-2}$	0.0226	60	0.0380	92	0.0770	64	1.913*	1.759*	1.468	2.531**	1.640	1.730*
371	$ARX(2) - G_{t-2}$	0.0181	7	0.0234	16	0.0556	21	0.614	2.035**	1.772*	1.642	2.279**	1.654*
372	$ARX(2) - G_{w1,t-2} - SA$	0.0290	177	0.0362	84	0.0866	83	2.440**	1.532	1.629	2.786***	1.428	1.592
373	$ARX(2) - G_{w2,t-2} - SA$	0.0392	408	0.0846	332	0.2383	408	1.325	0.995	0.763	1.293	0.910	0.717
374	$ARX(2) - G_{w3,t-2} - SA$	0.0297	192	0.0509	179	0.1337	187	2.716***	1.574	1.308	2.636***	1.308	1.230
375	$ARX(2) - G_{w4,t-2} - SA$	0.0251	101	0.0425	128	0.0841	78	2.408**	1.873*	1.532	2.791***	1.722*	1.682*
376	$ARX(2) - G_{t-2} - SA$	0.0203	29	0.0275	30	0.0610	31	1.368	1.822*	2.080**	2.293**	1.963**	2.217**
377	$ARX(2) - IC_{w1,t-2} - G_{w1,t-2}$	0.0311	216	0.0536	189	0.1371	194	1.752*	1.455	0.983	2.505**	1.358	0.935
378	$ARX(2) - IC_{w2,t-2} - G_{w2,t-2}$	0.0351	302	0.0740	270	0.1925	287	1.673*	1.375	1.140	1.758*	1.365	1.104
379	$ARX(2) - IC_{w3,t-2} - G_{w3,t-2}$	0.0262	122	0.0456	148	0.1223	170	2.495**	1.810*	1.473	2.964***	1.549	1.423
380	$ARX(2) - IC_{w4,t-2} - G_{w4,t-2}$	0.0262	125	0.0423	126	0.1006	114	2.146**	1.641	1.535	2.921***	1.463	1.490
381	$ARX(2) - IC_{t-2} - G_{t-2}$	0.0203	30	0.0276	31	0.0689	49	1.236	2.189**	1.725*	2.021**	2.363**	1.864*
382	$ARX(2) - IC_{w1,t-2} \ldots IC_{w4,t-2} - G_{w1,t-2} \ldots G_{w4,t-2}$	0.0745	517	0.1626	514	0.4310	517	3.264***	1.524	1.307	2.920***	1.342	1.116
383	$ARX(2) - IC_{w1,t-2} - G_{w1,t-2} - SA$	0.0320	239	0.0469	159	0.1271	173	1.982**	1.605	1.256	2.507**	1.689*	1.275
384	$ARX(2) - IC_{w2,t-2} - G_{w2,t-2} - SA$	0.0499	491	0.1080	458	0.3107	472	1.857*	1.199	0.827	1.896*	1.080	0.747
385	$ARX(2) - IC_{w3,t-2} - G_{w3,t-2} - SA$	0.0332	264	0.0574	199	0.1428	198	2.818***	1.692*	1.349	2.791***	1.487	1.336
386	$ARX(2) - IC_{w4,t-2} - G_{w4,t-2} - SA$	0.0282	164	0.0435	136	0.1010	116	2.746***	1.608	1.858*	3.282***	1.426	1.771*
387	$ARX(2) - IC_{t-2} - G_{t-2} - SA$	0.0230	68	0.0316	54	0.0669	43	2.123**	1.715*	1.981**	3.134***	1.824*	2.458**
388	$ARX(2) - IC_{w1,t-2} \ldots IC_{w4,t-2} - G_{w1,t-2} \ldots G_{w4,t-2} - SA$	0.0809	520	0.1347	486	0.3768	507	3.711***	1.369	1.081	3.528***	1.336	0.999
389	$ARMAX(1,1) - G_{w1,t}$	0.0278	158	0.0512	182	0.1069	136	2.592***	1.748*	1.430	3.095***	1.777*	1.419
390	$ARMAX(1,1) - G_{w2,t}$	0.0299	197	0.0804	302	0.2524	428	2.611***	1.191	0.675	3.733***	1.042	0.660
