Modeling Lunar Calendar Holiday Effects in Taiwan

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Abstract

The three most important Chinese holidays, Chinese New Year, the Dragon-boat Festival, and Mid-Autumn Holiday have dates determined by a lunar calendar and move between two solar months. Consumption, production, and other economic behavior in countries with large Chinese population including Taiwan are strongly affected by these holidays. For example, production accelerates before lunar new year, almost completely stops during the holidays and gradually rises to an average level after the holidays. This moving holiday often creates difficulty for empirical modeling using monthly data and this paper employs an approach that uses regressors for each holiday to distinguish effects before, during and after holiday. Assuming that the holiday effect is the same for each day of the interval over which the regressor is nonzero in a given year, the value of the regressor in a given month is the proportion of this interval that falls in the month. Bell and Hillmer (1983) proposed such a regressor for Easter which is now extensively used in the U.S. and Europe. We apply the Bell and Hillmer's method to analyze ten important series in Taiwan, which might be affected by moving holidays. AICC and out-of-sample forecast performance were used for selecting number of holiday regressors and their interval lengths. The results are further checked by various diagnostic checking statistics including outlier detection and sliding spans analysis. The empirical results support this approach. Adding holiday regressors can effectively control the impact of moving holidays and improves the seasonal decomposition. AICC and accumulated forecast error are useful in regressor selection. We find that unemployment rates in Taiwan have holiday effects and seasonal factors cannot be consistently estimated unless the holiday factor is included. Furthermore, as the unemployment is rising, the magnitude of holiday and seasonal factor are decreasing. Finally, we find that holiday factors are generally smaller than seasonal factors but should not be ignored.

1 Introduction

People live by the calendar and act accordingly. For example, Christmas and solar new year have been the most important holiday for western countries. During the holidays, production either significantly scales down or completely halts, but consumption, and shopping activities surge. While the Gregorian calendar which is based upon solar system is the official calendar in most countries nowadays, important holidays in some countries are determined by other calendars. Examples are the Lunar New Year of the Chinese lunar calendar, Easter of the Christian calendars, and Ramadan of the Islamic calendar. As a result, these holidays have moving dates in the Gregorian calendar. For example, the dates of the lunar new year between 1998 and 2001 are January 28, February 16, February 5 and January 24 respectively. More precisely, the lunar new year date move between January 21 and February 20, making the time lags between the lunar and solar new years vary from 21 to 51 days. Dragon-boat Festival and Mid-Autumn Holiday are other two important lunar holidays with dates moving between May-June and September-October respectively. See webexhibits.org/calendars/calendar-chinese.html for more details.

For further exposition of the effects of moving holiday on economic statistics, let us consider exports. During the month containing lunar new year, export will be much lower than in other months mainly because there are fewer working days in that month. As a result, monthly growth rates as compared with same month last year will be much lower for, say, February 1999 and January 2001 but very high for January 1999 and February 2001. Econometric modeling, seasonal adjustment, and empirical economic analyses using monthly data are difficult unless the effects of these moving holidays can be estimated with some precision. There have been no general methods or models for estimating these effects. This paper employs a general approach that uses regressors for each holiday to distinguish effects before, during and after the holiday. Assuming that the holiday effect is the same for each day of the interval over which the regressor is nonzero in a given year, the value of the regressor in a given month is the proportion of this interval that falls in the month. Bell and Hillmer (1983) proposed such a regressor for Easter which is now extensively used in the U.S. and Europe. The fundamental model selection issues are how many intervals to use and the length of each interval. AICC and out-of-sample forecast performance can be used for model selection and various properties of the seasonal adjustment obtained after adjusting for the holiday effects can be used for diagnostic checking.

We apply the Bell and Hillmer approach to analyze ten important economic series in Taiwan which could be affected by the lunar calendar holidays. To illustrate this modeling approach, we provide a detailed account of model selection and diagnostic checking process for the unemployment rate. The empirical results support this approach. Use of holiday regressors is, indeed, able to produce a better seasonal decomposition.

In addition to this introduction, Section 2 summarizes the procedures of seasonal adjustment. The regARIMA modeling and X-12-ARIMA are elaborated here. Various diagnostic checking is also introduced. Bell and Hillmer's approach is discussed in Section 3. Section 4 provides empirical results and Section 5 concludes.

2 Procedures of seasonal adjustment

Seasonal adjustment involves two stages. In the first stage, a regARIMA model is built for the time series under investigation or its transformed values, e.g. logs. The model is used to pre-adjust the series for various effects and for forecasting and backcasting. The regARIMA time series regression error is the output of this stage. In the second stage, this error is fed into X-12 for seasonal adjustment. The adjusted series is decomposed into trend, seasonal and irregular components. The corresponding decomposition of the original series can be easily recovered by adding back the regressor effects and taking the inverse transformation if logs were modeled. Here are some summaries. See Findley, Monsell, Bell, Otto and Chen (1998) for details.

2.1 regARIMA models

A regARIMA model is used for forecasting, backcasting and preadjustments. X-12-ARIMA adjustment is best with a two-sided filter and a time series model is needed to simulate data outside the beginning and end of the sample period so that two-sided filters can be applied. In addition, preadjustments outliers, trading-day effects and other effects including those of moving holidays are performed at this stage. Monthly flow variables are often influenced by the weekday composition of the month. More precisely, such variables depend upon which days of the week occur five times in the month. To illustrate, let us consider industrial production, export and import analyzed in this paper. Since weekend days are official holidays, customs and most factories are closed then. The three variables above tend to be smaller for the months with 5 Saturdays, or 5 Sundays than those with only 4 weekend days. Young (1965) proposed to control for trading day effects by introducing 7 regressors, D_{jt}, measuring the number of occurrences of day j in month $t, 1 \leq j \leq 7$.

It is sometimes useful to transform a series prior to estimating a regARIMA model in order to stabilize the variance. More specifically,

$$y_t = f(Y_t) = \begin{cases} Y_t \\ log(Y_t) \\ \lambda^2 + (Y_t^{\lambda} - 1)/\lambda, \quad \lambda \neq 0. \end{cases}$$

The regARIMA model then becomes:

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D(y_t-\beta' X_t)=\theta_q(B)\Theta_Q(B^s)\epsilon_t,$$

where ϵ_t is white noise with mean 0 and variance σ_ϵ^2. $\phi_p(z), \Phi_P(z), \theta_q(z)$, and $\Theta_Q(z)$ are polynomials of degree p, P, q, Q respectively and have all roots outside unit circle. For example, $\phi_p(z) = 1-\phi_1 z-\phi_2 z^2-\ldots-\phi_p z^p$ and $|\phi(z)| \neq 0$, $\forall |z| \leq 1$ The model above can be rewritten as

$$\begin{aligned}(1-B)^d(1-B^s)^D y_t &= \sum_{i=1}^{r}\{\beta_i(1-B)^d(1-B^s)^D x_{it}\}+w_t\\ \phi_p(B)\Phi_P(B^s)w_t &= \theta_q\Theta_Q(B^s)\epsilon_t.\end{aligned}$$

2.2 X-12-ARIMA

Use X-12-ARIMA to decompose the adjusted series, $z_t = y_t-\beta' X_t$ into trend, T_t, seasonal, S_t, and irregular, I_t components. The decomposition can be either in multiplicative or in additive form.

$$\begin{aligned}\text{Multiplicative} : z_t &= T_t S_t I_t,\\ \text{Additive} : z_t &= T_t+S_t+I_t.\end{aligned}$$

The X-12-ARIMA seasonal adjustment calculation has three stages. In stage 1, an initial trend estimated is obtained via the centered 12-term moving average, $T_t^{(1)} = 1/24 z_{t-6}+1/12 z_{t-5}+\cdots+1/12 z_t+\cdots+1/12 z_{t+5}+1/24 z_{t+6}$ Divide or subtract the trend from z_t to obtain *SI* ratio. Then apply the $3\times(2n+1)$ seasonal moving average to give preliminary seasonal factor, $\hat{S}_t^{3\times(2n+1)}$.

$$\hat{S}_t^{(1)} = 1/3(\hat{S}_{t-12}^{2n+1}+\hat{S}_t^{2n+1}+\hat{S}_{t+12}^{2n+1}).$$

where

$$\hat{S}_t^{2n+1}=\frac{1}{2n+1}\sum_{j=-n}^{n} SI_{t+12j}.$$

For example, $n=1, \hat{S}_t = 1/9 SI_{t-24}+2/9 SI_{t-12}+3/9 SI_t+2/9 SI_{t+12}+1/9 SI_{t+24}$

Adjust the preliminary seasonal factor series to make the 12-month total of seasonal adjusted series to be close to the corresponding total of unadjusted series.

$$S_t^{(1)} = \frac{\hat{S}_t^{(1)}}{1/24\hat{S}_{t-6}^{(1)}+1/12\hat{S}_{t-5}^{(1)}+\ldots+1/12\hat{S}_{t+5}^{(1)}+1/24\hat{S}_{t+6}^{(1)}}$$

or

$$S_t^{(1)} = \hat{S}_t^{(1)} - (1/24\hat{S}_{t-6}^{(1)} + 1/12\hat{S}_{t-5}^{(1)} + \ldots + 1/12\hat{S}_{t+5}^{(1)} + 1/24\hat{S}_{t+6}^{(1)}).$$

Thus, seasonal adjusted series of the first stage is

$$A_t = \frac{z_t}{S_t}$$

or

$$A_t = z_t - S_t.$$

The process is repeated three times to complete the seasonal adjustment. In second and third stage, $(2H+1)$-term Henderson coefficients and seasonal factor via "3x5" (or other) seasonal moving average are used to obtain trend and preliminary seasonal factors, and the latter are then further adjusted to control the 12-month totals.

2.3 Diagnostic Checking

ACF, PACF, ACF of squared residuals, and histogram of standardized residuals are used for diagnostically checking regARIMA modeling. Outlier detection based upon Chang, Tiao and Chen (1988) is used to detect additive outliers (AO), temporary outliers (TO), and level shifts (LS). The spectrum can be used to detect remaining seasonal or trading-day effects in the residual.

M1-M11, Q, as well as the spectrum of the adjusted series and irregular term are computed for diagnostic checking of the quality of the seasonal adjustment and related trading day and holiday adjustment.

Findley, Monsell, Shulman and Pugh (1990) proposes the use of sliding-spans to analyze stability of the seasonal adjustment. First, divide the whole sample into four overlapping subspans. For the months that occur in overlapping spans, differences between the largest and smallest adjustments from the different spans are used as diagnostic statistics. X-12-ARIMA offers three statistics. Let $S_t(k)$ denote the seasonal factor estimated from span k for month t, $A_t(k)$ be the seasonally adjusted value from span k for month t, $MM_t(k)$ represent the month-to-month percentage change in the adjusted series from span k for month t, and $YY_t(k)$ stand for the year-to-year percentage change in the adjusted series from span k for month t. Define $N_t = \{k$: month t is in k-th span $\}$, $N1_t = \{k$: months t and $t-1$ are in k-th span$\}$, $N12_t = \{k$: months t and $t-12$ are in span $k\}$.

