# Forecasting the US Unemployment Rate: Another Look

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## Abstract

Twenty years ago, an eminent group of economic forecasters and statisticians published a seminal work on forecasting the US unemployment rate, certainly one of the most important economic measures of the US economy. Montgomery, Zarnowitz, Tiao, and Tsay (MZTT, 1998) reported that linear and nonlinear time series models are useful in predicting unemployment rates relatively accurately, in both short-term (one month) and medium-term (five months) prediction. One interesting and important finding was that the weekly unemployment claims were a statistically significant input in forecasting the US unemployment rate over the 1959–1993 time period. The weekly unemployment claims time series is a component of the US Leading Economic Indicators (LEI). In this paper, we replicated and extended the MZTT analysis for the 1959 to 2019 time period. We report out-of-sample, one-step to 12-step ahead monthly prediction performance of various models for the 1990-2019 period, using a no-change (random walk) model as a forecasting benchmark. Results obtained from this study include: (1) weekly unemployment claims are indeed a useful and statistically significant input in a transfer function model to forecast the unemployment rate; (2) the leading economic indicators time series is a statistically significant input in a transfer function model to forecast the unemployment rate; (3) a seasonal ARIMA (SARIMA) model outperforms the no-change benchmark for all forecasting horizons; (4) the SARIMA and transfer function models are statistically, significantly better forecasting models than a null, or no-change, forecast, particularly during the Global Financial Crisis (GFC) of 2008–2019. Improved upon MZTT, this paper provides a set of analysis that serves as an updated benchmark for comparison of forecasting methods and approaches on unemployment prediction.

## Keywords

time series forecasting, transfer function modeling, the unemployment rate

## 1 Introduction

The unemployment rate is one of the most important measures of an economy and has been extensively studied since early twentieth century. The unemployment rate has been linked to traditional business cycles (Burns and Mitchell, 1946; Harberler, 1937; Keynes, 1936; Klein, 1950; Matthews, 1959; Mitchell, 1913; Mitchell and Gay, 1927; Moore, 1961a; Persons, 1931; Samuelson, 1948; Zarnowitz, 1992). It was generally agreed that during an expansion, employment, production, prices, money, wages, interest rates, and profits are usually rising, while the reverse occurs during a contraction.

The impact of business cycle on unemployment is widely recognized. Rapid increases in the unemployment rate were often accompanied by recessions declared by the NBER business cycle committee. Thus, the unemployment rate was often studied in terms of the (traditional) business cycle. Economists have also studied Keynes's general theory of the trade cycle and unemployment, including Brunner and Meltzer (1993), Hahn and Solow (1995), Harberler (1937), Keynes (1936) and Lucas (1983), mainly considering the trade cycle as being one of under-consumption. It is noted that an important influence on employment can be a reduction in wages which is accompanied by decreases in prices and incomes, which will diminish the need for cash. Two final distinctions in the Keynesian trade cycle are theories of prolonged associated unemployment with voluntary and involuntary unemployment, which decomposed unemployment into voluntary, or frictional, unemployment, and involuntary unemployment, which is zero "when full employment" is reached, and equilibrium can exist with unemployment only with rigid wages, in the downward direction. The question of rigid wages was addressed in Hahn and Solow (1995).

Based on the Solow Growth Model (e.g., Romer (2019)) and the rational expectations-based model of Lucas (1983), the unemployment rate (over frictional unemployment) is considered a deadweight loss to society, which monetary and fiscal policies seek to eliminate. Kydland and Prescott (1982), in discussion of Real Business Cycles, argue that stocks, driven by technology advances, caused growth and effectiveness of labor. Relying on the real business cycle model, various economic models for unemployments were developed, including efficiency-wage model, the Shapiro-Stiglitz model, and the European unemployment model (e.g., Romer, 2019).

One of the most used hypotheses of unemployment over the past 50 years has been that the percentage rate of change of money wages is inversely associated with the level and the percentage rate of change in unemployment (the Phillips curve), which was empirically demonstrated in Phillips (1958) and Lipsey (1965). The expectations-augmented Phillips curve of Friedman (1968) posited that the inflation rate depends on the expected inflation and the deviation of unemployment from its natural rate. Ball *et al.* (1988) and Ball and Mazumder (2019) provided an empirical analysis of the Phillips curve. The Phillips curve analysis of Friedman (1968) introduced the concept of the natural rate of unemployment, defined as the rate of unemployment to which the economy would converge in the long run. An implication of the definition is that expansionary monetary policy would produce higher inflation, but might not be able to lower unemployment (Estrella and Mishin, 1999; Taylor, 1999).

Okun (1962) reported a negative short-run correlation between unemployment and output for the United States that has become a staple of macroeconomic textbooks. An *et al.* (2019) tested Okun's Law for 70 countries using IMF data for the 1990–2015 time period, and reported that a linear combination of Okun-based unemployment forecasts and WEO unemployment forecasts can deliver significant forecast accuracy gains for developing economies.

Economic theory indicates that an appropriate level of unemployment is the key to economic development. A high unemployment rate leads to human suffering and many other negative societal consequences, while an extremely low unemployment rate leads to an increase in labor costs and subsequent inflation. One of the certain mission of government monetary policy is to control the unemployment rate at the ideal level while controlling inflation (reference). Hence, it is vital to be able to accurately forecast the unemployment rate in the near and long term, based on the limited current information of the economy.

In this paper, we revisit the approaches used in the seminal paper of Montgomery, Zarnowitz, Tsay, and Tiao (Montgomery et al., 1998), hereafter denoted as MZTT, on forecasting US unemployment rate. Based on the monthly observations during the period 1959 to 1993, they demonstrated that time series models are useful in predicting one-month to five-month ahead unemployment rates and they compared the out-of-sample prediction performance of a range of models. More than 20 years have passed and it is useful and necessary to re-examine these models post-publication, as well as to investigate new phenomenon aroused since, including the financial crisis of 2018. We pay special attention to the relationship between US unemployment rate and the lagged US weekly unemployment claims, as well as the US Leading Economic Indicator (LEI) series constructed by The Conference Board.

Because of its importance, there is an extensive literature on forecasting unemployment rate. MZTT modeled the US unemployment rate as a function of the weekly unemployment claims time series, 1948–1993. MZTT reported that nonlinear models, such as Threshold AR models (Tong, 1990; Tong and Lim, 1980), reduced forecasting errors by as much as 28%, being more effective in periods of economic contraction and rising unemployment. The majority of the reduced forecasting error occurs in the first quarter following the forecasting origin while one-third of the forecasting error occurs in the second quarter. The transfer function modeling using unemployment claims in MZTT did not reduce the forecasting error. Thomakos and Guerard Jr. (2004) re-examined several sets of transfer function modeling sets, including the MZTT US unemployment rate, weekly unemployment claims, and LEI relationships in the 1952–1998 time period. Thomakos and Guerard reported that the leading indicator and the initial unemployment claims provided RMSE reductions of 7.6% and 8.6%, respectively, over the no-change model. The RMSE reductions were not statistically significant. The coefficients of the TF and VAR models were generally statistically significant and of the correct sign in the Thomakos and Guerard rolling regressions.