391	$ARMAX(1,1) - G_{w3,t}$	0.0256	107	0.0468	158	0.1098	148	2.114**	2.283**	1.484	3.076***	2.044**	1.548
392	$ARMAX(1,1) - G_{w4,t}$	0.0245	90	0.0336	67	0.0680	44	2.522**	1.380	0.957	2.960***	1.465	1.276
393	$ARMAX(1,1) - G_{t}$	0.0216	47	0.0254	23	0.0508	13	1.906*	0.945	0.722	2.632***	1.221	1.060
394	$ARMAX(1,1) - G_{w1,t} - SA$	0.0274	144	0.0503	173	0.1035	122	2.283**	1.136	1.073	2.775***	1.160	0.929
395	$ARMAX(1,1) - G_{w2,t} - SA$	0.0365	360	0.1132	471	0.3126	473	1.487	0.730	0.610	1.689*	0.678	0.575
396	$ARMAX(1,1) - G_{w3,t} - SA$	0.0248	97	0.0342	70	0.0936	99	1.586	0.941	0.834	2.108**	0.965	0.782
397	$ARMAX(1,1) - G_{w4,t} - SA$	0.0258	116	0.0330	62	0.0624	37	2.455**	1.346	1.000	3.063***	1.656*	1.260

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Table 16 − continued

	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-St	2-St	3-St	HLN 1-St	2-St	3-St
398	$ARMAX(1,1)-G_t-SA$	0.0167	2	0.0166	3	0.0350	1	0.060	0.177	0.000	2.145**	1.219	0.000
399	$ARMAX(1,1)-IC_{w1,t}-G_{w1,t}$	0.0290	175	0.0539	190	0.1161	160	2.609***	1.956*	1.667*	3.575***	1.776*	1.465
400	$ARMAX(1,1)-IC_{w2,t}-G_{w2,t}$	0.0283	166	0.0682	234	0.1940	291	2.615***	1.195	0.759	2.963***	1.026	0.718
401	$ARMAX(1,1)-IC_{w3,t}-G_{w3,t}$	0.0276	153	0.0510	181	0.1350	189	2.042**	1.689*	1.221	2.342**	1.329	1.132
402	$ARMAX(1,1)-IC_{w4,t}-G_{w4,t}$	0.0252	102	0.0462	154	0.0958	106	1.955*	1.401	1.099	2.680***	1.291	1.063
403	$ARMAX(1,1)-IC_t-G_t$	0.0211	40	0.0270	28	0.0648	39	2.357**	1.514	1.403	3.304***	1.701*	1.709*
404	$ARMAX(1,1)-IC_{w1,t}\dots IC_{w4,t}-G_{w1,t}\dots G_{w4,t}$	0.0273	143	0.0315	53	0.1114	150	2.105**	1.059	1.604	2.792***	1.522	1.794*
405	$ARMAX(1,1)-IC_{w1,t}-G_{w1,t}-SA$	0.0351	301	0.0680	233	0.1525	205	3.467***	1.768*	1.163	4.271***	1.571	1.096
406	$ARMAX(1,1)-IC_{w2,t}-G_{w2,t}-SA$	0.0306	208	0.0708	246	0.1647	222	2.808***	1.380	1.076	2.374**	1.234	1.032
407	$ARMAX(1,1)-IC_{w3,t}-G_{w3,t}-SA$	0.0352	304	0.0620	213	0.1345	188	2.665***	1.231	1.034	2.290**	1.043	0.924
408	$ARMAX(1,1)-IC_{w4,t}-G_{w4,t}-SA$	0.0332	263	0.0574	200	0.1284	176	3.839***	1.200	0.885	3.252***	1.049	0.806
409	$ARMAX(1,1)-IC_t-G_t-SA$	0.0245	89	0.0387	98	0.0933	98	1.946*	1.055	0.703	3.247***	1.052	0.625
410	$ARMAX(1,1)-IC_{w1,t}\dots IC_{w4,t}-G_{w1,t}\dots G_{w4,t}-SA$	0.0253	103	0.0682	235	0.2129	357	1.502	2.008**	1.587	2.258**	1.813*	1.530