Then month t is said to have an unreliable seasonal factor if either one of the following three conditions holds:

$$S_t^{\max} = \frac{\max_{k\in N_t} S_t(k) - \min_{k\in N_t} S_t(k)}{\min_{k\in N_t} S_t(k)} > .03$$

$$MM_t^{\max} = \max_{k \in N1_t} MM_t(k) - \min_{k \in N1_t} MM_t(k) > .03$$
$$YY_t^{\max} = \max_{k \in N12_t} YY_t(k) - \min_{k \in N12_t} YY_t(k) > .10.$$

3 Modeling lunar calendar holiday effects

Bell and Hillmer (1993) proposed to model the effect of moving Easter Day with a simple holiday regressor. They assume that the holiday affects the economy for a total length of τ days and the effect is the same for each day during this interval. Let τ_t denote number of days in month t that belong to this interval. The holiday regressor, $H(\tau, t)$ is then defined as

$$H(\tau, t) = \frac{\tau_t}{\tau}.$$

While one single regressor is sufficient for modeling Easter in the U.S., several might be needed for modeling other holidays, such as Chinese New Year. Typically, the economic activity surges before the holiday, stops during the holiday and slowly accelerates after the holiday. In this case, there are three regressors, $H_1(\tau, t), H_2(\tau, t), H_3(\tau, t)$ for before, around and after the holiday. The model becomes:

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D(y_t - \beta' X_t - \sum_{i=1}^{3} \alpha_i H_i(\tau, t)) = \theta_q(B)\Theta_Q(B^s)\epsilon_t.$$

There might be prior information about τ for some series but its true value is generally unknown. Models with different τ are non-nested and, hence, a typical likelihood ratio test for model comparison is not appropriate. Findley and Soukup (2001) suggested two alternatives. One is using the AICC criterion proposed by Hurvich and Tsai (1989), a modification of Akaike's AIC and the other compares the out-of-sample forecast performance.

AICC is defined as below:

$$AICC = -2\text{log likelihood} + 2p\frac{1}{1 - \frac{p+1}{T-12D-d}},$$

where p is the number of estimated parameters, D order of seasonal differencing, and d order of regular differencing. The model with the smallest AICC value is preferred.

Let the h-step out-of-sample forecast of Y_{t+h} be defined as $Y_{t+h|t} = f^{-1}(y_{t+h|t})$ and the associated forecast error, $e_{t+h|t} = Y_{t+h} - Y_{t+h|t}$. With N denoting the series length and $1 \leq N < N - h$ denoting a number of observations larger enough for model coefficient estimation, consider the accumulating sums of squared out-of-sample forecast errors

$$SS_{h,M} = \sum_{t=N_0}^{M} e^2_{t+h|t}, \quad M = N_0, \ldots, N-h.$$

The weighted differences $SS_{h,M}^{(1)} - SS_{h,M}^{(2)}$ from two competing models, defined by

$$SS_{h,M}^{1,2} = \frac{SS_{h,M}^{(1)} - SS_{h,M}^{(2)}}{SS_{h,N-h}^{(2)}/(N-h-N_0)}, N_0 \le M \le N-h,$$

can be used to compare the forecasting performance of two competing models over the time interval $N_0 \le M \le N-h$. For example, over an interval of M values where $S_{h,M}^{1,2}$ is persistently decreasing, the h-step forecast errors from first model are persistently smaller in magnitude, i.e. better.

Morris and Pfeffermann (1984) proposed a different approach. They suggest to incorporate the moving holiday effect into a dynamic linear model where the holiday effect evolves stochastically in time. Liu (1980) employ a different modeling strategy. He uses an intervention analysis within an ARMA model where proportion of new year period in each month is the regressor variable.

4 Empirical Results

We have analyzed ten series of Taiwan which include the unemployment rate, the nanny salary, the average salary of non-agricultural sectors, the production index of Electrical and the Electronic industry, exports, imports, M1a, M1b, M2, and the Taiwan Weighted Stock Index (TAIEX). Unemployment rate, money supply, industrial production index, average wage rate and TAIEX are all important variables constantly monitored by the government and frequently used in local macroeconomic models. The nanny salary is selected for possible holiday effects for Mid-Autumn Festival. We discuss the results on the unemployment rate in great detail as it attracts much attention recently and then summarize the findings for the other nine series.

4.1 Data

The nanny salary is a wage index with December 1997 set to be 100 while the average salary of non-agricultural sectors is measured in New Taiwan Dollar. All data are seasonally unadjusted monthly series with ending month at either September or October of 2001, the most recent data available. All have a time span of length more than ten years. The exact time span is listed in the second column of Table (2) and the time series plots are put in Figure (1). The Unemployment rates, nanny salary, and average salary of non-agricultural sector are compiled by the Directorate General of Budget Accounting and Statistics, Executive Yuan, R.O.C.; the Production index of Electrical and Electronic industry is compiled by Ministry of Economic Affairs, R.O.C while Exports and Imports and TAIEX are compiled by Ministry of Finance, R.O.C. Money supply, M1a, M1b, and M2 are all prepared by the Central Bank of China, R.O.C.

4.2 Statistical Packages

The statistical package used in this study is X-12-ARIMA developed by the Bureau of Census, United Stated of America, which can be retrieved at http://www.census.gov/pub/ts/x12a/final/pc/. TRAMO/SEAT is another competing program which is fully model-based and can also be fully automatic. See Maravall (1995). We adopt X-12-ARIMA in this study since this program is powerful, fully documented and well connected to SAS for graphic analysis. This program will typically produce a default output of more than 80 pages for a single run of one series. The regression matrix with the values of the regressor $H(\tau, t)$ needed by X-12-ARIMA to estimate the three lunar holiday effects were produced by the program *genho* provided by Brian Monsell of the U.S. Census Bureau. The program requires the holiday dates for a sufficient span of years. It is available from http://www.census.gov/srd/www/x12a/x12down_pc.html#x12other.

4.3 Unemployment rates

The Unemployment rate in Taiwan remained stably below 2 percent during 1970's, climbed up in the first half of 1980's once to 4 percent and then slowly declined back to 2 percent during late 1980's and early 1990's. However, since 1996, the unemployment rate started to increase, and jumped over 5 percent in late 2001.

The highest unemployment rate in the year typically occurs in September, when university graduates first enter the labor market. It has become a tradition for employers in Taiwan to distribute annual bonus before the lunar new year holidays. Seniority and corporate profits are two important factors determining the amount of bonus for each employee. Thus, those who wish to change jobs often do not make the move until after the holiday. The unemployment rate stays low before the lunar new year holiday and jumps up after holiday. See Figure (2).

While it is tempting to take logarithmic transformation of unemployment rates to account for increasing volatility during 1983-1986, we decide to use the additive model for the original series without any transformation. The reason is simple. As the unemployment rate is measured as a ratio, taking logarithmic transformation is conceptually unnatural and usually dubious statistically. We limit the model time span to start at January of 1988 to avoid using the samples during 1983-1986. The automodel procedure of X-12-ARIMA selected no transformation and additive adjustment. We also analyzed the case with all samples included (not reported here). The program has detected a lot of outliers. It is an open question how long a series is needed for reliable estimation of holiday effects. Some simulation experiments might be helpful but will be pursued in the future.

To determine the the length of holiday interval, we compute the AICC for $\tau = 0, \tau = 3, \tau = 7$ and $\tau = 15$. $\tau = 0$ means holiday is not modeled. For the regressor $H_2(\tau, t)$ for the middle

Table 1: Sliding span statistics for models with and without holiday factors

Series	S(%)	MM(%)	YY(%)
With Holiday Factor	5.1 (6/117)	9.5 (11/116)	0.0 (0/105)
No Holiday Factor	6.8 (8/117)	16.4 (19/116)	0.0 (0/105)

interval, we always use $\tau = 6$. $\tau = 3$ means 3 days each for $H_1(\tau, t)$ and $H_3(\tau, t)$. $\tau = 7$ means 7 days for $H_1(\tau, t)$ and $H_3(\tau, t)$ and similar for $\tau = 15$. The resulting AICC values are -155.5573, -188.9441, -198.4942, and -228.2111 respectively. Obviously, $\tau = 15$ beats the other three cases. We also computed accumulated forecast errors of three cases and put the results in Figure (3). These show that $\tau = 15$ outperforms the other three choices for one-period-ahead forecast by a big margin, and its 12-period-ahead forecasting is not worse. Furthermore, the fact that 15-day holiday factors are significant in regARIMA regression confirms the importance of moving holiday. So, we conclude that $\tau = 15$ gives the best results.

Seasonal, trend, irregular components and original series are put in Figure (2). The holiday, seasonal and combined factors for $\tau = 15$ are put in Figure (4). From the figures, we make the following observations. First, holiday factor is smaller than seasonal factor. Second, the magnitude of holiday and seasonal factors are decreasing since mid 1990's. The declining factor effects in recent years can be explained by the rising unemployment rate. During the high unemployment years, university graduates regain their relative competitiveness and their unemployment rates drop relatively in August and September. Also, an increase in the difficulty of acquiring a new job discourages people from switching jobs after the lunar new year holiday. The spectrum for the original and adjusted series are put in Figure (5). The figure clearly shows that the peak at seasonal frequency exists for the original series but is removed for the adjusted series.

To assess the impact of adding holiday regressors, we compare the difference of seasonal factors and put the results in Figure (6). From the figure, we observe that without holiday adjustment, the seasonal factors are mistakenly enlarged or shrunk in January and February.

Further, we check the stability of our seasonal adjustment by sliding spans. There are four spans, with January 1990 the first month of first span. S and MM values above the threshold of 3% are considered unstable. Percentages of unstable months greater than 15% as measured by S or greater than as measured by MM are regarded too high. The results for the unemployment rate are listed in Table (1).

Although the model without holiday factors has percentages of unstable months within acceptable limits, these percentages are worse than those from the model with holiday factors. Further, by examining the breakdowns of unstable months, we find that unstable months often occur during the first three months of the year, January, February and March for model without holiday factors. Adding holiday factors greatly reduce the sum of unstable months during the first quarter from 5 to 3 in term of S and from 13 to 2 in term of MM respectively.

4.4 Salaries

We analyze two salaries, the average salary of the non-agricultural sector and the average nanny salary. The former is an important wage aggregate and the latter is included because of the presence of Mid-Autumn and Dragon Boat Festival holiday effects.