Guerard *et al.* (2020) and Vinod and Guerard (2020) studied the US real GDP and unemployment rate forecasting, and reported that an adaptive averaging autoregressive model and the adaptive learning model produced forecasts have significantly smaller root mean square errors and lower mean absolute errors than the no-change model forecasts reported in Mincer and Zarnowitz (1969) in the 1959 to 2018 time period. Guerard *et al.* (2020) used Kyriazi *et al.* (2019) adaptive learning model and AutoMetrics, the automatic time series modeling and forecasting system of Hendry and Krolzig (2005), Castle *et al.* (2013), Hendry and Doornik (2014), Castle and Hendry (2019), Doornik and Hendry (2015) with its emphasis on structural breaks. Guerard *et al.* (2020) reported that the transfer functions using LEI and weekly unemployment claims of approximately 25% relative to no-change model forecasts for the 1959-2018 time period. The RMSE and MAE were statistically significant, although the transfer function model RMSE and MAE reductions were slightly less than the adaptive learning model forecasts.

Vinod and Guerard (2020) applied the transfer function methodology and Granger-causality test based on Chen and Lee (1990) to report the casual relationship in which LEI led the US employment rate for the 1959–2018 time period, but only concurrent statistical association during the 1959–1993 time period. Several sets of regression and time series-based models have established that transfer functions with LEI and weekly unemployment claims data were highly statistically significant for modeling the MZTT unemployment rate data. The 1994 to 2018 time period was one of economic growth, despite the Global Finance Crisis of 2008–2009. This result is important because the authors did not find the MZTT result that economic contractions and rising unemployment were primarily periods of RMSE reductions.

Following MZTT, in this paper, we employ the SARIMA and transfer function modeling using the leading economic indicators and one of its components, weekly unemployment claims, to forecast the US unemployment rate. We report that the SARIMA and the LEI-based transfer function models significantly outperform the no-change (or simple random walk) models. The US unemployment rate was approaching a 60-year low during 2018. Moreover, the LEI was at an all-time high. There have been statistically significant relationships among the unemployment rate, weekly unemployment claims, and the LEI time series, reported in MZTT, Guerard *et al.* (2020), and Vinod and Guerard (2020). These time series have been addressed before, but our results are more statistically significant using more recently developed time series modeling techniques and software. The MZTT results are validated, post-publication, and additional time series modeling enhances the statistical significance of the seminal study results. Our results are very consistent with the forecasting analysis of Guerard *et al.* (2020) and Vinod and Guerard (2020).

The paper is organized as follows. In Section 2, we provide details of the data set used in the analysis. Section 3 lists the models entertained. Several other models were entertained but were found to be less desirable hence omitted here. In Section 4, we report the detailed findings. Section 5 concludes.

## 2 Data description

The composite indexes of leading (LEI), coincident, and lagging indicators produced by The Conference Board are summary statistics for the US economy. Wesley Clair Mitchell of Columbia University discussed the phases of the business cycle in 1913. Later, in 1938, with Arthur Burns, Mitchell reported 72 variables that lead business revivals, and 21 of these variables that were "trustworthy" indicators of business cycle revivals. Moore (1961b) further enhanced testing of the Mitchell and Burns trustworthy variables to become the National Bureau of Economic Research leading group, to serve as a barometer of economic activity. The leading group series was developed to turn upward before aggregate economic activity increased, and decrease before aggregate economic activity diminished. The Mitchell and Burns and Moore leading group series of variables became the Leading Economic Indicators of the National Bureau of Economic Research, see Moore (1961b) and Auerbach (1982). Historically, the cyclical turning points in the leading index have occurred before those in aggregate economic activity, cyclical turning points in the coincident index have occurred at about the same time as those in aggregate economic activity, and cyclical turning points in the lagging index generally have occurred after those in aggregate economic activity.

The Conference Board's components of the composite leading index for the year 2002 reflected the work and variables shown in Zarnowitz (1992) list, which continued work of Mitchell (1913, 1951), Mitchell and Gay (1927), Burns and Mitchell (1946), and Moore (1961a).[1] Specifically, LEI is an equally weighted index in which its components are standardized to produce constant variances. The detailed information of its components and its construction can be found at The Conference Board website.[2] The interest rate spread is based on the difference between the interest rates of 10-year Treasury bonds and the federal funds.

The monthly unemployment rate we study is from 1959/01 to 2019/12. For the transfer function modeling, we use the LEI, the monthly initial claims for unemployment (ICSA), and the interest rate spread (INT) as predictors. These four series are plotted in Figure 1.