411	$ARMAX(1,1)-G_{w1,t-1}$	0.0287	172	0.0503	174	0.1074	138	2.655***	2.139**	1.529	3.377***	2.079**	1.513
412	$ARMAX(1,1)-G_{w2,t-1}$	0.0374	378	0.1095	463	0.3529	491	2.142**	0.935	0.654	2.119**	0.830	0.619
413	$ARMAX(1,1)-G_{w3,t-1}$	0.0276	155	0.0497	172	0.1275	174	3.022***	2.111**	1.513	4.137***	1.851*	1.540
414	$ARMAX(1,1)-G_{w4,t-1}$	0.0229	67	0.0412	122	0.0740	56	2.174**	2.103**	1.518	3.489***	2.087**	1.796*
415	$ARMAX(1,1)-G_{t-1}$	0.0214	46	0.0325	59	0.0655	41	1.624	1.518	1.224	2.989***	1.841*	1.328
416	$ARMAX(1,1)-G_{w1,t-1}-SA$	0.0314	230	0.0481	164	0.1117	151	1.989**	1.113	0.995	2.487**	1.181	0.851
417	$ARMAX(1,1)-G_{w2,t-1}-SA$	0.0342	279	0.1102	465	0.3603	495	1.417	0.761	0.582	1.638	0.703	0.543
418	$ARMAX(1,1)-G_{w3,t-1}-SA$	0.0218	49	0.0289	36	0.0926	96	1.439	0.784	0.833	2.551**	0.858	0.758
419	$ARMAX(1,1)-G_{w4,t-1}-SA$	0.0263	128	0.0326	60	0.0764	61	2.466**	1.213	1.110	2.886***	1.364	1.158
420	$ARMAX(1,1)-G_{t-1}-SA$	0.0201	27	0.0217	10	0.0570	24	1.094	0.981	0.941	2.116**	1.373	0.941
421	$ARMAX(1,1)-IC_{w1,t-1}-G_{w1,t-1}$	0.0373	375	0.0729	266	0.1738	234	3.179***	2.771***	2.018**	4.250***	2.356**	2.073**
422	$ARMAX(1,1)-IC_{w2,t-1}-G_{w2,t-1}$	0.0304	206	0.0687	238	0.1930	288	2.648***	1.282	0.915	3.131***	1.222	0.870
423	$ARMAX(1,1)-IC_{w3,t-1}-G_{w3,t-1}$	0.0302	203	0.0564	194	0.1333	186	3.842***	2.488**	1.569	4.570***	1.891*	1.429
424	$ARMAX(1,1)-IC_{w4,t-1}-G_{w4,t-1}$	0.0296	189	0.0464	156	0.0986	111	3.603***	1.794*	1.408	3.721***	1.528	1.348
425	$ARMAX(1,1)-IC_{t-1}-G_{t-1}$	0.0209	36	0.0301	42	0.0683	46	1.538	1.722*	1.960**	3.037***	1.964**	2.050**
426	$ARMAX(1,1)-IC_{w1,t-1}\dots IC_{w4,t-1}-G_{w1,t-1}\dots G_{w4,t-1}$	0.0345	286	0.0903	385	0.2649	441	2.306**	1.564	1.369	2.873***	1.382	1.160
427	$ARMAX(1,1)-IC_{w1,t-1}-G_{w1,t-1}-SA$	0.0472	477	0.0992	427	0.2256	385	2.992***	1.643	1.031	2.821***	1.390	0.972
428	$ARMAX(1,1)-IC_{w2,t-1}-G_{w2,t-1}-SA$	0.0336	272	0.0818	310	0.2280	388	2.545**	1.537	1.089	3.098***	1.386	0.996
429	$ARMAX(1,1)-IC_{w3,t-1}-G_{w3,t-1}-SA$	0.0262	123	0.0369	86	0.1023	118	1.954*	1.047	0.906	2.641***	0.962	0.796
430	$ARMAX(1,1)-IC_{w4,t-1}-G_{w4,t-1}-SA$	0.0321	242	0.0439	139	0.1027	119	2.604***	1.588	1.464	2.968***	1.574	1.399
431	$ARMAX(1,1)-IC_{t-1}-G_{t-1}-SA$	0.0270	138	0.0303	44	0.0751	58	2.262**	1.565	1.350	3.417***	1.987**	1.203