As is obvious from Figure (7), the average salary for the non-agricultural sector displays a strong peak in either January or February. This is due to the end-of-the-year bonus distributed to employees before the lunar new year holiday. Meaningful empirical analysis cannot be performed without successful removal of the holiday effect. Again, we use AICC and accumulated forecasting error to select τ and $\tau = 7$ gives the best results. We find that the sharp peak has been removed in the adjusted series. Seasonal and holiday factors are both factors strong and stable over time.

It has been a tradition to pay extra money to nannies during the three major festivals, Dragon Festival, Moon Festival and Lunar New Year. The time series plot in Figure (8) confirms this observation. Three holiday factors are used and $\tau = 15$ is selected for all three holiday factors. From the figure, we find a strong dip for the irregular component and remaining seasonality for the seasonally adjusted series. Also, some outliers are detected. All of these indicate that the current model can be improved, although this is a very difficult series to model.

4.5 Production, export and import

As expected, all three series are affected by number of trading days in the month, although the magnitude of the trading day factor is small compared with the magnitude of the holiday and seasonal factors. It is interesting to observe that all three factors tend to cancel out each other rather than re-enforce the factor effects. See Figures (11, 12, 13). The holiday effect occurs before the holiday. The regressor $H_2(\tau, t)$ and $H_3(\tau, t)$ are not used.

4.6 Money supply

$M1a$ has the strongest holiday and seasonal factors while $M2$ has the weakest factor. This is not surprising since by definition, $M1a, M1b$ are all component of $M2$ and changes in the components of money supply usually result in smaller change in the aggregate. All patterns of three money supply seem to be stable over time without obvious change of magnitude. See Figures (14, 15, 16). It is worth noting that Perng (1982) used the daily money supply to compute the seasonal and holiday factors. He further recommended to seasonally adjust individual components of money supply first and then aggregated the each adjusted component to obtain the aggregate.

4.7 TAIEX

Holiday effects are found to be insignificant which is not surprising. Somewhat surprisingly, months from February to July have the seasonal factor above 100 percent while the other months are below 100 percent. As is shown in Figure (17), the magnitude of the seasonal factors increase slightly in recent years.

4.8 Summary of empirical results

Here is the summary of the empirical findings.

1. Adding holiday regressors can effectively control the impact of moving holidays and improves the seasonal decomposition.

2. AICC and accumulated forecast error are useful in determining the exact length of the intervals of the holiday effects.

3. The Lunar new year is the most important festival, which affects many series. Only very few series are affected by Mid-Autumn and Dragon Boat Festival. Some are affected before the holidays while some others are affected both before and after the holidays. The length also vary between series.

4. Holiday effects are generally smaller than seasonal effects but should not be ignored.

5. There is a holiday effect in the unemployment rate of Taiwan. Seasonal factors cannot be consistently estimated unless the holiday effect is controlled for. As the unemployment rises, the magnitudes of holiday and seasonal factors decrease. There is an intuitive explanation for this but it would be interesting to investigate if there is a general relationship between magnitudes of holiday and seasonal factors and the level of the series.

6. There is no holiday effect for TAIEX.

5 Conclusions

In this study, we have modeled the impact of moving lunar new year and other holidays on ten selected series in Taiwan by using the holiday regressors. This regressors measure the length of the period before, around and after the holiday in each month. Our analysis show that adding holiday regressors can effectively control the impact of moving holidays and improves the seasonal decomposition. AICC and accumulated forecast error are useful in determining the number and exact length of holiday factors.

Table 2: Summary of regARIMA modeling results

Variable	Span	model	% Forecast Error *
Unemployment Rate	1978.1-2001.9	15 days before and after CNY Additive, None, $(2,1,2)(0,1,1)_{12}$,	11.22%
Average salary of Non-agricultural Sector	1980.1-2001.8	7 days before and after CNY AO1994.FEB, AO1994.JAN,AO1997.JAN AO1997.FEB,AO1999.FEB,AO2000FEB AO2001.JAN Multiplicative, Log, $(1,0,1)(1,0,0)_{12}$	1.25%
Electrical Electronic Production Ind.	1986.1-2001.8	15 days before and after CNY TD,AO1999.SEP, TD$^{\#}$ Multiplicative, Log, $(0,1,2)(2,1,0)_{12}$	10.62%
Exports	1991.1-2001.9	30 days before CNY AO1991.APR, AO1992.JAN, TD Multiplicative, Log, $(0,1,1)(2,1,0)_{12}$	13.88%
Imports	1991.1-2001.9	30 days before CNY, TD Multiplicative, Log, $(0,1,1)(0,1,2)_{12}$	18.8%
Nanny Salary	1991.1-2001.10	15 days before and after 3 major holidays AO1994.FEB 17 AO outliers Multiplicative, Log, $(2,1,0)(0,1,1)_{12}$	0.86%
M_{1A}	1970.1-2001.9	15 days before and after CNY AO1997.DEC Multiplicative, Log, $(0,1,2)(2,1,0)_{12}$	2.82%
M_{1B}	1991.1-2001.9	15 days before and after CNY Multiplicative, Log, $(0,1,1)(0,1,1)_{12}$	3.62%
M_2	1991.1-2001.9	15 days before and after CNY Multiplicative, Log, $(0,1,1)(0,1,1)_{12}$	0.88%
TAIEX	1991.1-2001.8	No holiday effects Multiplicative, Log, $(0,1,2)(2,1,0)_{12}$	20.09%

* Average absolute percentage error in within-sample forecasts of the last three years.

TD means trading day variable and Log denotes natural log.