## 3 Models and their estimated parameters

### 3.1 SARIMA Model

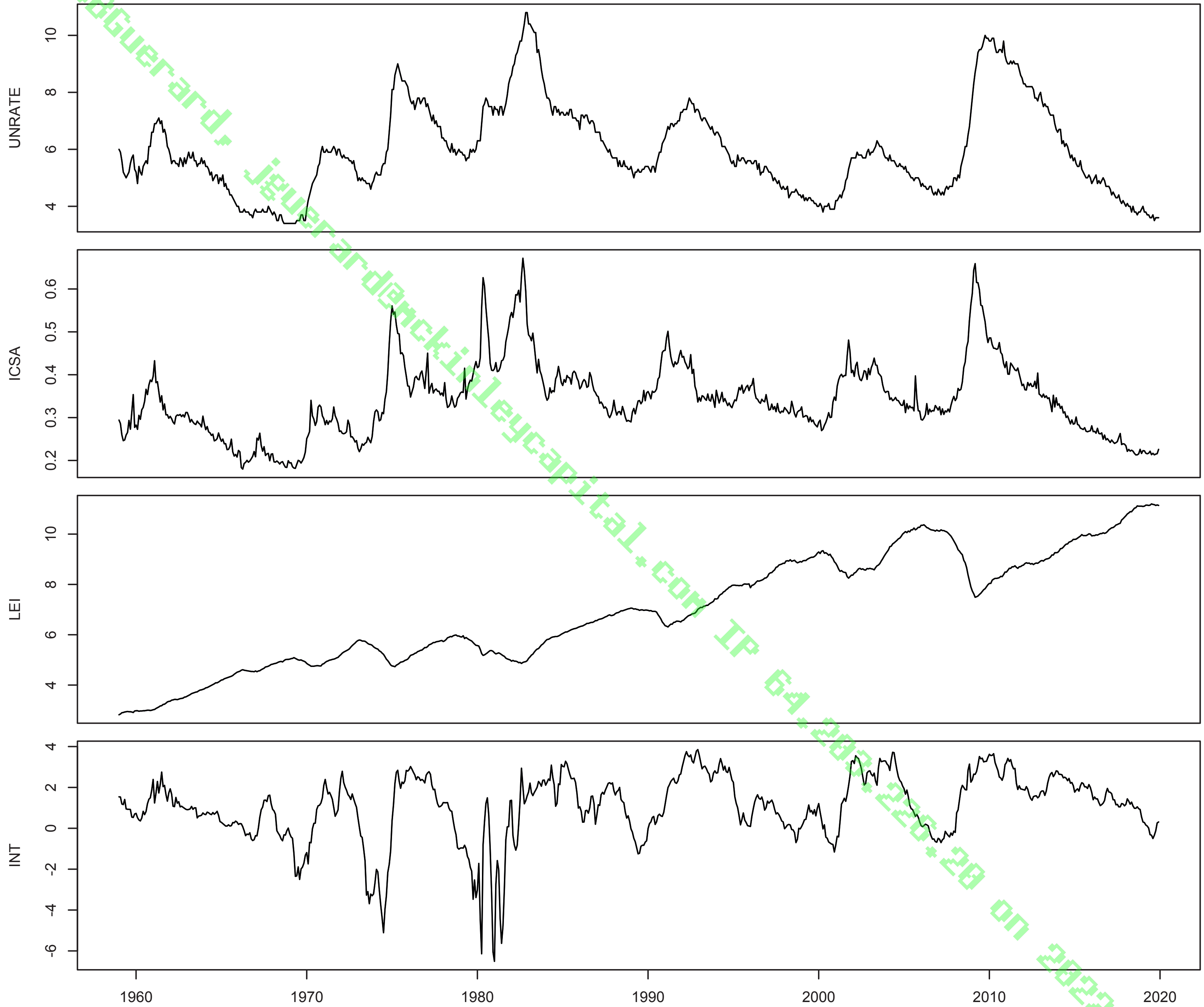
The first model we consider is th seasonal ARIMA model (Box *et al.*, 2015). It does not involve any exogenous variables. Various model selection procedures indicate that SARIMA$(2,1,2)\times(1,0,1)_{12}$ is a reasonable model. The fitted model to the whole time series is given by

$$(1-1.10B+0.19B^2)(1-0.53B^{12})\Delta x_t=(1-1.10B+0.34B^2)(1-0.80B^{12})a_t,$$

where $a_t$ are assumed to be independent and identically distributed (IID), following a normal distribution, with estimated variance 0.026. The estimated coefficients and their standard errors are given in the table below.

| Parameter | $\varphi_1$ | $\varphi_2$ | $\theta_1$ | $\theta_2$ | $\Phi_1$ | $\Theta_1$ |
|---|---|---|---|---|---|---|
| Estimate | 1.10 | −0.19 | −1.10 | 0.34 | 0.53 | −0.80 |
| SE | 0.24 | 0.23 | 0.23 | 0.19 | 0.07 | 0.05 |

**Figure 1: Monthly unemployment rate (UNRATE), initial claims (ICSA), LEI and interest rate spread (INT).**



All the coefficients except for $\phi_2$ and $\theta_2$ are highly significant. If we remove one of the two lag-2 coefficients $\phi_2$ and $\theta_2$, the other becomes highly significant. For the purpose of prediction, we choose to use the current model. Diagnostics show that the model is adequate and the residuals are white.

### 3.2 TAR Model

The second model we employ is the thresholded autoregressive (TAR) model of Tsay (1989), fitted to differenced unemployment rate $\Delta x_t$. Again, after a careful analysis and model building excises, we choose $\Delta x_{t-3}$ as the threshold variable, and use two regimes depending on whether $\Delta x_{t-3} \le c$ or not. The estimated threshold value $c$ is 0.1, indicating that the dynamic of the unempolyment rate is different, depending on whether the change of the rate three months ago is greater than 10% or not. In each regime, an AR(6) model is fitted. The estimated model is given by

$$\Delta x_t = \begin{cases} -0.08\Delta x_{t-1} + 0.20\Delta x_{t-2} + 0.12\Delta x_{t-3} \\ \quad + 0.21\Delta x_{t-4} + 0.13\Delta x_{t-5} + 0.03\Delta x_{t-6} + a_t^{(1)} & \text{when } \Delta x_{t-3} \le 0.1 \\ 0.16\Delta x_{t-1} + 0.15\Delta x_{t-2} + 0.19\Delta x_{t-3} \\ \quad + 0.07\Delta x_{t-4} - 0.10\Delta x_{t-5} + 0.04\Delta x_{t-6} + a_t^{(2)} & \text{when } \Delta x_{t-3} > 0.1 \end{cases}$$

where $a_t^{(1)}$ and $a_t^{(2)}$ are assumed to be IID Normal, with estimated variances 0.027 and 0.031, respectively. During the entire sample period, the proportion of times the process is in Regime 1 is about 0.78. The model is "self-excited" as it does not depend on exogenous variables, but changes it dynamic based on its own past.

The estimated coefficients and their standard errors are reported below.

| Lag | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| $\Delta x_{t-3} \le 0.1$ | −0.08 | 0.20 | 0.12 | 0.21 | 0.13 | 0.03 |
| SE | 0.04 | 0.04 | 0.05 | 0.04 | 0.04 | 0.04 |
| $\Delta x_{t-3} > 0.1$ | 0.16 | 0.15 | 0.19 | 0.07 | −0.10 | 0.04 |
| SE | 0.07 | 0.08 | 0.06 | 0.08 | 0.08 | 0.07 |

Most coefficients in the model are significant. We choose to use the past six months for the prediction and keep the insignificant terms in the model for simplicity. Residual analysis of the model is satisfactory. The total residual sum of squares is 19.55, comparing with 18.67 of the SARMA model, though the TAR model uses more parameters.

### 3.3 Transfer function modeling

We also consider the transfer function models (Box *et al.*, 2015) using the initial claims for unemployment (ICSA/1000, denoted by $u_t$), the leading economic index (LEI/10, difference, denoted by $v_t$), and the interest rate spread (INT/100, denoted by $z_t$). Three models are entertained, one with ICSA only, one with ICSA and LEI, and the other with all three predictors: ICSA, LEI and INT.