432	$ARMAX(1,1)-IC_{w1,t-1}\dots IC_{w4,t-1}-G_{w1,t-1}\dots G_{w4,t-1}-SA$	0.0688	513	0.1637	516	0.4389	518	3.489***	1.868*	1.634	3.756***	1.769*	1.457
433	$ARMAX(1,1)-G_{w1,t-2}$	0.0265	132	0.0354	78	0.0790	68	2.210**	1.766*	1.354	3.434***	1.767*	1.699*
434	$ARMAX(1,1)-G_{w2,t-2}$	0.2906	529	0.4935	529	0.7039	527	1.112	0.587	0.546	1.071	0.549	0.497
435	$ARMAX(1,1)-G_{w3,t-2}$	0.0281	161	0.0543	191	0.1423	197	3.096***	2.174**	1.895*	4.232***	2.045**	1.889*
436	$ARMAX(1,1)-G_{w4,t-2}$	0.0268	135	0.0402	111	0.0769	63	3.520***	2.182**	1.786*	4.089***	2.207**	2.011**
437	$ARMAX(1,1)-G_{t-2}$	0.0243	87	0.0285	35	0.0601	30	2.273**	1.332	1.341	3.291***	1.671*	1.637
438	$ARMAX(1,1)-G_{w1,t-2}-SA$	0.0292	182	0.0335	66	0.0834	76	2.107**	1.356	1.342	2.895***	1.778*	1.605
439	$ARMAX(1,1)-G_{w2,t-2}-SA$	0.2222	526	0.1455	498	0.2416	412	1.196	0.818	0.957	1.157	0.780	0.836
440	$ARMAX(1,1)-G_{w3,t-2}-SA$	0.0258	115	0.0405	114	0.1325	183	2.032**	1.360	1.326	2.931***	1.265	1.190
441	$ARMAX(1,1)-G_{w4,t-2}-SA$	0.0282	163	0.0408	117	0.0910	93	2.367**	1.324	1.329	2.697***	1.253	1.272
442	$ARMAX(1,1)-G_{t-2}-SA$	0.0259	118	0.0350	74	0.0850	79	1.877*	1.359	1.520	2.650***	1.322	1.346
443	$ARMAX(1,1)-IC_{w1,t-2}-G_{w1,t-2}$	0.0336	269	0.0663	227	0.1360	193	1.991**	1.698*	1.431	2.122**	1.437	1.328
444	$ARMAX(1,1)-IC_{w2,t-2}-G_{w2,t-2}$	0.0500	492	0.0915	391	0.1738	235	2.017**	1.489	1.142	2.171**	1.428	1.136
445	$ARMAX(1,1)-IC_{w3,t-2}-G_{w3,t-2}$	0.0326	254	0.0729	265	0.1711	229	3.674***	2.234**	1.741*	3.745***	1.979**	1.653*
446	$ARMAX(1,1)-IC_{w4,t-2}-G_{w4,t-2}$	0.0291	178	0.0494	171	0.1190	164	3.071***	2.359**	1.836*	3.985***	2.159**	1.748*
447	$ARMAX(1,1)-IC_{t-2}-G_{t-2}$	0.0279	159	0.0431	132	0.0951	104	3.839***	1.712*	1.809*	3.877***	1.549	1.745*

(Continued on next page)

Table 16 – continued

	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-St	2-St	3-St	HLN 1-St	2-St	3-St
448	$ARMAX(1,1) - IC_{w1,t-2} \dots IC_{w4,t-2} - G_{w1,t-2} \dots G_{w4,t-2}$	0.0715	514	0.2381	525	0.6829	525	3.275***	1.860*	1.436	3.038***	1.647*	1.269
449	$ARMAX(1,1) - IC_{w1,t-2} - G_{w1,t-2} - SA$	0.0320	240	0.0855	342	0.1986	299	2.567**	1.239	1.042	2.936***	1.246	0.950
450	$ARMAX(1,1) - IC_{w2,t-2} - G_{w2,t-2} - SA$	0.0503	495	0.1038	442	0.2927	467	2.453**	1.386	1.056	2.343**	1.277	0.936