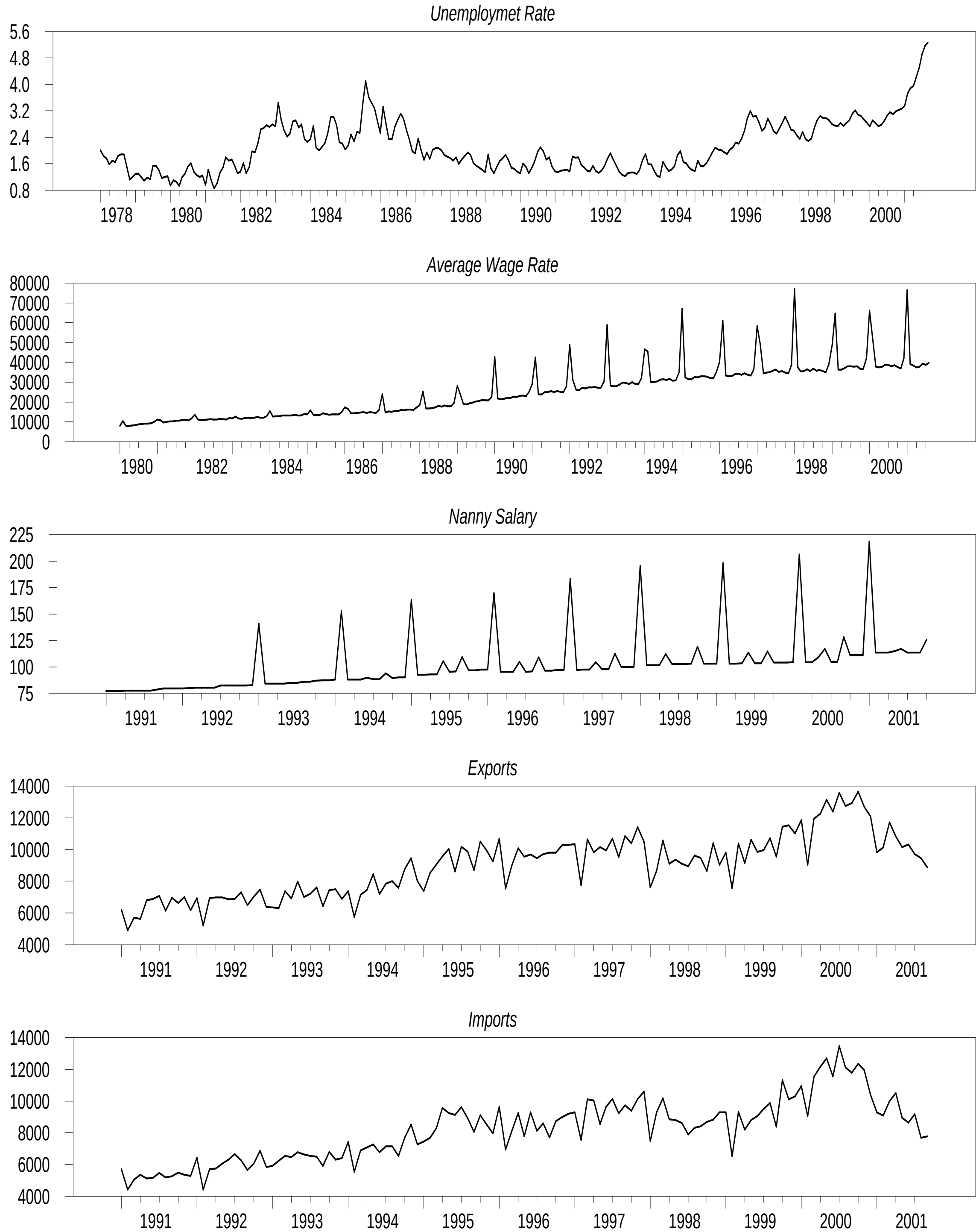

Figure 1: Time Series Plots of Ten Variables

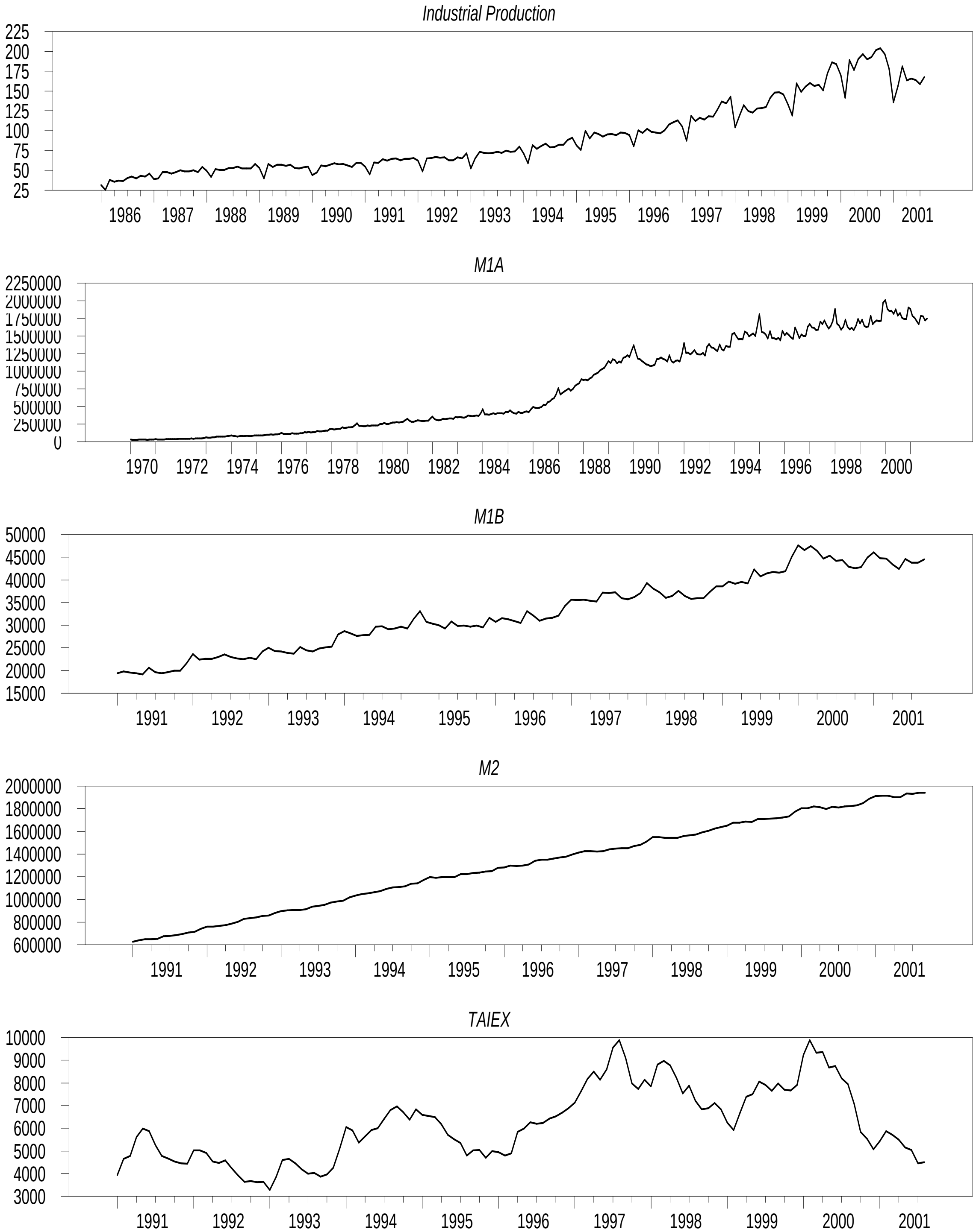

Figure 1: Time Series Plots of Ten Variables: Continued

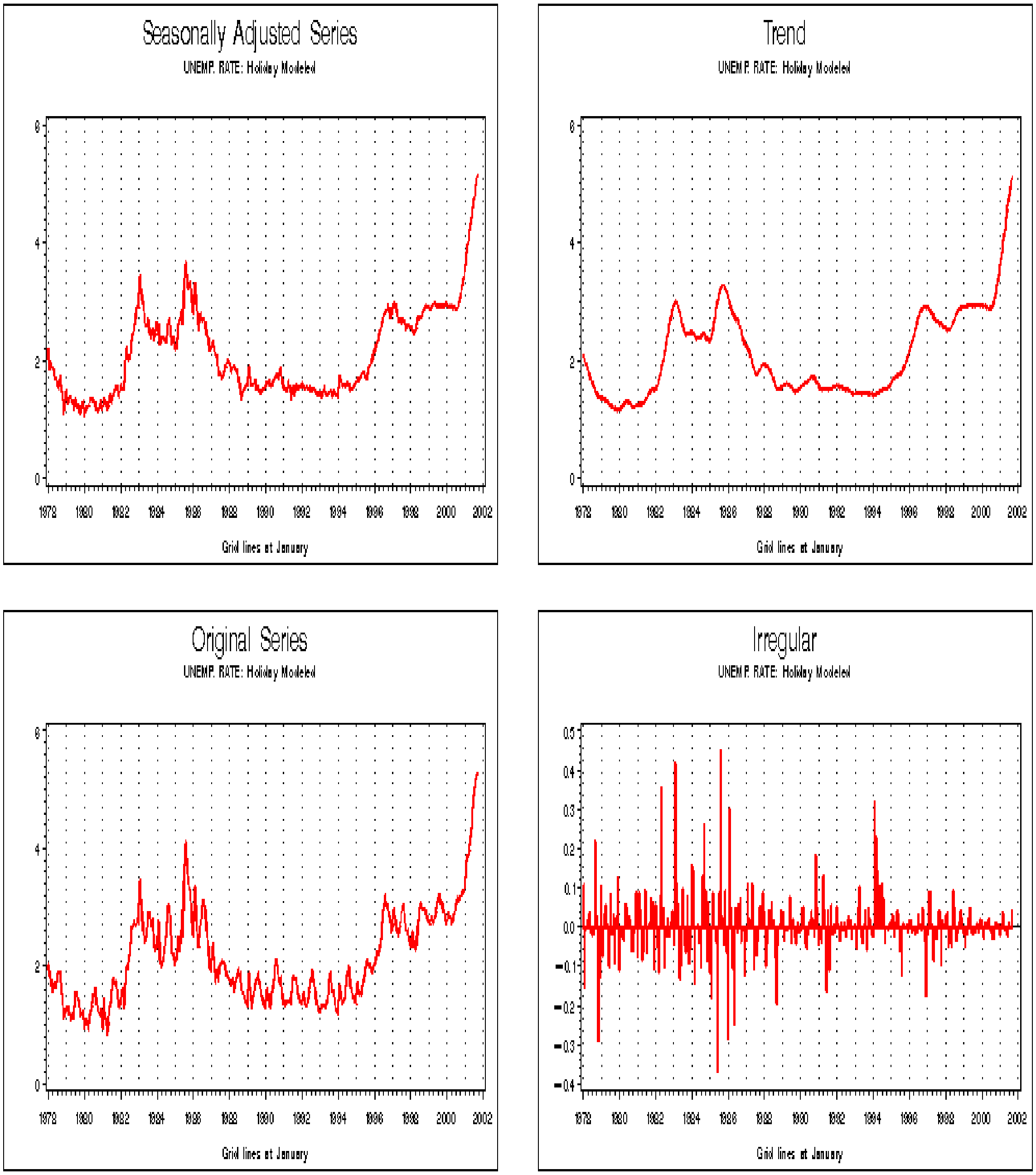

Figure 2: Seasonal Decomposition Components for the Unemployment Rate

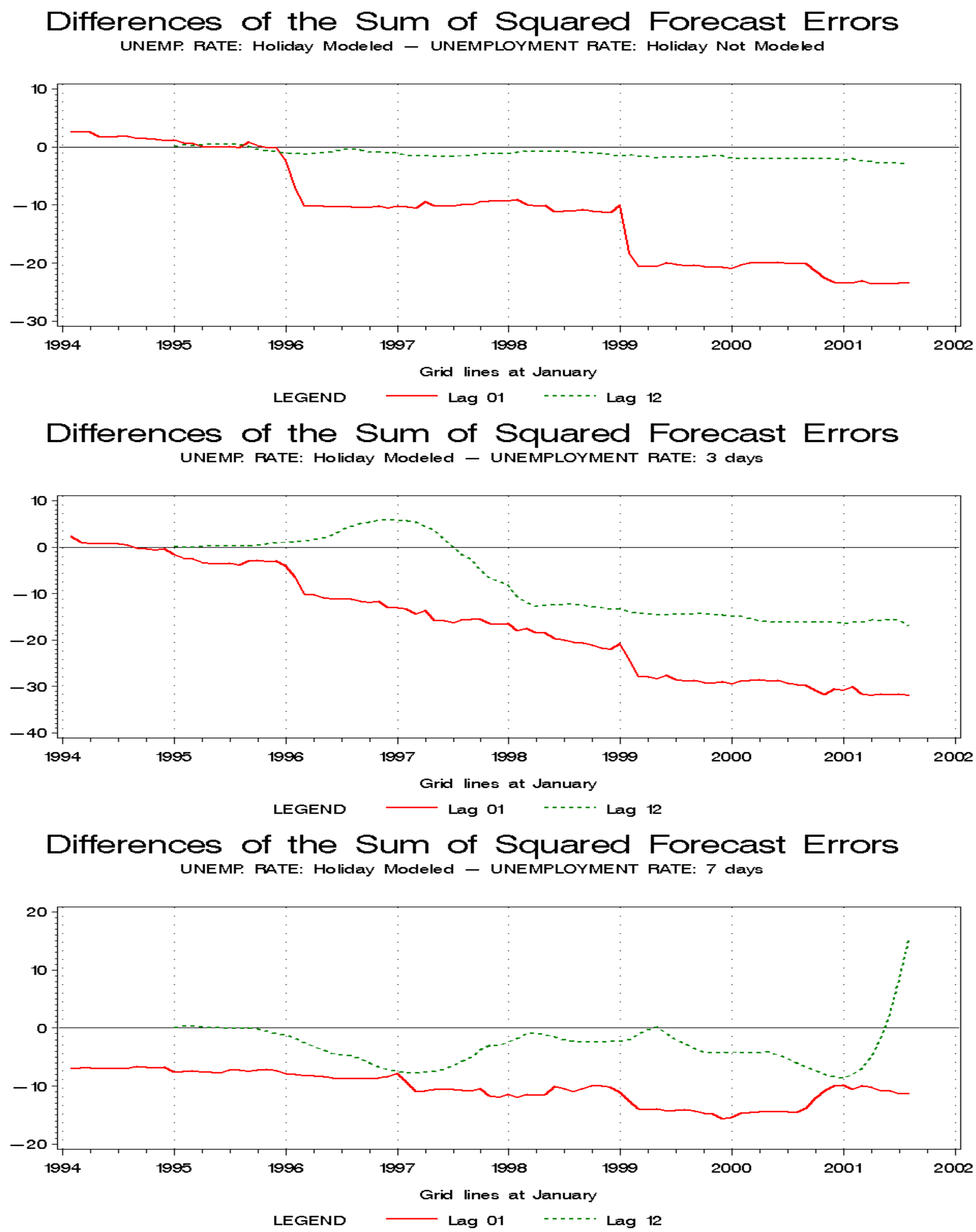

Figure 3: Differences of the squared forecast error for models with different τ compared with holiday model with $\tau = 15$