The selected transfer function model for $\Delta x_t$ is a SARIMA$(2,0,2)\times(1,0,1)_{12}$ with lags 1 to 6 of ICSA, which is estimated as

$$\Delta x_t = 2.02u_{t-1} + 0.09u_{t-2} - 1.43u_{t-3} - 0.50u_{t-4} + 0.51u_{t-5} - 0.68u_{t-6} + w_t,$$
$$(1 - 1.16B + 0.22B^2)(1 - 0.57B^{12})w_t = (1 - 1.35B + 0.50B^2)(1 - 0.80B^{12})a_t,$$

where $a_t$ are assumed to be IID Normal, with estimated variance 0.021. Although this model only slightly reduces the residual variance comparing to the SARIMA model in Section 3.1, at the expense of six more parameters, it outperforms SARIMA model in terms of out-sample prediction, to be reported later in Section 4. We summarize the estimated coefficients together with their standard errors in the following table.

| Coefficients of SARIMA | $\varphi_1$ | $\varphi_2$ | $\theta_1$ | $\theta_2$ | $\Phi_1$ | $\Theta_1$ |
|---|---|---|---|---|---|---|
| Estimate | 1.16 | −0.22 | −1.35 | 0.50 | 0.57 | −0.80 |
| SE | 0.13 | 0.13 | 0.12 | 0.11 | 0.08 | 0.06 |
| Coefficients of $u_{t-k}$ | 2.02 | 0.09 | −1.43 | −0.5250 | 0.51 | −0.68 |
| SE | 0.30 | 0.47 | 0.44 | 0.44 | 0.44 | 0.29 |

Most coefficients are significant at 5% level. Since the significance levels of the estimated coefficients change when different periods of data are used (for out-sample prediction excise), we keep all the terms in the model.

The estimated transfer function model of a SARIMA$(2,0,2)\times(1,0,1)_{12}$ with lags 1 to 6 of both the ICSA and the LEI is

$$\Delta x_t = 1.69u_{t-1} + 0.14u_{t-2} - 1.49u_{t-3} - 0.32u_{t-4} + 0.43u_{t-5} - 0.40u_{t-6},$$
$$-0.18v_{t-1} - 0.21v_{t-2} - 0.32v_{t-3} - 0.02v_{t-4} - 0.02v_{t-5} - 0.49v_{t-6} + w_t,$$
$$(1 - 1.04B + 0.13B^2)(1 - 0.54B^{12})w_t = (1 - 1.27B + 0.40B^2)(1 - 0.79B^{12})a_t,$$

with estimated residual variance to be 0.020. The estimated coefficients and their standard errors are reported below.

| Coefficients of SARIMA | $\varphi_1$ | $\varphi_2$ | $\theta_1$ | $\theta_2$ | $\Phi_1$ | $\Theta_1$ |
|---|---|---|---|---|---|---|
| Estimate | 1.04 | −0.13 | −1.27 | 0.40 | 0.54 | −0.79 |
| SE | 0.14 | 0.14 | 0.13 | 0.13 | 0.07 | 0.05 |
| Coefficients of $u_{t-k}$ | 1.69 | 0.14 | −1.49 | −0.32 | 0.43 | −0.40 |
| SE | 0.34 | 0.52 | 0.51 | 0.50 | 0.50 | 0.33 |
| Coefficients of $v_{t-k}$ | −0.18 | −0.21 | −0.32 | −0.02 | −0.02 | −0.49 |
| SE | 0.17 | 0.19 | 0.19 | 0.19 | 0.19 | 0.15 |

Although most coefficients of $u_{t-k}$ and $v_{t-k}$ are not significant, we still keep all the terms in the model to explore their potential for the predictions. The reader may ask if simpler models are preferred and why we report a transfer function model forecast using both ICSA and LEI variables. We do so because both ICSA and LEI bivariate models offer forecasting improvement relative to an ARIMA model of the unemployment rate, see Guerard *et al.* (2020).

The estimated transfer function model of a SARIMA$(2,0,2)\times(1,0,1)_{12}$ with lags 1 to 6 of the ICSA, LEI and INT is

$$
\begin{aligned}
\Delta x_t = &\ 1.58u_{t-1} + 0.21u_{t-2} - 1.60u_{t-3} - 0.28u_{t-4} + 0.46u_{t-5} - 0.32u_{t-6},\\
&- 0.11v_{t-1} - 0.31v_{t-2} - 0.42v_{t-3} + 0.04v_{t-4} + 0.02v_{t-5} - 0.40v_{t-6}\\
&- 1.20z_{t-1} - 0.19z_{t-2} + 5.68z_{t-3} - 5.71z_{t-4} + 0.58z_{t-5} + 0.13z_{t-6} + w_t,\\
(1 - 0.99B + 0.08B^2)&(1 - 0.53B^{12})w_t = (1 - 1.21B + 0.35B^2)(1 - 0.81B^{12})a_t,
\end{aligned}
$$

with estimated residual variance to be 0.020. The estimated coefficients and their standard errors are reported below.

| Coefficients of SARIMA | $\varphi_1$ | $\varphi_2$ | $\theta_1$ | $\theta_2$ | $\Phi_1$ | $\Theta_1$ |
|---|---|---|---|---|---|---|
| Estimate | 0.99 | −0.08 | −1.21 | 0.35 | 0.53 | −0.81 |
| SE | 0.15 | 0.15 | 0.14 | 0.14 | 0.07 | 0.05 |
| Coefficients of $u_{t-k}$ | 1.58 | 0.21 | −1.60 | −0.28 | 0.46 | −0.32 |
| SE | 0.35 | 0.52 | 0.50 | 0.48 | 0.48 | 0.33 |
| Coefficients of $v_{t-k}$ | −0.11 | −0.31 | −0.42 | 0.04 | 0.02 | −0.40 |
| SE | 0.17 | 0.18 | 0.19 | 0.18 | 0.18 | 0.16 |
| Coefficients of $z_{t-k}$ | −1.20 | −0.19 | 5.68 | −5.71 | 0.58 | 0.13 |
| SE | 1.14 | 1.95 | 2.09 | 2.10 | 2.00 | 1.16 |

Although most coefficients of $u_{t-k}$, $v_{t-k}$ and $z_{t-k}$ are not significant, we still keep all the terms in the model to explore their potential for the predictions.

## 4 Out-sample rolling forecast performance

We compare the rolling forecast performances of the models considered in Section 2. The predictions are made for the change of the unemployment rate, i.e., for the differenced series $\Delta x_t$. A null model which always predicts the unemployment rate change as 0 is also included as a benchmark. Specifically, the following methods/models are compared.

I. Null. Always predict $\Delta x_t$ as 0.
II. SARIMA$(2,0,2)\times(1,0,1)_{12}$ for $\Delta x_t$, as given in Section 3.1.
III. TAR. The two regime TAR model in Section 3.2.
IV. Transfer-1. SARIMA$(2,0,2)\times(1,0,1)_{12}$ and lagged ICSA, in Section 3.3.
V. Transfer-2. SARIMA$(2,0,2)\times(1,0,1)_{12}$, lagged ICSA and LEI, in Section 3.3.
VI. Transfer-3. SARIMA$(2,0,2)\times(1,0,1)_{12}$, lagged ICSA, LEI, and INT, in Section 3.3.
VII. Random forest, using lagged differences of the UNRATE, lagged ICSA, LEI, and INT.
VIII. Average. The average of the predictions given by II–VI.