451	$ARMAX(1,1) - IC_{w3,t-2} - G_{w3,t-2} - SA$	0.0340	277	0.0655	223	0.1850	264	2.922***	1.592	1.398	2.937***	1.241	1.189
452	$ARMAX(1,1) - IC_{w4,t-2} - G_{w4,t-2} - SA$	0.0456	469	0.0803	301	0.2051	321	3.255***	1.557	1.877*	3.234***	1.551	1.584
453	$ARMAX(1,1) - IC_{t-2} - G_{t-2} - SA$	0.0304	205	0.0410	118	0.0832	74	2.958***	1.652*	1.487	3.340***	1.695*	1.253
454	$ARMAX(1,1) - IC_{w1,t-2} \dots IC_{w4,t-2} - G_{w1,t-2} \dots G_{w4,t-2} - SA$	0.0767	519	0.2117	523	0.6219	523	3.652***	1.902*	1.402	4.032***	1.836*	1.269
455	$ARMAX(2,2) - G_{w1,t}$	0.0264	131	0.0460	153	0.1044	126	2.033**	1.782*	2.339**	2.946***	1.885*	2.094**
456	$ARMAX(2,2) - G_{w2,t}$	0.0285	168	0.0611	211	0.1899	280	2.791***	1.685*	0.861	4.592***	1.404	0.833
457	$ARMAX(2,2) - G_{w3,t}$	0.0229	65	0.0393	103	0.1058	129	1.570	2.045**	1.855*	2.736***	2.188**	1.966**
458	$ARMAX(2,2) - G_{w4,t}$	0.0199	22	0.0235	17	0.0559	23	0.636	1.083	0.989	1.200	1.190	1.341
459	$ARMAX(2,2) - G_{t}$	0.0228	64	0.0305	46	0.0689	48	1.755*	1.156	1.285	2.579***	1.248	1.416
460	$ARMAX(2,2) - G_{w1,t} - SA$	0.0234	72	0.0441	142	0.0951	103	1.502	1.524	1.636	3.091***	1.720*	1.259
461	$ARMAX(2,2) - G_{w2,t} - SA$	0.0262	124	0.0572	198	0.1883	276	1.844*	1.554	0.954	3.559***	1.437	0.899
462	$ARMAX(2,2) - G_{w3,t} - SA$	0.0217	48	0.0333	64	0.1042	124	1.262	1.405	1.611	3.006***	1.782*	1.482
463	$ARMAX(2,2) - G_{w4,t} - SA$	0.0184	9	0.0263	26	0.0599	29	0.442	1.153	0.993	2.116**	1.563	1.287
464	$ARMAX(2,2) - G_{t} - SA$	0.0179	6	0.0163	2	0.0382	5	0.312	0.136	0.295	1.370	1.291	0.579
465	$ARMAX(2,2) - IC_{w1,t} - G_{w1,t}$	0.0271	140	0.0448	145	0.1093	147	1.990**	2.095**	1.526	2.954***	1.951*	1.578
466	$ARMAX(2,2) - IC_{w2,t} - G_{w2,t}$	0.0274	145	0.0482	165	0.1467	201	2.625***	1.490	1.028	3.905***	1.387	0.985
467	$ARMAX(2,2) - IC_{w3,t} - G_{w3,t}$	0.0257	113	0.0453	146	0.1288	177	1.912*	2.191**	1.375	2.616***	1.770*	1.346
468	$ARMAX(2,2) - IC_{w4,t} - G_{w4,t}$	0.0196	17	0.0309	47	0.0727	54	0.757	1.240	1.176	1.508	1.173	1.178
469	$ARMAX(2,2) - IC_{t} - G_{t}$	0.0225	58	0.0302	43	0.0716	51	1.612	1.508	1.284	3.039***	1.240	1.375
470	$ARMAX(2,2) - IC_{w1,t} \dots IC_{w4,t} - G_{w1,t} \dots G_{w4,t}$	0.0257	110	0.0277	32	0.1006	113	1.348	0.768	1.171	2.028**	1.194	1.329
471	$ARMAX(2,2) - IC_{w1,t} - G_{w1,t} - SA$	0.0268	134	0.0569	196	0.1028	120	2.297**	1.876*	1.559	3.119***	1.479	1.527