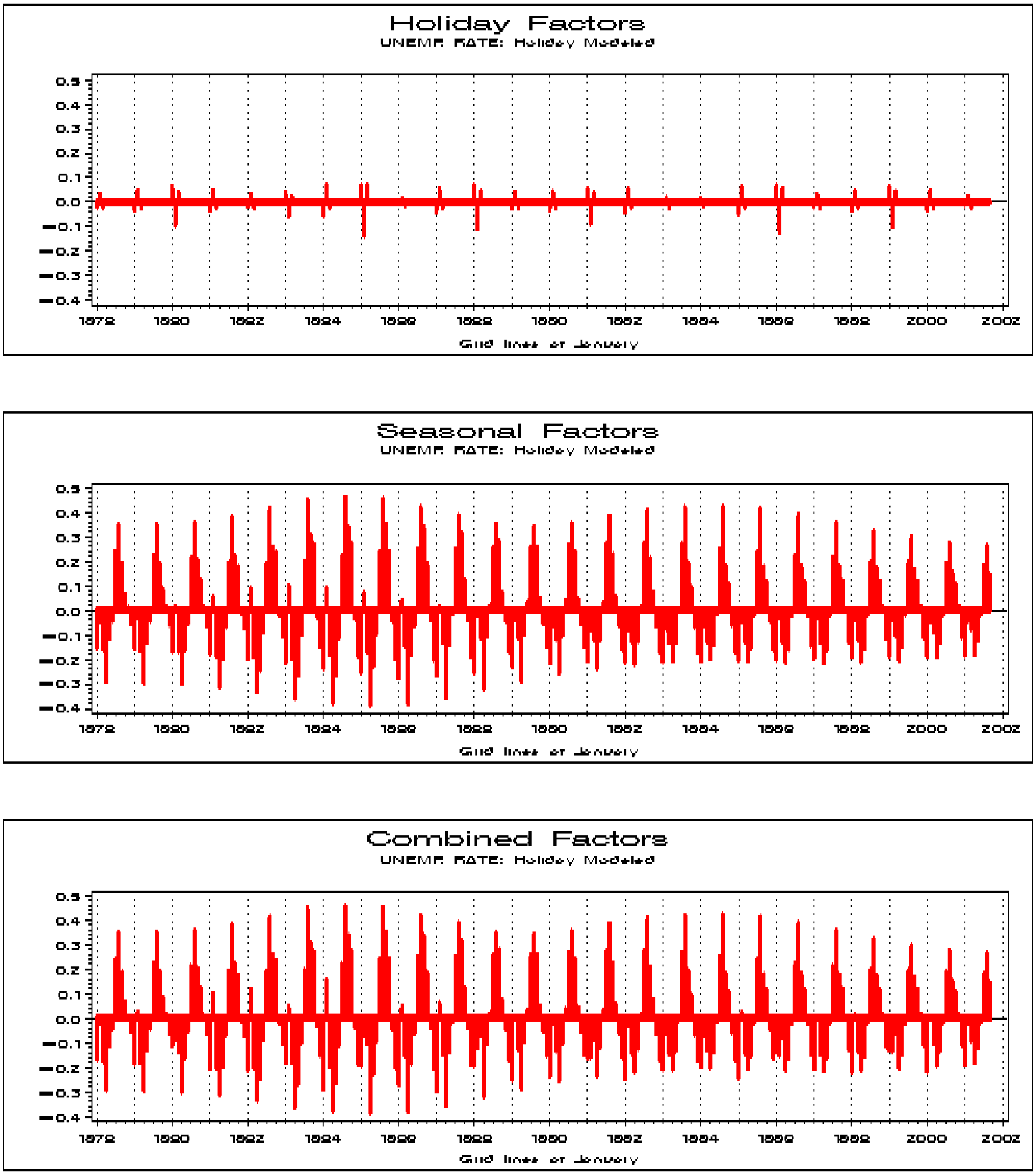

Figure 4: Holiday, Seasonal and Combined Factors for Unemployment Rates

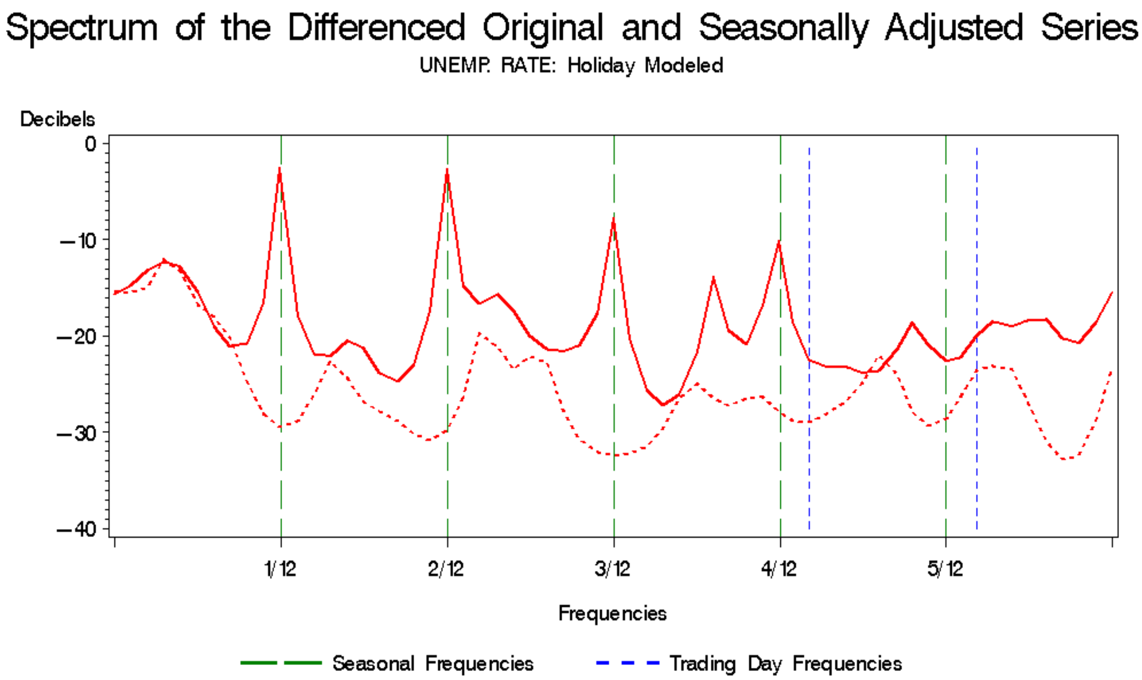

Figure 5: Spectra of the Seasonally Adjusted (dashed) and Unadjusted (solid) Unemployment Rates $\tau = 15$

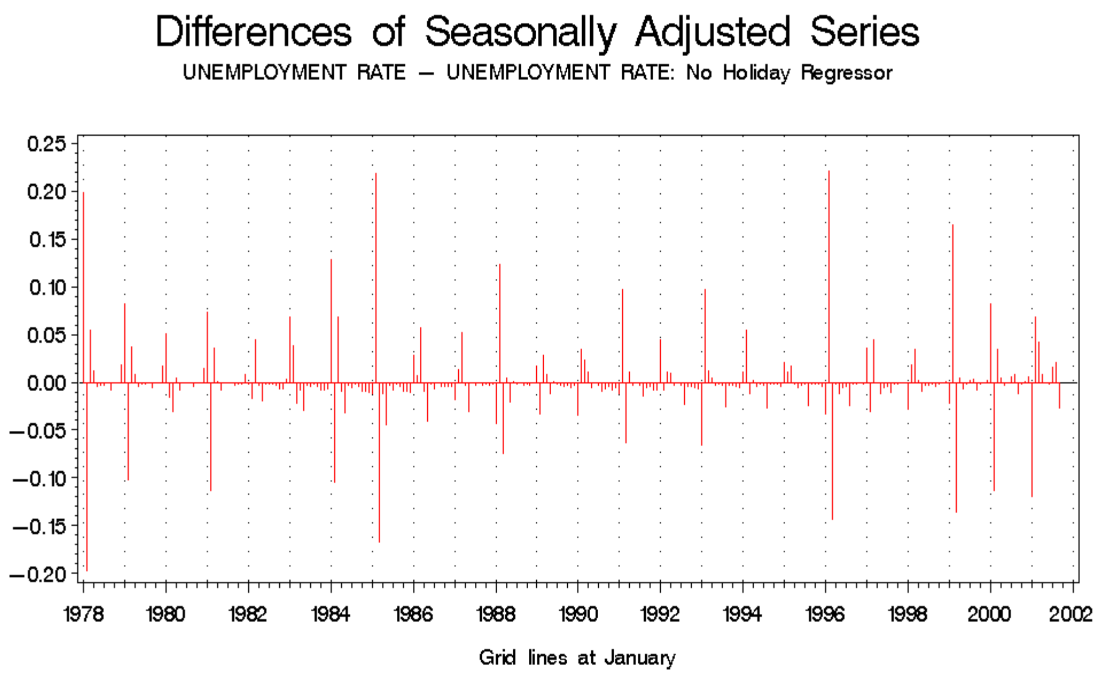

Figure 6: Difference of Seasonal Factors obtained using Models with and without Holiday regressors

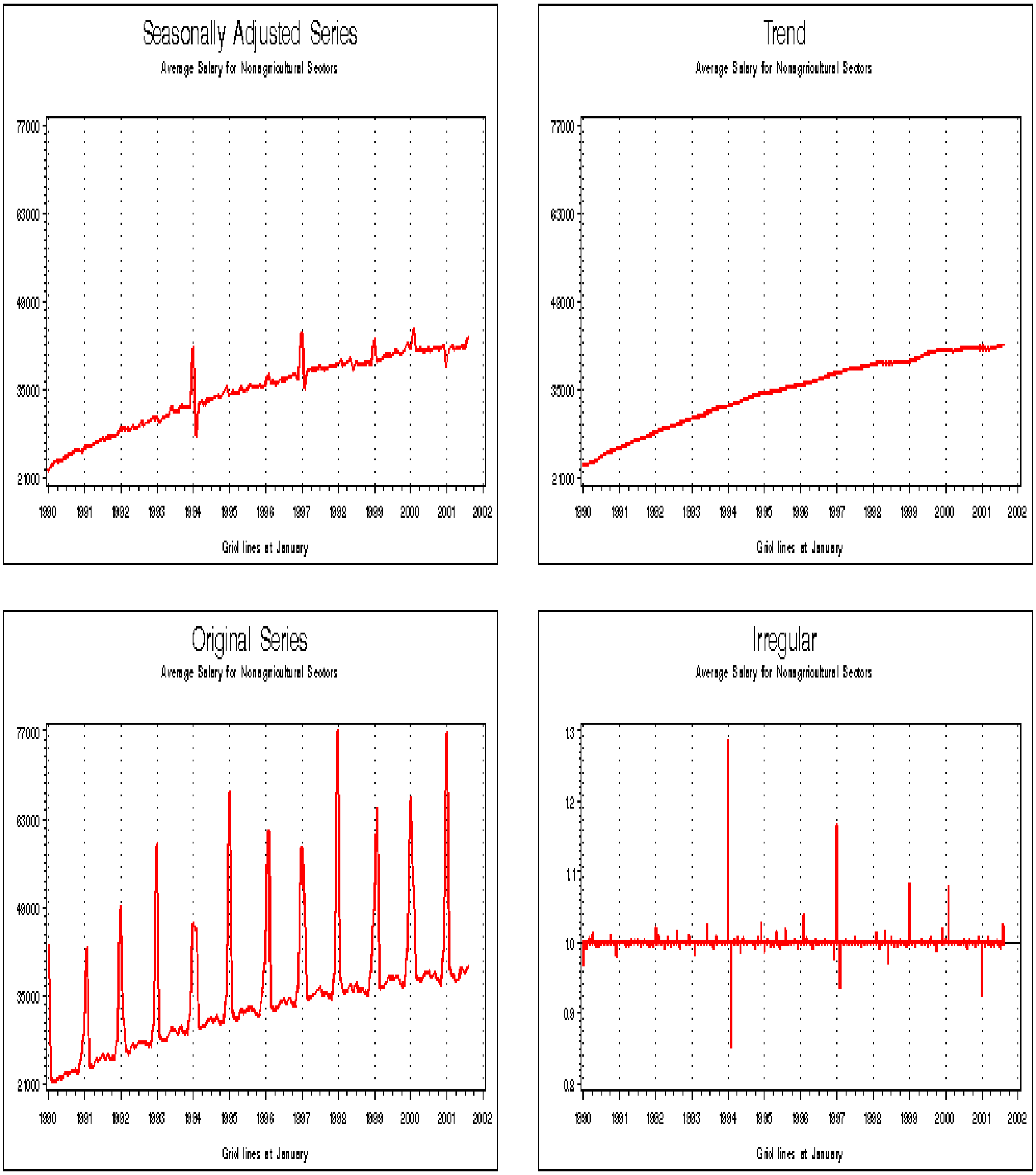

Figure 7: Seasonal Decomposition Components for Average Salary for Non-agricultural Sector