For models I and II, it is straightforward to predict with an arbitrary horizon. For the TAR model in III, one-step to three-step prediction can be done using the estimated model in the regime that $\Delta x_{t+h-3}$ indicates, where $h$ is the prediction horizon. For longer prediction horizon, we use simulation procedure, based on the estimated innovation distribution. For the transfer function models IV, V and VI, using the model specified in Section 3.3 would require the knowledge of future ICSA and LEI values, or require a separate accurate prediction method for ICSA and LEI. To mitigate the difficulty, we make the following modifications. If $1 \le h \le 6$, we fit a model with only lag-$h$ to lag-6 ICSA and LEI in the model, and use this model to make a $h$-step-ahead prediction. If $7 \le h \le 12$, we fit a model with only the lag-$h$ indicator in the model, and then make a $h$-step-ahead forecast using this model. We also compare with the random forest prediction, using the lagged differences of the UNRATE, and the lagged ICSA, LEI, and INT as the predictors. The way these predictors enter the model is similar to the transfer function models.

The rolling forecast are performed from January 1990 to December 2019. Specifically, for every month during the period, we use the available data before that month to estimate the models, then perform 1-step ahead to 12-step ahead prediction, and compare with the observed values. We report in Table 1 the mean squared forecast errors for every five years, as well as the mean squared errors for the 30 years together. We also use a one-sided paired $t$ test to compare the absolute forecast errors generated by each pair of two models. In Table 2, a small $p$-value, denoted by "1" or "2", indicates that the method indexed by the row performs better than the one indexed by the column based on the one-sided test at 10% or 5% level, respectively. For example, in the first cell of 4-th row (Transfer-1), the three "2" indicates that the Transfer-1 significantly outperforms the Null model in terms of 1, 2 and 5 steps ahead predictions, at 5% level, and the one "1" means that it outperforms the Null model for the 2-step head forecasts at 10% level. The rest four "-" suggests that the Transfer-1 is not significantly better than the Null model in performing forecasts of the corresponding horizons. Note that Table 2 could have been reported as a "tournament" table giving the competition results (win/loss/tie) of different models. However, to simplify the symbols, we choose to indicate only when one model wins over the other, which contains the same information as the "tournament" table. In the literature, the Diebold-Mariano test (Diebold and Mariano, 2002) has been commonly used to compare the predictive accuracy. We choose to use the paired $t$-test here for the purpose of making the one-sided comparison.

From Table 1, it is seen that among models/methods I–V, the ICSA transfer functions produce the smallest 1-step forecasting errors, with forecasting MSE reductions of 28.9% comparing to the no-change model, during the 1990–2019 time periods. The 1-step error reduction is consistent with the RMSE results. The 1-step MSE error reductions of Transfer-1 are 10.2% and 18.1%, with the SARIMA and TAR models, respectively. Policy makers do not often call a recession until they are at least halfway over (Zarnowitz and Moore, 1992). The average recession, most often accompanied with rising unemployment, has lasted 10.3 months during the 1945–2020 time period.[3] The three-month, four-month, and six-month MSE reductions with the null model, often exceeding 15% for the SARIMA, three transfer function models, and the average forecast, are large reductions within periods less than halfway through a recession. Policy makers have time for data analysis and policy adjustments. The Transfer-2 (with both ICSA and LEI) tends to predict better with horizon 5 and 6. It seems the random forest method is not as competitive for the prediction of the unemployment rate. The difficult period to predict is P4 (05-09), which includes the subprime financial crisis period. We observe that Transfer-2 has the best prediction performance over this period for almost 10 all horizons except for the 12-step forecasts. The Transfer-3 model, incorporating in addition the interest rate spread, an LEI component, produced large transfer function MSE reductions in the three-month, four-month, and six-month P4 periods. The levels and change in short-term and long-term interest rate variable was documented in Friedman (1986). We also compare the mean absolute prediction error (MAE), and report the results in Table 3, which is in the Appendix. Similar conclusions can be drawn based on MAE.

We report in Table 2 that the weekly unemployment claims transfer function (Transfer-1) produces the smallest forecasting errors with the one-month to four-month forecasting horizons than all other models, including the no-change models, consistent with the Guerard *et al.* (2020) results. The SARIMA model reduces forecasting errors relative to the no-change models. We substantiate the TAR model reductions reported in the seminal MZTT study, although the TAR model does not dominate the transfer function models on forecasting effectiveness.

We also observe that method VIII (by taking the average of the predictions given by II–VI) leads to the smallest forecast errors, for one-month to five-month horizons. The statistically significant forecast enhancements of the composite models in the six-step-ahead forecast gives researchers a reasonable period to implement the forecasting models. The dominance of the composite forecasting model performance is consistent with the Madridakis forecasting competitions of the past 38 years. The forecasting literature has an extensive literature reporting that the average forecast is the better forecast out of sample, see Bates and Granger (1969), Clemen (1989), Makridakis and Hibon (1979) and the summary results from the M-forecasting competitions (Makridakis *et al.*, 1982, 1993), Makridakis and Hibon (2000), Makridakis *et al.* (2020). When the horizons are larger than six months, it is harder to make significantly better predictions than the no-change model, indicating the non-predictability at large horizons.

**Table 1: Mean squared rolling forecase error (MSE) ($\times 10^2$) by five-year periods. The first row gives the MSE of the Null model. The rest of the table should be understood as a $4 \times 2$ block matrix, corresponding to 1, 2, 3, 4, 5, 6, 9 and 12-step ahead forecasts, respectively. In particular, the top two blocks are for 1-step and 2-step predictions, and the rest are self-evident. For each of the eight blocks, the rows correspond to models, and the columns P1 to P6 the five-year periods: 90–94, 95–99, 00–04, 05–09, 10–14, 15–19, respectively. The column "All" gives the MSE over all 30 years.**

| | P1 | P2 | P3 | P4 | P5 | P6 | All | P1 | P2 | P3 | P4 | P5 | P6 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **One Step Ahead** | | | | | | | **Two Step Ahead** | | | | | | |
| I | 2.00 | 1.95 | 1.72 | 4.02 | 2.88 | 1.55 | 2.35 | | | | | | | |
| II | 1.56 | 2.09 | 1.38 | 2.29 | 2.34 | 1.51 | 1.86 | 1.56 | 2.06 | 1.38 | 2.32 | 2.33 | 1.50 | 1.86 |
| III | 1.89 | 1.95 | 1.52 | 2.43 | 2.95 | 1.53 | 2.04 | 1.88 | 2.04 | 1.59 | 2.67 | 2.96 | 1.56 | 2.12 |
| IV | 1.67 | 1.78 | 1.24 | 1.96 | 2.05 | 1.31 | 1.67 | 1.62 | 2.02 | 1.26 | 2.01 | 2.03 | 1.43 | 1.73 |
| V | 2.08 | 1.87 | 1.50 | 1.77 | 2.38 | 1.20 | 1.80 | 1.91 | 2.13 | 1.40 | 1.66 | 2.48 | 1.44 | 1.83 |
| VI | 1.89 | 1.68 | 1.71 | 1.74 | 2.07 | 1.29 | 1.73 | 1.64 | 1.88 | 1.64 | 1.72 | 2.31 | 1.40 | 1.77 |
| VII | 1.78 | 2.00 | 1.36 | 1.76 | 2.68 | 1.37 | 1.82 | 1.82 | 1.99 | 1.34 | 2.07 | 2.78 | 1.47 | 1.91 |
| VIII | 1.60 | 1.74 | 1.21 | 1.68 | 2.24 | 1.30 | 1.63 | 1.53 | 1.88 | 1.25 | 1.76 | 2.32 | 1.40 | 1.69 |
| | **Three Step Ahead** | | | | | | | **Four Step Ahead** | | | | | | |
| II | 1.50 | 2.05 | 1.39 | 2.66 | 2.22 | 1.50 | 1.88 | 1.58 | 2.16 | 1.41 | 2.86 | 2.12 | 1.47 | 1.93 |
| III | 1.74 | 2.07 | 1.61 | 2.95 | 2.86 | 1.52 | 2.13 | 1.80 | 2.13 | 1.67 | 3.19 | 2.78 | 1.49 | 2.18 |
| IV | 1.51 | 2.09 | 1.41 | 2.53 | 2.22 | 1.47 | 1.87 | 1.60 | 2.22 | 1.43 | 2.85 | 2.17 | 1.43 | 1.95 |
| V | 1.89 | 2.19 | 1.59 | 1.68 | 2.59 | 1.48 | 1.90 | 1.90 | 2.59 | 1.63 | 1.96 | 2.59 | 1.63 | 2.05 |
| VI | 1.75 | 2.07 | 1.65 | 1.80 | 2.40 | 1.46 | 1.85 | 1.92 | 2.45 | 1.73 | 2.73 | 2.08 | 1.48 | 2.07 |
| VII | 1.89 | 2.16 | 1.62 | 2.67 | 2.83 | 1.53 | 2.12 | 2.02 | 2.14 | 1.69 | 3.01 | 2.88 | 1.54 | 2.21 |
| VIII | 1.47 | 1.97 | 1.33 | 2.07 | 2.38 | 1.44 | 1.77 | 1.53 | 2.17 | 1.40 | 2.50 | 2.26 | 1.46 | 1.89 |
| | **Five Step Ahead** | | | | | | | **Six Step Ahead** | | | | | | |
| II | 1.61 | 2.09 | 1.38 | 3.01 | 2.12 | 1.57 | 1.96 | 1.62 | 2.06 | 1.40 | 3.32 | 2.21 | 1.53 | 2.02 |
| III | 1.86 | 2.04 | 1.58 | 3.31 | 2.75 | 1.56 | 2.19 | 1.88 | 2.01 | 1.63 | 3.45 | 2.86 | 1.55 | 2.23 |
| IV | 1.63 | 2.11 | 1.39 | 2.97 | 2.18 | 1.57 | 1.97 | 1.65 | 2.07 | 1.41 | 3.31 | 2.25 | 1.56 | 2.04 |
| V | 1.69 | 2.06 | 1.32 | 2.19 | 2.33 | 1.59 | 1.87 | 1.51 | 1.94 | 1.32 | 2.71 | 2.28 | 1.53 | 1.88 |
| VI | 1.90 | 2.10 | 1.66 | 3.08 | 2.15 | 1.52 | 2.07 | 1.82 | 2.04 | 1.55 | 3.35 | 2.14 | 1.40 | 2.05 |
| VII | 2.00 | 2.24 | 1.66 | 3.12 | 2.82 | 1.58 | 2.24 | 2.10 | 2.31 | 1.89 | 2.93 | 2.88 | 1.59 | 2.28 |
| VIII | 1.54 | 1.99 | 1.34 | 2.79 | 2.22 | 1.53 | 1.90 | 1.55 | 1.96 | 1.36 | 3.15 | 2.27 | 1.48 | 1.96 |
| | **Nine Step Ahead** | | | | | | | **Twelve Step Ahead** | | | | | | |
| II | 1.70 | 2.09 | 1.47 | 3.74 | 2.21 | 1.58 | 2.13 | 1.71 | 2.13 | 1.45 | 3.99 | 2.32 | 1.70 | 2.22 |
| III | 2.01 | 1.92 | 1.69 | 3.81 | 2.94 | 1.53 | 2.32 | 2.02 | 1.95 | 1.70 | 3.90 | 3.02 | 1.65 | 2.37 |
| IV | 1.75 | 2.10 | 1.50 | 3.81 | 2.24 | 1.65 | 2.17 | 1.76 | 2.12 | 1.48 | 4.10 | 2.35 | 1.73 | 2.26 |
| V | 1.63 | 2.16 | 1.38 | 3.08 | 2.36 | 1.56 | 2.03 | 1.72 | 2.12 | 1.49 | 4.16 | 2.35 | 1.74 | 2.26 |
| VI | 1.66 | 2.20 | 1.44 | 3.35 | 2.16 | 1.43 | 2.04 | 1.68 | 2.11 | 1.51 | 4.51 | 2.27 | 1.60 | 2.28 |
| VII | 2.20 | 2.20 | 1.93 | 3.53 | 3.20 | 1.72 | 2.46 | 2.04 | 2.46 | 1.78 | 3.84 | 2.69 | 1.37 | 2.36 |
| VIII | 1.65 | 2.02 | 1.41 | 3.49 | 2.30 | 1.52 | 2.06 | 1.72 | 2.04 | 1.49 | 4.08 | 2.41 | 1.66 | 2.23 |

**Table 2: Comparing the absolute forecast errors by paired *t* tests. "2" and "1" stand for a *p*-value less than or equal to 0.05 and 0.10, respectively, and indicates that the row method is better than the column method in terms of absolute forecast errors. "–" stands for a *p*-value larger than 0.1. For each pairwise competition, there are 8 "–", "1" and/or "2", corresponding to 1, 2, 3, 4, 5, 6, 9, 12-step ahead forecasts, respectively.**

| | Null | SARIMA | TAR | Transfer-1 | Transfer-2 | Transfer-3 | Average |
|---|---|---|---|---|---|---|---|
| **Null** | | –––––––– | ––––––22 | –––––––– | –––––––– | –––––––– | –––––––– |
| **SARIMA** | 11112––– | | 2222221– | –––––122 | –––1–––2 | –––21––– | –––––––– |
| **TAR** | –––––––– | –––––––– | | –––––––– | –––––––– | –––––––– | –––––––– |
| **Transfer-1** | 221–2––– | 2––––––– | 222222–– | | –––1–––– | –––21––– | –––––––– |
| **Transfer-2** | ––––22–– | –––––2–– | –1––222– | –––––21– | | ––––21–– | –––––––– |
| **Transfer-3** | 1–––––1– | ––––––1– | 222––12– | ––––––2– | ––1––––– | | –––––––– |
| **Average** | 2222222– | 222–122– | 2222222– | ––2–1222 | 2222–––2 | 1––22––– | |

**Table 3: Empirical coverage probabilities of the 95% prediction intervals. The prediction intervals are constructed for the rolling forecasts from January 1990 to December 2019. The second row for each method reports the average width of the prediction intervals.**

| | 1-step | 2-step | 3-step | 4-step | 5-step | 6-step | 9-step | 12-step |
|---|---|---|---|---|---|---|---|---|
| **Null** | 0.975 | 0.975 | 0.975 | 0.975 | 0.975 | 0.975 | 0.972 | 0.972 |
| | 0.707 | 0.707 | 0.708 | 0.708 | 0.709 | 0.709 | 0.711 | 0.712 |
| **SARIMA** | 0.981 | 0.981 | 0.975 | 0.978 | 0.975 | 0.967 | 0.967 | 0.967 |
| | 0.658 | 0.659 | 0.672 | 0.678 | 0.684 | 0.688 | 0.697 | 0.701 |
| **TAR** | 0.969 | 0.972 | 0.967 | 0.972 | 0.967 | 0.967 | 0.967 | 0.964 |
| | 0.679 | 0.679 | 0.694 | 0.711 | 0.724 | 0.729 | 0.737 | 0.741 |
| **Transfer 1** | 0.978 | 0.981 | 0.975 | 0.978 | 0.975 | 0.967 | 0.967 | 0.967 |
| | 0.600 | 0.624 | 0.655 | 0.669 | 0.677 | 0.682 | 0.693 | 0.697 |
| **Transfer 2** | 0.969 | 0.986 | 0.978 | 0.978 | 0.978 | 0.978 | 0.969 | 0.967 |
| | 0.584 | 0.609 | 0.631 | 0.642 | 0.657 | 0.667 | 0.676 | 0.695 |
| **Transfer-3** | 0.978 | 0.981 | 0.978 | 0.978 | 0.969 | 0.967 | 0.969 | 0.961 |
| | 0.575 | 0.595 | 0.625 | 0.637 | 0.642 | 0.651 | 0.660 | 0.677 |

We also report in Table 3 the empirical coverage probabilities of the 95% prediction intervals corresponding to each of the first six methods, as well as the average length of the prediction intervals given by each method. More details of the tables are provided in the captions. It can be seen that the empirical coverage of the prediction interval is slightly higher than the designed coverage of 95%, showing the estimated prediction variance is larger than the truth. On the other hand, the prediction interval length is less than 0.7% (or $\pm 0.35\%$) for the transfer function models, showing that the out-of-sample predictions are quite accurate. The interval length would be smaller if we set the empirical coverage to 95%.

## 5 Conclusion and suggestions for future research

In this study, we study the performance of a seasonal ARIMA model, a threshold AR model, a transfer function model using ISCA along, a second transfer function model using both ICSA and LEI, and another transfer function model using ICSA, LEI and INT, for the purpose of forecasting the US unemployment rate during the 1959–2019 time period. We report additional statistically significant association regarding the relationship among transfer functions and average forecast models in the 1-step to 6-step ahead forecasts during the 1990–2019 time period. We replicate the seminal study of MZTT and extend the analysis to cover a much longer and post-publication period. It serves as an updated benchmark analysis from that offered by MZTT. Moreover, the statistical models produce lower relative errors in the Global Financial Crisis and its aftermath time period, 2008–2019. That is, the average recession, most often accompanied with rising unemployment, lasted 10.3 months during the 1945–2020 time period. The SARIMA, three transfer function models, and the average models substantially reduce the forecasting errors relative to a no-change model for three months, four months, and six months during this period. Policy makers have time for data analysis and policy adjustments. In summary, we report on the statistically significant impact of the LEI and weekly unemployment claims time series on the unemployment rate series. The MZTT variable relationships are confirmed, in-sample, and post-publication. The unemployment rate was at a 50-year low at the time we estimated our LEI and unemployment rate analysis. It will be interesting, at the end of the pandemic, to examine the relationship between the LEI and its components and the unemployment rate.

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## Endnotes

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1. Geoffrey Moore passed in 2000. Pami Dua edited a collection of papers to honor Moore, entitled *Business Cycles and Economic Growth* (Oxford University Press, New York). The reader is referred to papers in the volume by Victor Zarnowitz, John Guerard, Lawrence Klein, and S. Ozmucur, and D. Ivanova and Kajal Lahiri. The Conference Board index of leading indicators was composed of the following variables in 2001; Average weekly hours (mfg.); Average weekly initial claims for unemployment insurance; Manufacturers' new orders for consumer goods and materials; Vendor performance; Manufacturers' new orders of non-defense capital goods; Building permits of new private housing units; Index of stock prices; Money supply; Interest rate spread; and the Index of consumer expectations.
2. The reader is referred to Zarnowitz (1992), an IJF Associate Editor for many years, for his seminal development of underlying economic assumption and theory of the LEI and business cycles. The Zarnowitz *et al.* (2001a), Zarnowitz *et al.* (2001b) and Zarnowitz (2004) publications drove development of the LEI at The Conference Board.
3. See the NBER website: https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

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## Appendix

We provide the comparison of different models/methods in terms of the mean absolute rolling forecast error (MAE) in Table 4.