472	$ARMAX(2,2) - IC_{w2,t} - G_{w2,t} - SA$	0.0379	384	0.0830	319	0.1818	252	2.228**	1.190	1.137	1.991**	1.081	1.092
473	$ARMAX(2,2) - IC_{w3,t} - G_{w3,t} - SA$	0.0299	195	0.0440	140	0.1327	184	1.777*	1.288	0.908	2.114**	1.224	0.819
474	$ARMAX(2,2) - IC_{w4,t} - G_{w4,t} - SA$	0.0445	453	0.0864	350	0.1605	215	1.906*	0.950	0.763	1.630	0.849	0.721
475	$ARMAX(2,2) - IC_{t} - G_{t} - SA$	0.0362	350	0.0577	201	0.0855	81	2.302**	0.861	0.604	1.849*	0.787	0.603
476	$ARMAX(2,2) - IC_{w1,t} \dots IC_{w4,t} - G_{w1,t} \dots G_{w4,t} - SA$	0.0310	214	0.0799	295	0.1950	293	2.142**	1.260	1.156	1.782*	1.117	1.051
477	$ARMAX(2,2) - G_{w1,t-1}$	0.0248	95	0.0406	115	0.0952	105	2.211**	1.770*	1.529	3.721***	1.830*	1.689*
478	$ARMAX(2,2) - G_{w2,t-1}$	0.0890	521	0.1227	481	0.5435	521	1.204	0.832	0.554	1.218	0.744	0.513
479	$ARMAX(2,2) - G_{w3,t-1}$	0.0226	61	0.0491	169	0.1306	181	1.513	2.441**	2.446**	4.997***	2.705***	2.462**
480	$ARMAX(2,2) - G_{w4,t-1}$	0.0257	111	0.0441	141	0.0896	91	1.935*	1.821*	1.745*	3.422***	1.817*	1.879*
481	$ARMAX(2,2) - G_{t-1}$	0.0208	35	0.0350	75	0.0720	52	1.219	1.631	1.590	2.677***	1.732*	1.490
482	$ARMAX(2,2) - G_{w1,t-1} - SA$	0.0270	137	0.0428	129	0.0927	97	2.689***	2.270**	1.814*	4.524***	2.047**	1.646*
483	$ARMAX(2,2) - G_{w2,t-1} - SA$	0.1080	524	0.1657	518	0.6923	526	1.266	0.744	0.572	1.225	0.668	0.516
484	$ARMAX(2,2) - G_{w3,t-1} - SA$	0.0203	28	0.0371	87	0.1249	171	0.933	1.434	1.546	3.145***	1.609	1.502
485	$ARMAX(2,2) - G_{w4,t-1} - SA$	0.0274	146	0.0376	89	0.0985	110	2.394**	1.519	1.692*	3.655***	1.659*	1.790*
486	$ARMAX(2,2) - G_{t-1} - SA$	0.0224	55	0.0242	19	0.0685	47	1.757*	1.188	1.331	3.114***	1.441	1.299
487	$ARMAX(2,2) - IC_{w1,t-1} - G_{w1,t-1}$	0.0357	325	0.0513	183	0.1330	185	1.661*	2.198**	1.796*	2.122**	1.739*	1.872*
488	$ARMAX(2,2) - IC_{w2,t-1} - G_{w2,t-1}$	0.0618	510	0.0831	320	0.3927	511	1.119	0.853	0.561	1.164	0.772	0.515
489	$ARMAX(2,2) - IC_{w3,t-1} - G_{w3,t-1}$	0.0242	85	0.0475	160	0.1260	172	1.714*	1.876*	1.934*	3.482***	1.860*	1.809*
490	$ARMAX(2,2) - IC_{w4,t-1} - G_{w4,t-1}$	0.0260	119	0.0425	127	0.1009	115	1.865*	1.968**	1.778*	2.639***	1.850*	1.749*
491	$ARMAX(2,2) - IC_{t-1} - G_{t-1}$	0.0177	4	0.0273	29	0.0620	34	0.328	1.399	1.529	1.912*	1.534	1.736*