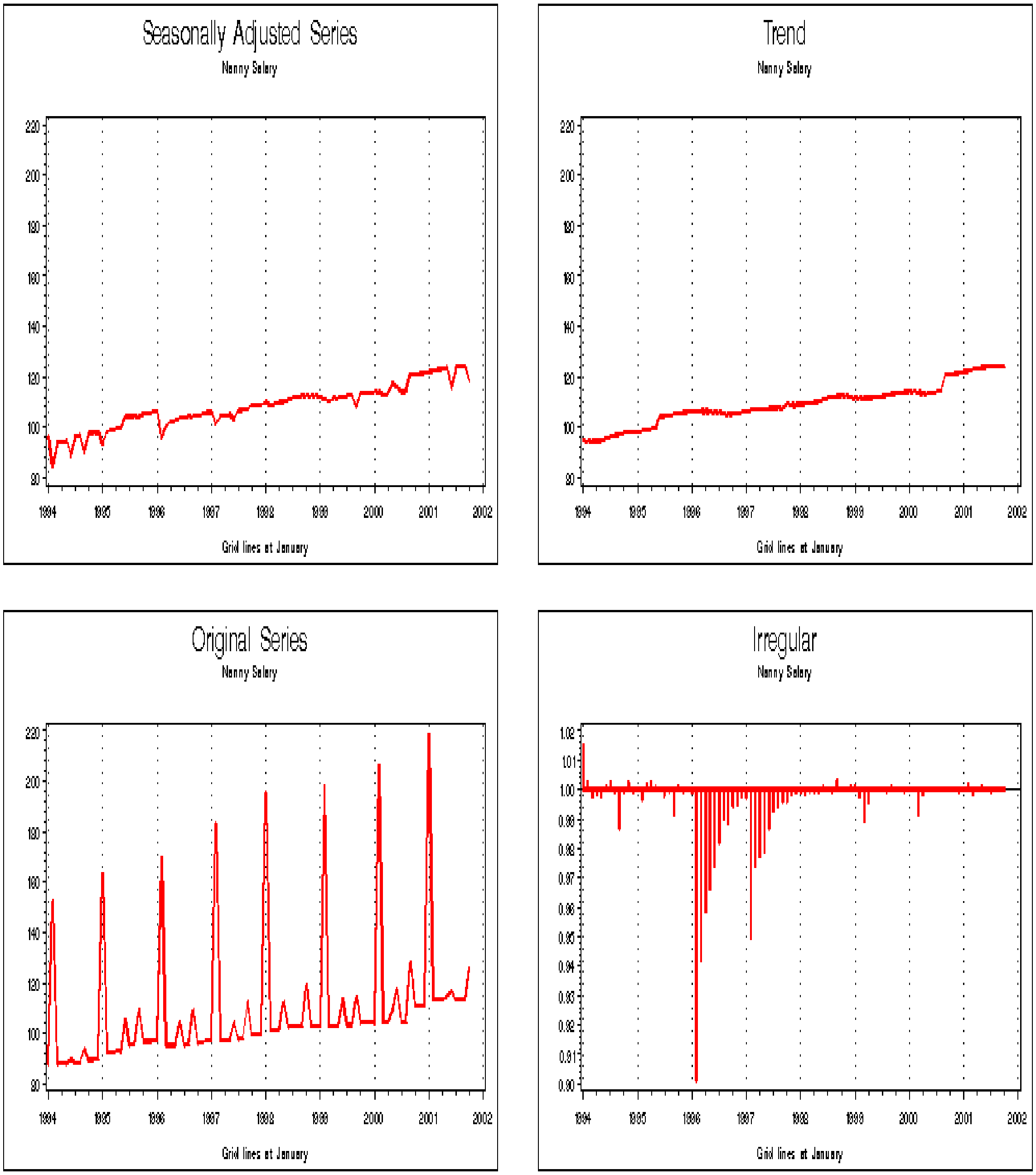

Figure 8: Seasonal Decomposition Components for Nanny Salary

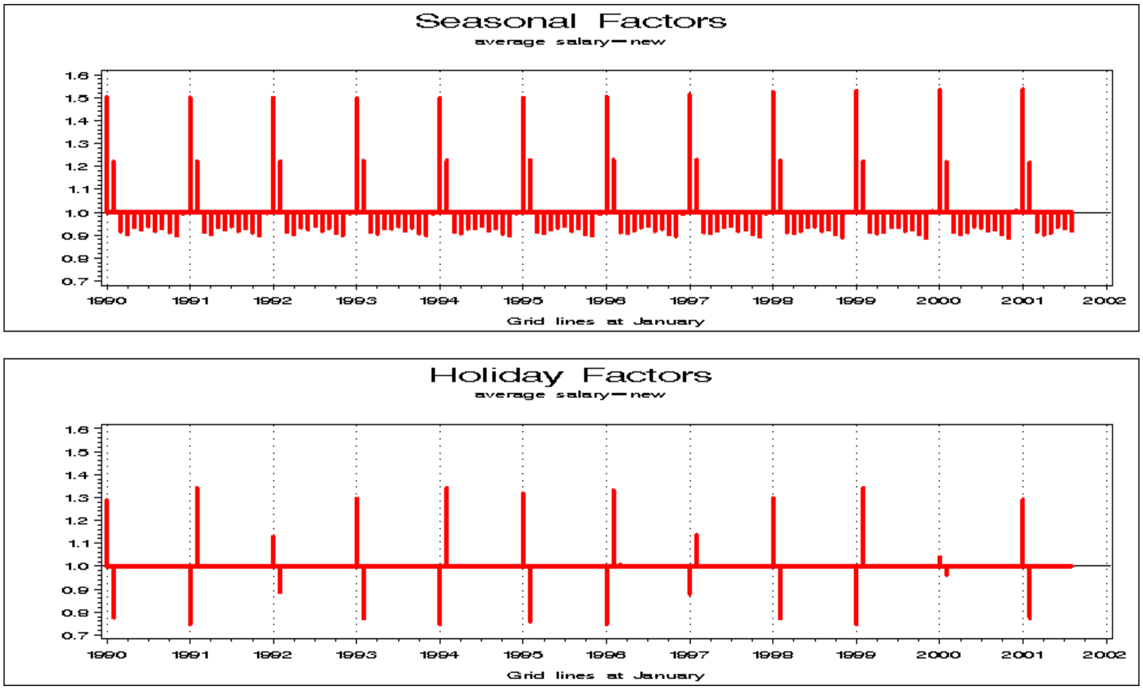

Figure 9: Seasonal and Holiday Factors for Average Salary of Non-agricultural Sector

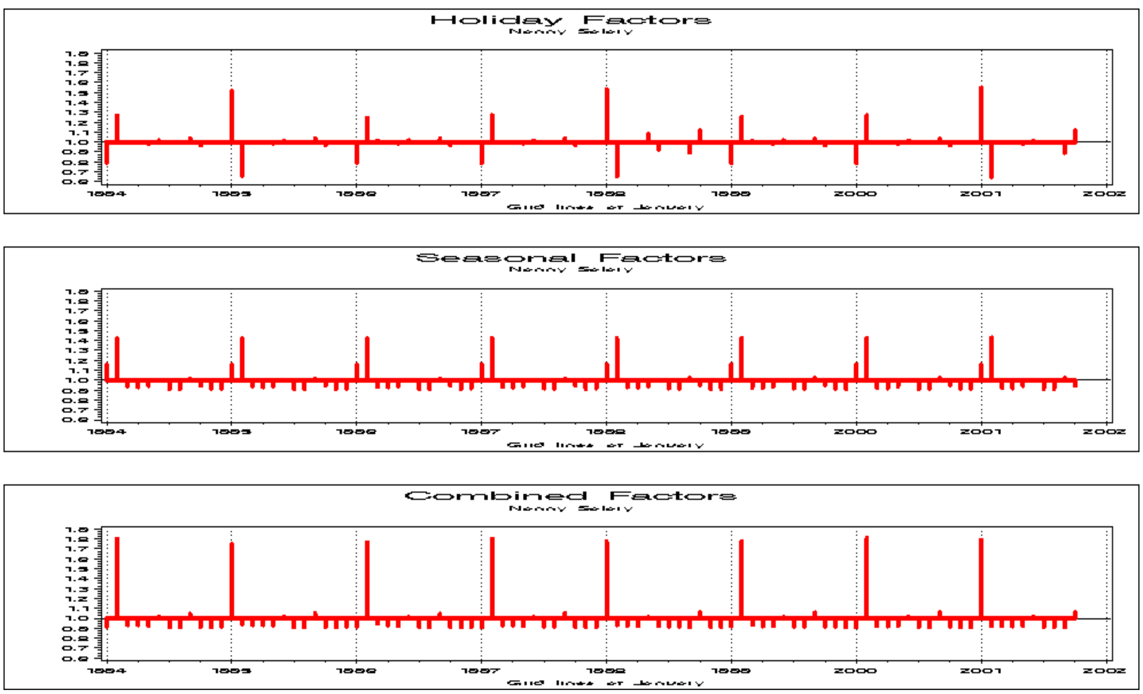

Figure 10: Holiday, Seasonal and Combined Factors for Nanny Salary

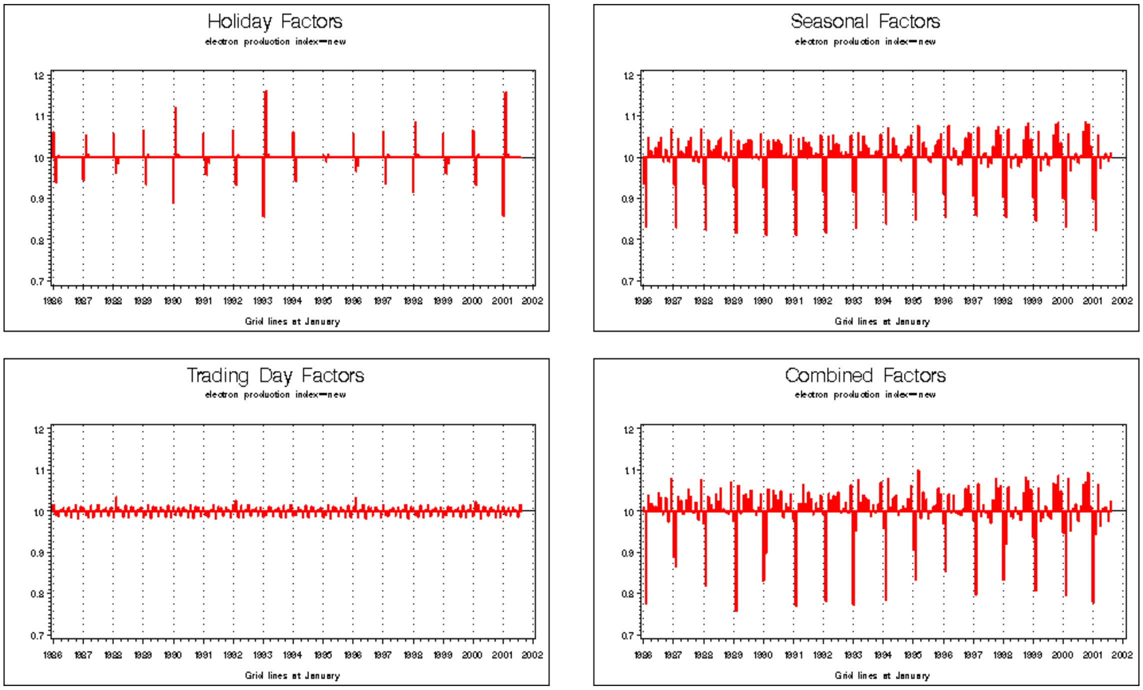

Figure 11: Four Factors for Electrical and Electronic Industry Production Index

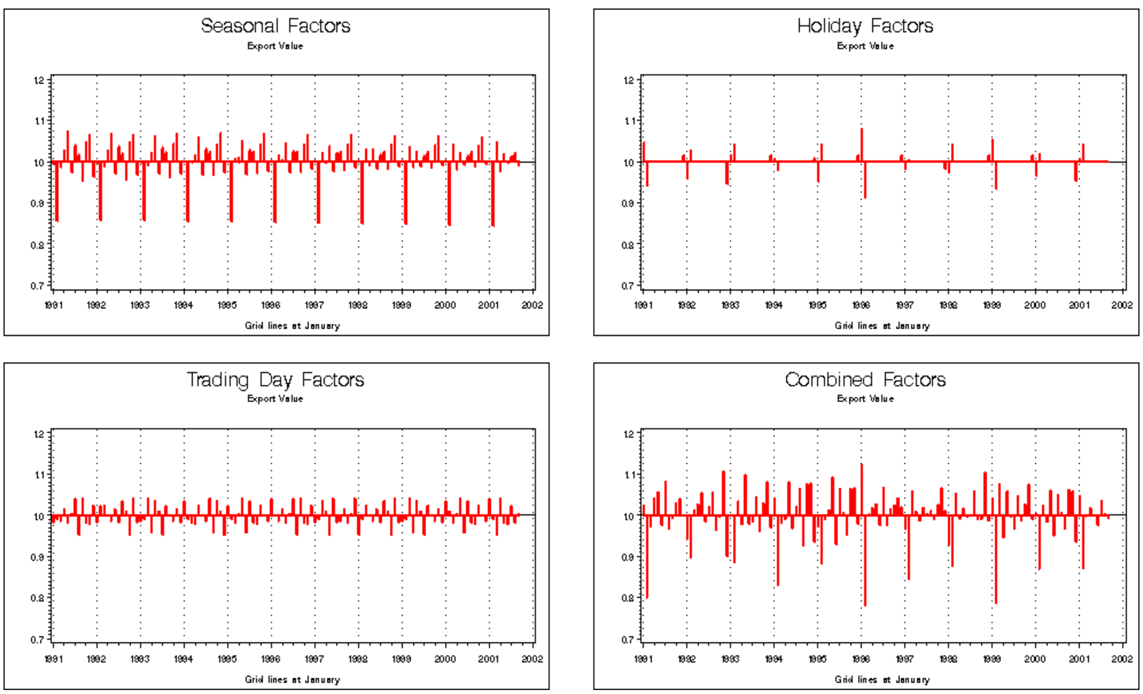

Figure 12: Four Factors for Exports

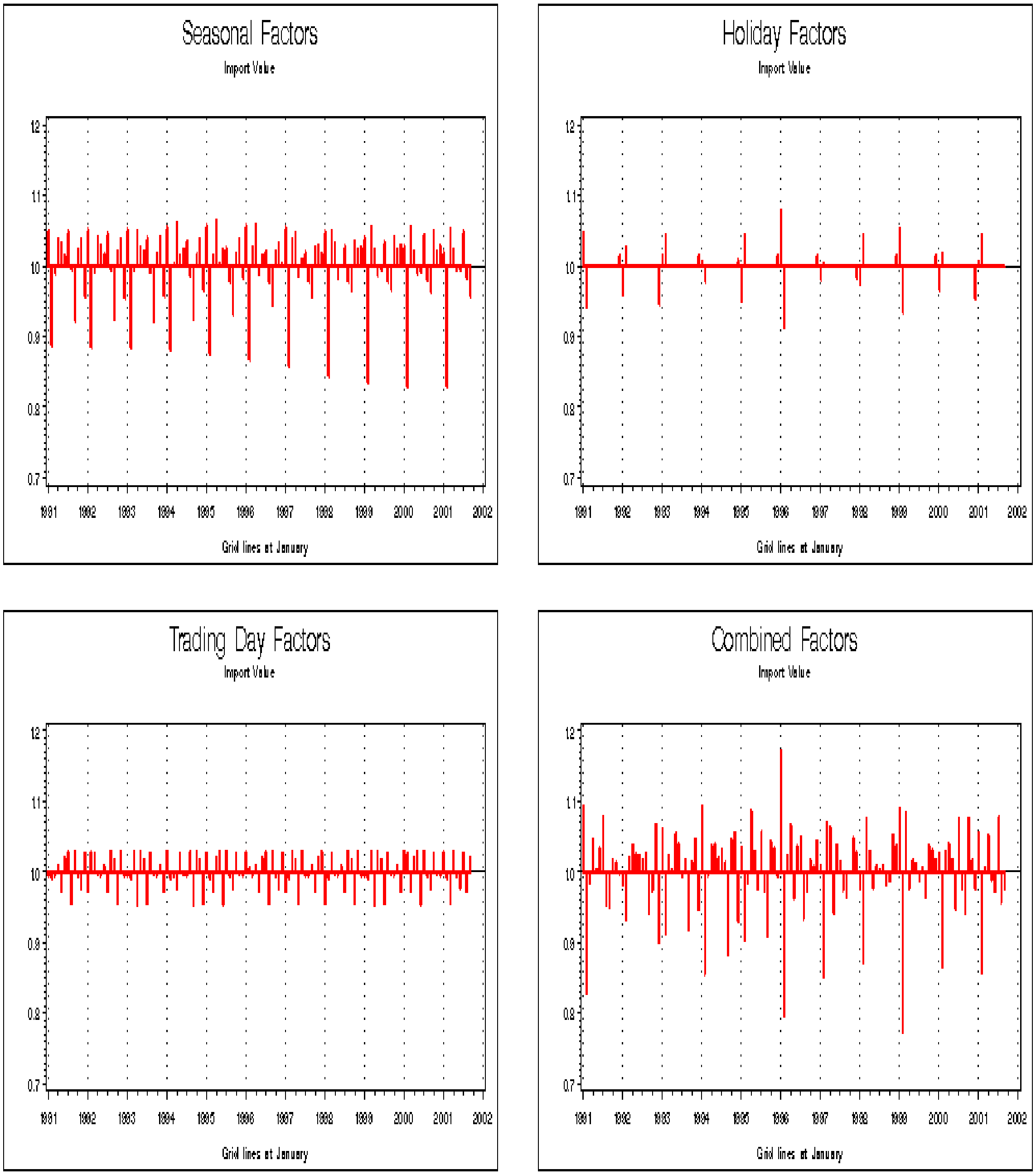

Figure 13: Four Factors for Imports

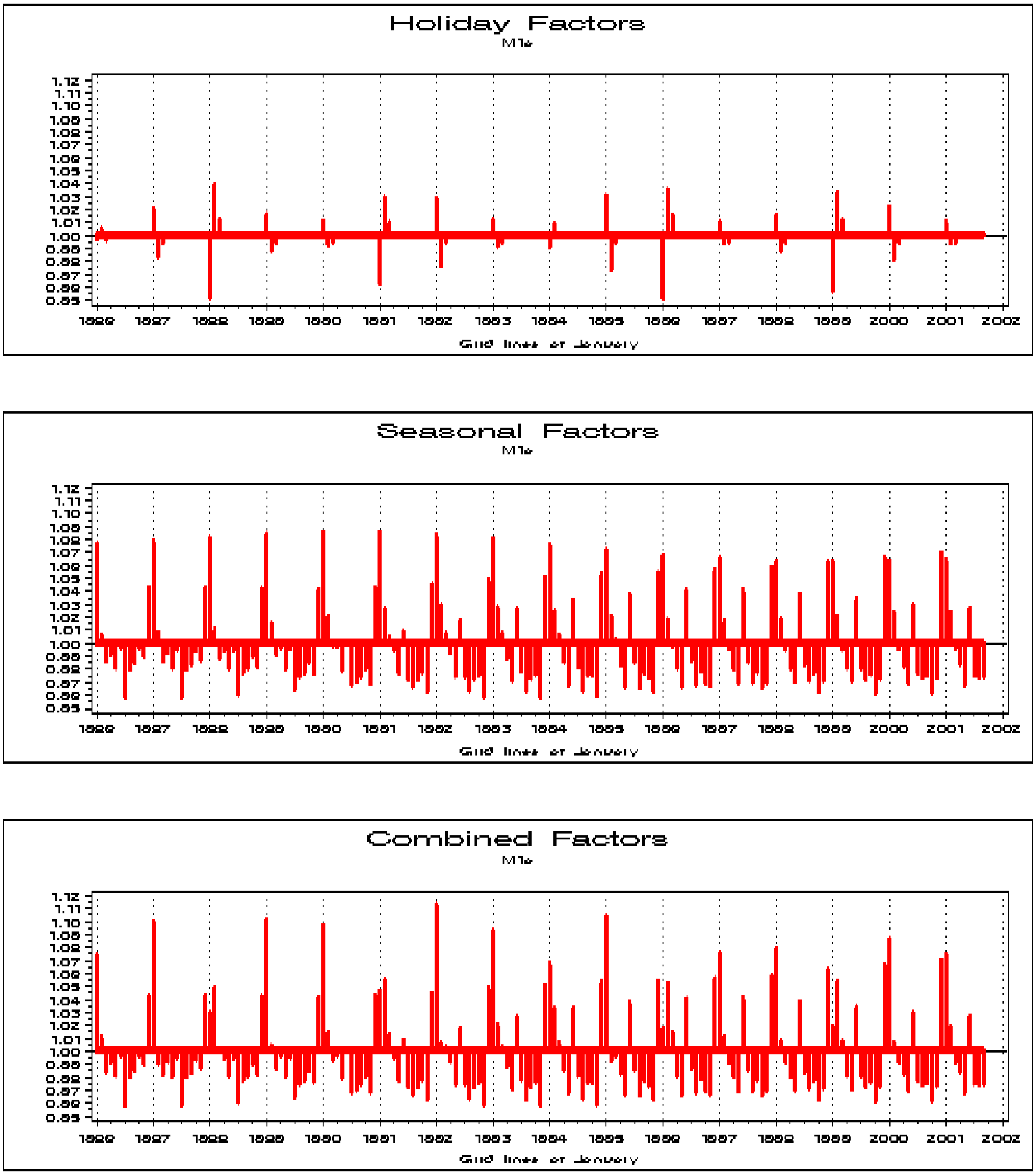

Figure 14: Holiday, Seasonal and Combined Factors for M1A

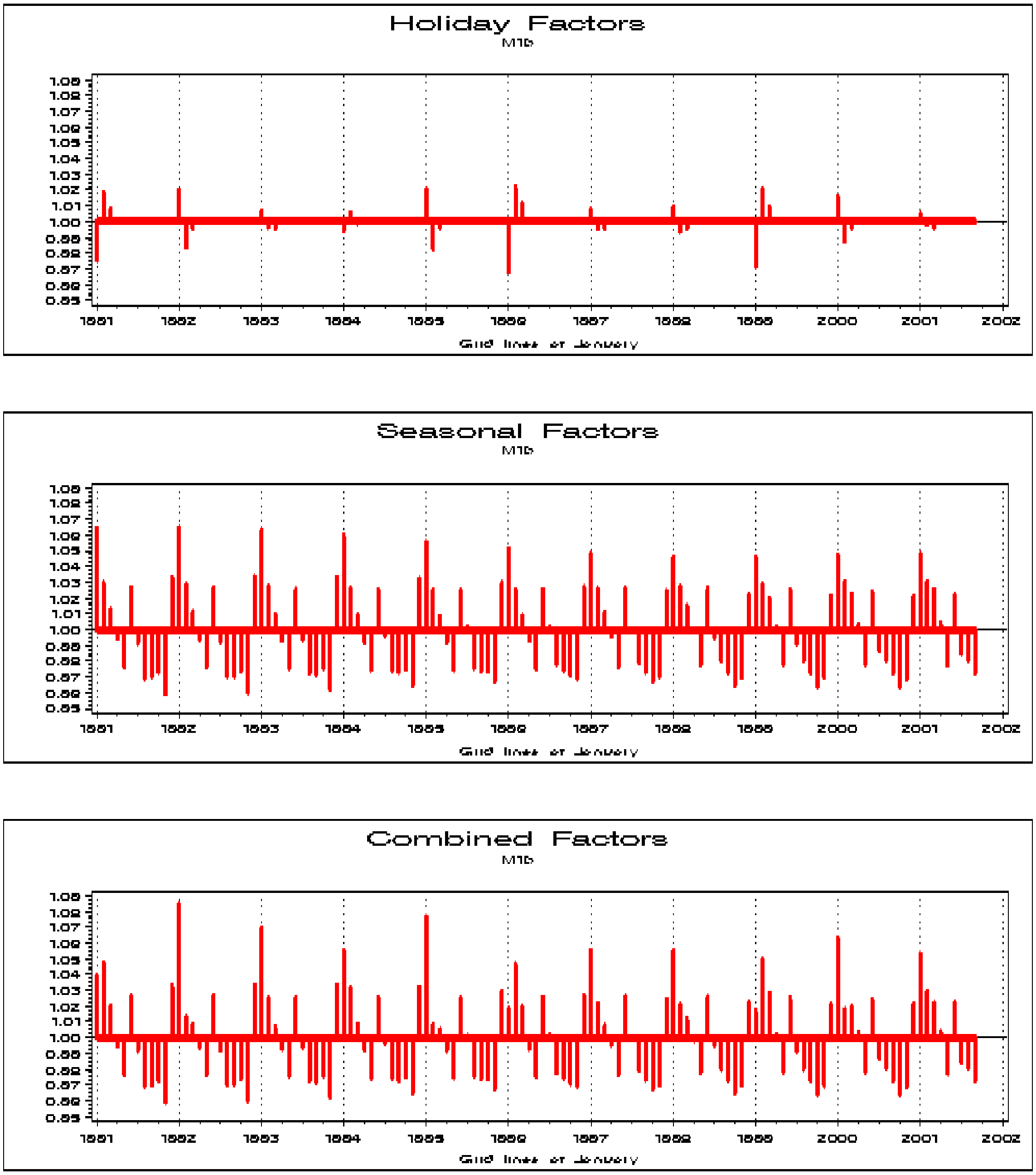

Figure 15: Holiday, Seasonal and Combined Factors for M1b

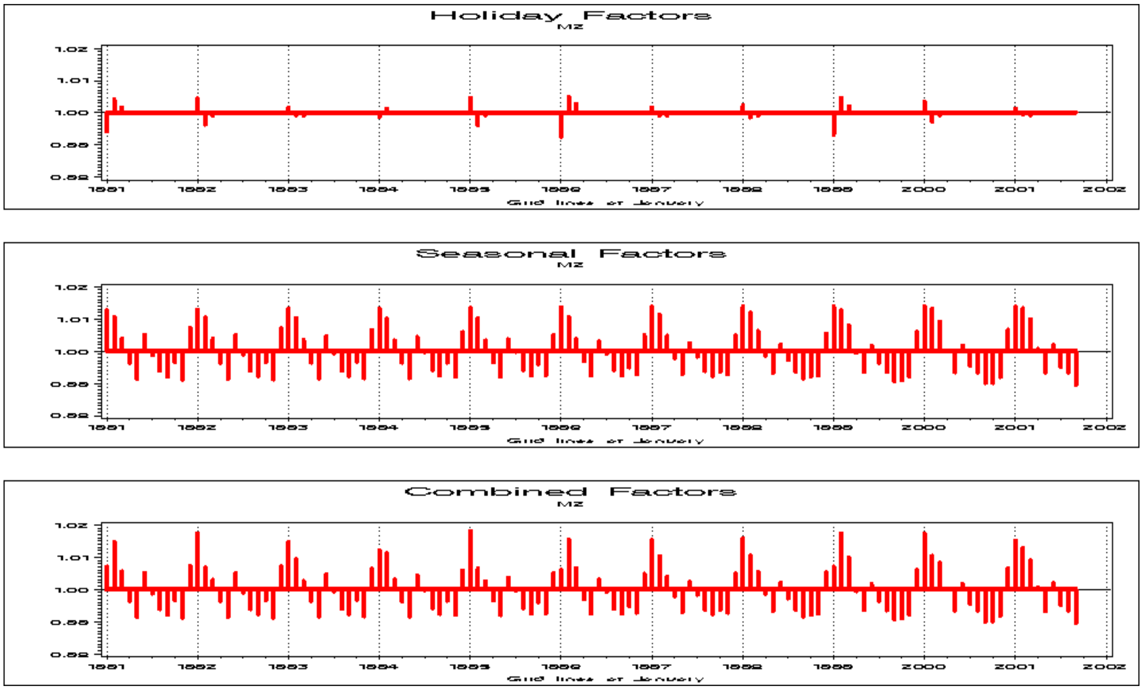

Figure 16: Holiday, Seasonal and Combined Factors for M2

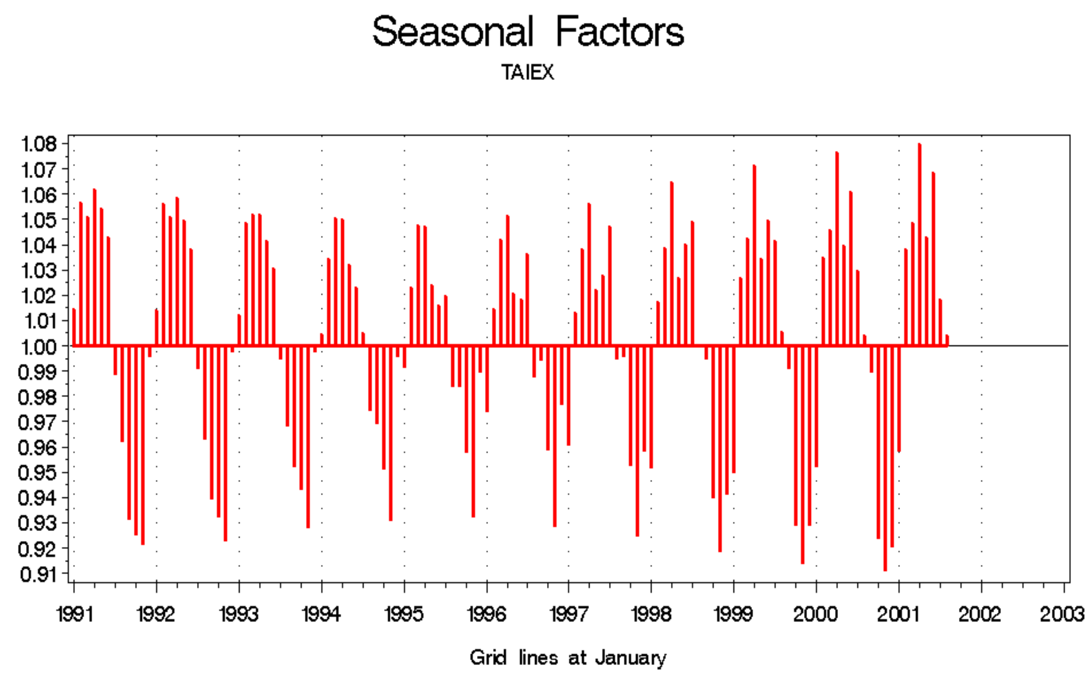

Figure 17: Seasonal Factor for TAIEX

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