**Table 4: Mean absolute rolling forecast error (MAE) (×10) by five-year periods. The first row gives the MAE of the Null model. The rest of the table should be understood as a 4×2 block matrix, corresponding to 1, 2, 3, 4, 5, 6, 9 and 12-step ahead forecasts, respectively. In particular, the top two blocks are for 1-step and 2-step predictions, and the rest are self-evident. For each of the eight blocks, the rows correspond to models, and the columns P1 to P6 the five-year periods: 90–94, 95–99, 00–04, 05–09, 10–14, 15–19, respectively. The column "All" gives the MAE over all 30 years.**

| | P1 | P2 | P3 | P4 | P5 | P6 | All | P1 | P2 | P3 | P4 | P5 | P6 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | One Step Ahead | | | | | | | | Two Step Ahead | | | |
| I | 1.12 | 1.02 | 0.97 | 1.48 | 1.25 | 1.03 | 1.14 | 1.12 | 1.02 | 0.97 | 1.48 | 1.25 | 1.03 | 1.14 |
| II | 1.05 | 1.12 | 0.94 | 1.22 | 1.19 | 1.05 | 1.09 | 1.06 | 1.12 | 0.94 | 1.22 | 1.18 | 1.04 | 1.09 |
| III | 1.15 | 1.06 | 0.97 | 1.26 | 1.33 | 1.04 | 1.13 | 1.15 | 1.09 | 0.99 | 1.32 | 1.33 | 1.04 | 1.15 |
| IV | 1.07 | 1.02 | 0.89 | 1.18 | 1.13 | 0.99 | 1.05 | 1.11 | 1.10 | 0.87 | 1.19 | 1.12 | 1.03 | 1.07 |
| V | 1.17 | 1.10 | 0.98 | 1.10 | 1.19 | 0.96 | 1.08 | 1.14 | 1.18 | 0.96 | 1.07 | 1.23 | 1.03 | 1.10 |
| VI | 1.10 | 1.02 | 1.09 | 1.08 | 1.14 | 0.98 | 1.07 | 1.05 | 1.10 | 1.07 | 1.08 | 1.21 | 1.00 | 1.08 |
| VII | 1.10 | 1.08 | 0.89 | 1.10 | 1.24 | 0.98 | 1.07 | 1.11 | 1.09 | 0.88 | 1.17 | 1.28 | 1.02 | 1.09 |
| VIII | 1.04 | 1.02 | 0.89 | 1.10 | 1.17 | 0.98 | 1.03 | 1.04 | 1.08 | 0.89 | 1.12 | 1.19 | 1.01 | 1.06 |
| | | | Three Step Ahead | | | | | | | | Four Step Ahead | | | |
| II | 1.03 | 1.09 | 0.95 | 1.30 | 1.19 | 1.06 | 1.10 | 1.04 | 1.12 | 0.97 | 1.32 | 1.12 | 1.05 | 1.10 |
| III | 1.06 | 1.10 | 1.00 | 1.37 | 1.32 | 1.05 | 1.15 | 1.07 | 1.14 | 1.03 | 1.41 | 1.29 | 1.04 | 1.16 |
| IV | 1.03 | 1.10 | 0.96 | 1.28 | 1.20 | 1.04 | 1.10 | 1.03 | 1.14 | 0.98 | 1.34 | 1.13 | 1.05 | 1.11 |
| V | 1.14 | 1.16 | 1.02 | 1.10 | 1.28 | 1.04 | 1.12 | 1.15 | 1.24 | 1.05 | 1.18 | 1.23 | 1.09 | 1.16 |
| VI | 1.06 | 1.12 | 1.06 | 1.10 | 1.19 | 1.02 | 1.09 | 1.13 | 1.21 | 1.09 | 1.32 | 1.14 | 1.07 | 1.16 |
| VII | 1.12 | 1.13 | 1.01 | 1.31 | 1.32 | 1.04 | 1.16 | 1.17 | 1.12 | 1.03 | 1.35 | 1.32 | 1.06 | 1.17 |
| VIII | 0.98 | 1.08 | 0.92 | 1.20 | 1.22 | 1.03 | 1.07 | 0.98 | 1.13 | 0.97 | 1.28 | 1.16 | 1.06 | 1.10 |
| | | | Five Step Ahead | | | | | | | | Six Step Ahead | | | |
| II | 1.04 | 1.09 | 0.94 | 1.34 | 1.10 | 1.07 | 1.10 | 1.06 | 1.09 | 0.95 | 1.41 | 1.14 | 1.06 | 1.12 |
| III | 1.11 | 1.07 | 1.00 | 1.39 | 1.28 | 1.04 | 1.15 | 1.12 | 1.06 | 1.01 | 1.42 | 1.30 | 1.05 | 1.16 |
| IV | 1.03 | 1.08 | 0.94 | 1.34 | 1.12 | 1.07 | 1.10 | 1.07 | 1.09 | 0.94 | 1.41 | 1.15 | 1.06 | 1.12 |
| V | 1.04 | 1.07 | 0.93 | 1.21 | 1.16 | 1.09 | 1.08 | 1.03 | 1.04 | 0.93 | 1.31 | 1.15 | 1.05 | 1.08 |
| VI | 1.13 | 1.10 | 1.04 | 1.36 | 1.15 | 1.06 | 1.14 | 1.08 | 1.08 | 0.97 | 1.40 | 1.12 | 1.02 | 1.11 |
| VII | 1.12 | 1.13 | 1.02 | 1.41 | 1.28 | 1.04 | 1.17 | 1.14 | 1.17 | 1.11 | 1.35 | 1.29 | 1.03 | 1.18 |
| VIII | 1.01 | 1.05 | 0.93 | 1.31 | 1.14 | 1.06 | 1.08 | 1.04 | 1.05 | 0.93 | 1.37 | 1.16 | 1.04 | 1.10 |
| | | | Nine Step Ahead | | | | | | | | Twelve Step Ahead | | | |
| II | 1.09 | 1.09 | 0.97 | 1.47 | 1.12 | 1.07 | 1.13 | 1.09 | 1.11 | 0.95 | 1.52 | 1.15 | 1.10 | 1.15 |
| III | 1.14 | 1.04 | 1.00 | 1.47 | 1.29 | 1.03 | 1.16 | 1.14 | 1.03 | 0.99 | 1.48 | 1.30 | 1.06 | 1.17 |
| IV | 1.10 | 1.10 | 0.97 | 1.48 | 1.12 | 1.10 | 1.14 | 1.10 | 1.11 | 0.95 | 1.54 | 1.15 | 1.11 | 1.16 |
| V | 1.06 | 1.13 | 0.95 | 1.34 | 1.16 | 1.07 | 1.12 | 1.08 | 1.11 | 0.97 | 1.55 | 1.15 | 1.11 | 1.16 |
| VI | 1.03 | 1.13 | 0.92 | 1.37 | 1.14 | 1.03 | 1.10 | 1.05 | 1.11 | 0.96 | 1.62 | 1.17 | 1.08 | 1.16 |
| VII | 1.19 | 1.13 | 1.11 | 1.46 | 1.42 | 1.06 | 1.23 | 1.13 | 1.24 | 1.05 | 1.53 | 1.28 | 0.97 | 1.20 |
| VIII | 1.06 | 1.08 | 0.93 | 1.40 | 1.14 | 1.06 | 1.11 | 1.08 | 1.09 | 0.95 | 1.53 | 1.17 | 1.09 | 1.15 |