492	$ARMAX(2,2) - IC_{w1,t-1} \dots IC_{w4,t-1} - G_{w1,t-1} \dots G_{w4,t-1}$	0.0456	468	0.0603	208	0.2532	429	1.633	1.002	0.715	1.512	0.849	0.656
493	$ARMAX(2,2) - IC_{w1,t-1} - G_{w1,t-1} - SA$	0.0413	439	0.0647	220	0.1442	199	1.875*	1.817*	1.427	2.341**	1.540	1.425
494	$ARMAX(2,2) - IC_{w2,t-1} - G_{w2,t-1} - SA$	0.0437	448	0.0847	335	0.2450	416	2.599***	1.416	0.849	2.383**	1.229	0.762
495	$ARMAX(2,2) - IC_{w3,t-1} - G_{w3,t-1} - SA$	0.0222	51	0.0400	109	0.1188	163	1.266	1.479	1.392	3.487***	1.512	1.248
496	$ARMAX(2,2) - IC_{w4,t-1} - G_{w4,t-1} - SA$	0.0276	154	0.0386	96	0.0993	112	2.277**	1.632	1.814*	3.758***	1.701*	1.920*
497	$ARMAX(2,2) - IC_{t-1} - G_{t-1} - SA$	0.0301	199	0.0407	116	0.0975	109	1.788*	1.400	1.150	2.324**	1.288	0.982

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Table 16 – continued

	Model	MSE 1-Step	Rank	2-Step	Rank	3-Step	Rank	DM 1-St	2-St	3-St	HLN 1-St	2-St	3-St
498	$ARMAX(2,2) - IC_{w1,t-1} \dots IC_{w4,t-1} - G_{w1,t-1} \dots G_{w4,t-1} - SA$	0.0629	511	0.0986	425	0.4177	515	1.846*	1.263	0.841	1.766*	1.130	0.744
499	$ARMAX(2,2) - G_{w1,t-2}$	0.0210	39	0.0366	85	0.0767	62	1.241	1.522	1.222	2.889***	1.420	1.585
500	$ARMAX(2,2) - G_{w2,t-2}$	0.2315	527	0.3639	528	0.6376	524	1.078	0.578	0.527	1.053	0.545	0.482
501	$ARMAX(2,2) - G_{w3,t-2}$	0.0229	66	0.0428	131	0.1205	168	1.633	2.339**	2.142**	3.304***	2.508**	2.210**
502	$ARMAX(2,2) - G_{w4,t-2}$	0.0258	114	0.0428	130	0.0905	92	2.445**	1.715*	1.890*	3.201***	1.602	1.884*
503	$ARMAX(2,2) - G_{t-2}$	0.0235	74	0.0341	69	0.0803	72	1.788*	1.473	1.159	2.687***	1.418	1.194
504	$ARMAX(2,2) - G_{w1,t-2} - SA$	0.0263	127	0.0378	90	0.0886	86	2.055**	1.728*	1.432	3.505***	1.758*	1.612
505	$ARMAX(2,2) - G_{w2,t-2} - SA$	0.1147	525	0.1565	511	0.5446	522	1.382	0.710	0.782	1.361	0.651	0.715
506	$ARMAX(2,2) - G_{w3,t-2} - SA$	0.0250	98	0.0393	104	0.1218	169	1.956*	1.784*	1.562	3.842***	1.718*	1.430
507	$ARMAX(2,2) - G_{w4,t-2} - SA$	0.0352	303	0.0477	161	0.1195	166	3.313***	1.313	1.728*	4.311***	1.306	1.540
508	$ARMAX(2,2) - G_{t-2} - SA$	0.0244	88	0.0360	82	0.0774	66	1.658*	1.486	1.400	3.019***	1.476	1.462
509	$ARMAX(2,2) - IC_{w1,t-2} - G_{w1,t-2}$	0.0302	202	0.0652	221	0.1355	192	2.045**	1.732*	1.205	2.573**	1.540	1.142
510	$ARMAX(2,2) - IC_{w2,t-2} - G_{w2,t-2}$	0.0539	504	0.0847	333	0.2840	460	2.002**	1.676*	0.953	1.947*	1.610	0.874
511	$ARMAX(2,2) - IC_{w3,t-2} - G_{w3,t-2}$	0.0276	150	0.0560	193	0.1540	208	2.723***	2.712***	1.901*	4.243***	2.246**	1.831*
512	$ARMAX(2,2) - IC_{w4,t-2} - G_{w4,t-2}$	0.0291	179	0.0435	137	0.1029	121	2.105**	1.647*	1.529	3.218***	1.545	1.580
513	$ARMAX(2,2) - IC_{t-2} - G_{t-2}$	0.0307	211	0.0432	134	0.0942	100	4.083***	1.970**	1.668*	4.064***	1.822*	1.694*
514	$ARMAX(2,2) - IC_{w1,t-2} \dots IC_{w4,t-2} - G_{w1,t-2} \dots G_{w4,t-2}$	0.0761	518	0.2362	524	0.7232	528	3.285***	1.705*	1.396	2.877***	1.499	1.221
515	$ARMAX(2,2) - IC_{w1,t-2} - G_{w1,t-2} - SA$	0.0278	157	0.0672	229	0.1646	221	2.076**	1.581	1.230	3.698***	1.720*	1.153
516	$ARMAX(2,2) - IC_{w2,t-2} - G_{w2,t-2} - SA$	0.0594	509	0.0969	415	0.2972	470	2.810***	1.625	1.135	2.620***	1.386	1.015
517	$ARMAX(2,2) - IC_{w3,t-2} - G_{w3,t-2} - SA$	0.0332	266	0.0744	273	0.2065	329	2.754***	1.749*	1.344	3.530***	1.529	1.172
518	$ARMAX(2,2) - IC_{w4,t-2} - G_{w4,t-2} - SA$	0.0552	505	0.0667	228	0.1718	231	2.995***	1.310	1.643	3.208***	1.329	1.356
519	$ARMAX(2,2) - IC_{t-2} - G_{t-2} - SA$	0.0363	353	0.0459	152	0.0972	108	2.973***	1.756*	1.652*	2.718***	1.796*	1.412
520	$ARMAX(2,2) - IC_{w1,t-2} \dots IC_{w4,t-2} - G_{w1,t-2} \dots G_{w4,t-2} - SA$	0.1010	523	0.2831	526	0.8950	529	3.195***	1.869*	1.583	3.299***	1.740*	1.423
	Nonlinear models												
521	$SETAR(2)$	0.0332	262	0.0388	101	0.0589	28	2.434**	1.053	0.758	2.925***	1.720*	1.447
522	$LSTAR(2)$	0.0368	366	0.0447	144	0.062	35	2.497**	1.190	0.790	3.015***	1.779*	1.411
523	$AAR(2)$	0.0342	280	0.0436	138	0.0652	40	2.337**	1.183	0.814	2.903***	1.721*	1.389
	State-level models												
524	simple avg	0.2845	528	0.3391	527	0.3966	513	5.300***	2.770***	1.992**	4.917***	2.306**	2.306**
525	labor force (LF)	0.0292	181	0.0310	48	0.0411	7	-0.133	-0.299	-1.166	2.681***	1.308	1.308
526	IU all × LF	0.0299	196	0.0314	51	0.0413	8	-0.062	-0.283	-1.161	2.746***	1.324	1.324
527	IU active × LF	0.0296	190	0.0318	56	0.0423	9	-0.091	-0.264	-1.137	2.686***	1.303	1.303
528	IU unempl. × LF	0.0298	194	0.0322	57	0.0425	10	-0.069	-0.251	-1.133	2.712***	1.312	1.312
529	IU unempl. × unempl.	0.0917	522	0.0690	242	0.0618	33	2.335**	0.648	-0.531	3.334***	1.661*	1.661*

Notes: Full sample: 1967:1-2009:6; short sample: 2004:1-2009:6. In both cases, out of sample: 2007:2-2009:6. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively.