TAIWAN ECONOMIC
FORECAST AND POLICY
43:1 (2012), 75–122

Stock Series Holiday Regressors Generated from Flow Series Holiday Regressors

David F. Findley*
Center for Statistical Research and Methodology
U.S. Census Bureau

Brian C. Monsell
Center for Statistical Research and Methodology
U.S. Census Bureau

Chieh-Tse Hou
Department of Finance
National Dong Hwa University

Keywords: Inventory time series, Seasonal adjustment, Holiday effects, Moving holidays, Forecasting, Easter effects, Chinese new year effects, X-12-ARIMA, X-13ARIMA-SEATS
JEL Classification: C82, C87

---

* Correspondence: David F. Findley, Center for Statistical Research and Methodology, U.S. Census Bureau, 4600 Silver Hill Road, Washington, DC 20233. Tel: 301-763-8773; Fax: 301-763-8399; E-mail: david.f.findley@census.gov. The impetus for this research was a question to the first author from Julian Chow of the U.K. Office of National Statistics about how to estimate Easter effects in stock series. William Bell and Eric Slud provided helpful suggestions and comments on earlier drafts of this paper.

ABSTRACT

Stock economic time series, such as end-of-month inventories, arise as the cumulative sum of monthly inflows and outflows over time, i.e., as accumulations of monthly net flows. In this article, we derive holiday regressors for stock series from cumulative sums of flow-series holiday regressors. This is similar to how stock trading day regressors have been derived. The stock holiday regressors from this approach have a very simple and appealing form when the flow regressors have standard properties. The modeling, forecasting and graphical results we present, for Easter effects in U.S. manufacturing inventories and for Chinese New Year effects in economic indicator inventory series of Taiwan, confirm the utility of this first general approach to modeling stock holiday effects. As with estimated holiday effects from flow series, we find that stock holiday effects are usually larger than trading day effects but smaller than seasonal effects.

1. OVERVIEW

Moving holidays such as Easter or the Chinese New Year (CNY) can impact several calendar month values of economic time series in a way that changes with the holiday's date from year to year. For flow series, Bell and Hillmer (1983) provided the most widely used approach to designing regressors for regARIMA models to estimate holiday effects. (regARIMA models are defined in Subsection 4.1 and discussed in Chapter 4 of U.S. Census Bureau (2009).) A general approach has been lacking for stock series. Stock economic time series, such as end-of-month inventories, arise as the cumulative sum of monthly inflows and outflows over time, i.e., from the accumulation of monthly net flows.[1]

In this article, we follow an approach similar to that used by Cleveland and Grupe (1983), Bell (1984, 1995) and Findley and Monsell (2009) to obtain stock trading day regressors: we derive holiday regressors for stock series from cumulative sums of flow-series holiday regressors of standard form. When the flow holiday regressors have certain quite common properties described in Section 2, the stock holiday regressors that result from this approach are shown in Section 3 have an attractively simple form: with $t = j + 12(M-1)$ indexing the j-th month of the M-th year of a series, and with $\tilde{H}(t)$ denoting the (centered and deseasonalized) flow series holiday regressor for this month,

$$\tilde{H}_S(t) = \sum_{i=1}^{j} \tilde{H}(i + 12(M-1)), \tag{1}$$

the sum of the flow regressors of the M-th year up through the j-th month. In Section 3, $\tilde{H}_S(t)$ is shown to inherit two properties of $\tilde{H}(t)$ valuable for seasonal adjustment: $\tilde{H}_S(t)$ is level-neutral and free of seasonality. For quarterly series, which we have no need to consider, the factor 12 in (1) is replaced by 4.

Our empirical studies of stock Easter and stock CNY effect estimation in Sections 5 and 7 both involve selection among several holiday regressors using an AIC-related criterion described in Subsection 4.1. The selected holiday

[1] For further discussion of stocks and flows, see Wikipedia Contributors (2009).

regressor is evaluated by out-of-sample forecast diagnostics and by graphical analyses of the extent to which holiday adjustment provides additional smoothing to the seasonally adjusted series around holiday months. The model selection procedures and forecast comparison diagnostics are described in Section 4 and the graphical diagnostics in Section 6.

Following a referee's recommendation, see Subsection 4.3, we also applied these diagnostics to compare seasonal adjustments with the selected stock holiday regressor's factors to the seasonal adjustments with the analogous flow holiday regressor's factors for the few stock series for which the model selection procedure preferred the flow regressor.

The regressors $\tilde{H}(t)$ of (1) used in the studies (or the components of a multivariate $\tilde{H}(t)$) are centered and deseasonalized versions of basic regressors associated with an interval of specified length whose endpoint is determined by the holiday's date. The basic regressors measure the proportion of the interval that lies in month t, see Subsection 2.1.

Section 5 provides precise formulas for the $\tilde{H}_S(t)$ from $\tilde{H}(t)$ defined by time intervals leading up to Easter. In Subsection 5.2, these $\tilde{H}_S(t)$ are applied to identify effects of the moving date of Easter on some of the U.S. manufacturing inventory series. For the series having statistically significant Easter effects, the estimated effects are small (as are seasonal and trading day effects). The average maximum Easter factor is 1.0095 (a 0.95% increase in a month affected by the holiday). See Table 3.

In Section 7, CNY regressors of the form (1), from CNY flow regressors $\tilde{H}(t)$ like those used in Lin and Liu (2003), are applied to effectively model CNY effects in some economic indicator inventory series of Taiwan. The CNY effect estimates are substantial in many of the series having such effects. The average maximum CNY factor is 1.047 (a 4.7% increase in a month affected by the holiday). See Table 7.

Section 8 presents modifications required to obtain holiday regressors for several situations in which the flow regressors $\tilde{H}(t)$ fail to have one or another of the properties required in Section 3. This includes a flow Easter-effect regressor $\tilde{H}(t)$ currently in use for which (1) holds, but whose seasonal component causes $\tilde{H}_S(t)$ from (1) to have level and seasonal components.

2. PROPERTIES OF FLOW REGRESSORS UTILIZED

The flow regressors $\tilde{H}(t)$ that will be accumulated to obtain stock regressors of the form (1) usually arise as deseasonalized and level-adjusted versions of more basic flow regressors $H(t)$ derived from conceptual considerations. We start from a primitive monthly flow series regressor $H(t)$ for a holiday whose dates change from year to year. The dates are assumed to repeat every P years for some positive integer $P > 1$. Hence $H(t)$ will be periodic with period $12P$,

$$H(t + 12P) = H(t). \tag{2}$$

As noted above, we define the time index t so that

$$t = j + 12(M - 1), \tag{3}$$

for the j-th calendar month of the M-th year under consideration, $1 \leq j \leq 12$, where $M = 1$ denotes the first year for which stock regressor values are needed. Let $M_0 \leq 1$ index some convenient possibly earlier initial year from which $H(t), t \geq t_0$ are available.

In addition to (2), we require $H(t)$ to have constant annual sums,

$$\sum_{j=1}^{12} H(j + 12(M - 1)) = K, \tag{4}$$

with K independent of $M \geq M_0$.

2.1 Basic Example: Interval-Proportion Regressors

The simplest type of $H(t)$ proposed by Bell and Hillmer (1983) for holiday effects is the basis of the flow regressors implemented in official seasonal adjustment programs for holiday effect estimation with regARIMA models. These

$H(t)$ are specified by an interval of length $w \geq 1$ days connected to the date of the holiday each year. The regressor treats the holiday's effect as being the same for every day in the interval. More precisely, for each $1 \leq j \leq 12$, let $n_j(M, w)$ denote the number of days of month j that fall in this interval of length w in year M. Then for $t = j + 12(M-1)$, the interval-proportion regressor $H(t)$ has the value

$$H(j + 12(M-1)) = \frac{n_j(M, w)}{w}, \quad 1 \leq j \leq 12. \tag{5}$$

For moving U.S. holidays (Easter, Labor Day, Thanksgiving), the allowed values of w in the built-in regressors of X-12-ARIMA are such that, for all $M \geq M_0$, the M-th year's holiday-linked interval lies within year M. Therefore $\sum_{j=1}^{12} n_j(M, w) = w$, which yields (4) with $K = 1$. Most of the regressors (5) underlying the Chinese New Year regression models used by Lin and Liu (2003) satisfy (4) with $K = 1$.

2.2 The Level and Seasonally Adjusted Regressors

The interval-proportion regressor can be used directly for forecasting. However, for seasonal and calendar adjustment, it is important that they be centered to have an average value of zero. This is done in order that removal of the estimated holiday effect from the series does not change the overall level of the series. It is also valuable, especially for the construction of stock regressors, see Subsection 8.3, that the regressors be adjusted to remove any fixed seasonal effects. Then holiday adjustment does not remove seasonal effects, and all stable seasonal effects are described by the seasonal factors calculated by the seasonal adjustment procedure that is applied after estimated holiday effects (and trading day effects) have been removed. When (2) holds, the twelve individual P-year calendar month averages,

$$\bar{H}_j = \frac{1}{P} \sum_{m=M}^{M+P-1} H(j + 12(m-1)), \quad 1 \leq j \leq 12, \tag{6}$$

identify the combined level-plus-seasonal component of $H(t)$.[2] Their values do not depend on $M \geq M_0$ because of (2). When $t = j + 12(M-1)$, the level and seasonally-adjusted (aka centered and deseasonalized) regressor is given by

$$\tilde{H}(t) = H(t) - \bar{H}_j, \quad 1 \leq j \leq 12, \tag{7}$$

see Bell (1984, 1995) and Findley and Soukup (2000). The regressor $\tilde{H}(t)$ satisfies

$$\tilde{H}(t + 12P) = \tilde{H}(t), \tag{8}$$

and, from (6), its level plus seasonal component is zero:

$$\frac{1}{P} \sum_{m=M}^{M+P-1} \tilde{H}(j + 12(m-1)) = \bar{H}_j - \bar{H}_j = 0, \quad 1 \leq j \leq 12. \tag{9}$$

Also, it follows from (4) and (6) that $\sum_{j=1}^{12} \bar{H}_j = (1/P)PK = K$. Therefore the annual sums $\sum_{j=1}^{12} \tilde{H}(j + 12(M-1)) = \sum_{j=1}^{12} H(j + 12(M-1)) - \sum_{j=1}^{12} \bar{H}_j$ satisfy

$$\sum_{j=1}^{12} \tilde{H}(j + 12(M-1)) = 0. \tag{10}$$

For most holiday regressors, there are months j where the non-negative regressors (5) are always zero. This is equivalent to $\bar{H}_j = 0$, so (10) is equivalent to

$$\sum_{1 \leq j \leq 12;\, \bar{H}_j \neq 0} \tilde{H}(j + 12(M-1)) = 0. \tag{11}$$

---

[2] For $H(t)$ that satisfy (2), this component is the function $\alpha_H(t)$ defined by

$$\alpha_H(j + 12(M-1)) = \bar{H}_j,$$

for $1 \leq j \leq 12$ and $M \geq M_0$. The level component is $\bar{H} = (1/12P) \sum_{t=1}^{12P} H(t) = (1/12) \sum_{j=1}^{12} \bar{H}_j$. This is easily seen to coincide with $\lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} H(t)$. Similarly $\bar{H}_j = \lim_{Q\to\infty}(1/Q) \sum_{m=M}^{M+Q-1} H(j + 12(m-1))$. The seasonal component is $\alpha(t) - \bar{H}$. To define these components, Bell (1984, 1995) assumes these limits' existence instead of assuming periodicity of $H(t)$.

3. THE END-OF-MONTH STOCK SERIES REGRESSORS

We start with flow series regressors $\tilde{H}(t)$ with the properties (8) and (9) that are available for $t = j + 12(M-1)$, with $1 \le j \le 12$ and $M \ge M_0$. Then we define the stock series regressor $\tilde{H}_S(t)$ generated by $\tilde{H}(t)$ to be

$$\tilde{H}_S(t) = \sum_{u=1+12(M_0-1)}^{t} \tilde{H}(u). \tag{12}$$

Until Subsection 8.1, we also assume (11). With this, (12) reduces to the sum (1) over the months in year M through time t,

$$\begin{aligned}\tilde{H}_S(t) &= \sum_{m=M_0}^{M-1} \sum_{i=1}^{12} \tilde{H}(i + 12(m-1)) + \sum_{i=1}^{j} \tilde{H}(i + 12(M-1)) \\ &= \sum_{i=1}^{j} \tilde{H}(i + 12(M-1)). \end{aligned} \tag{13}$$

($\sum_{m=M_0}^{M-1}$ is the null sum with value zero if $M - 1 < M_0$.) Note that if j_0 denotes the latest calendar month with non-zero values of $\tilde{H}(j_0 + 12(M-1))$, $M \ge M_0$, then from (11),

$$\tilde{H}_S(j + 12(M-1)) = 0, \quad j_0 \le j \le 12, \quad M \ge M_0. \tag{14}$$

3.1 Properties of $\tilde{H}_S(t)$

Since $\tilde{H}(i + 12(M + P - 1)) = \tilde{H}(i + 12(M-1))$ for $1 \le i \le j$ by (8), it follows from (13) that $\tilde{H}_S(t)$ also has period $12P$,

$$\tilde{H}_S(t + 12P) = \tilde{H}_S(t). \tag{15}$$

Also, its level-plus-seasonal component is zero: Indeed, for any $1 \leq j \leq 12$ and $M \geq M_0$,

$$\sum_{m=M}^{M+P-1} \tilde{H}_S(j + 12(m-1)) = 0. \tag{16}$$

due to $\sum_{m=M}^{M+P-1} \tilde{H}_S(j+12(m-1)) = P \sum_{i=1}^{j}\{(1/P) \sum_{m=M}^{M+P-1} \tilde{H}(i+12(m-1))\}$ and (9). From (16) and (15), it follows that

$$\sum_{t=t_0+1}^{t_0+12P} \tilde{H}_S(t) = 0, \quad t_0 \geq 12(M_0 - 1). \tag{17}$$

These are the main properties of interest.

The analogue of (11) does not hold. Instead, from (13) and (11),

$$\begin{aligned}
&\sum_{j=1}^{12} \tilde{H}_S(j + 12(M-1)) \\
&\quad = \sum_{j=1}^{12}\sum_{i=1}^{j} \tilde{H}(i + 12(M-1)) = \sum_{i=1}^{12}\sum_{j=i}^{12} \tilde{H}(i + 12(M-1)) \\
&\quad = \sum_{i=1}^{12}(13-i)\tilde{H}(i + 12(M-1)) \\
&\quad = \sum_{i=1}^{11}(12-i)\tilde{H}(i + 12(M-1)),
\end{aligned} \tag{18}$$

for $M \geq M_0$, the last from (11). This sum can be nonzero and can vary with M, see (24) below.

Using (17), it can the shown that the sum function $f(T) = \sum_{t=1+12(M_0-1)}^{T} \tilde{H}_S(t)$ is a level-neutral periodic function of period $12P$.

3.2 The Log Transform Case

For many positive-valued stock series, log transformation of the original data is required to obtain an adequately fitting regARIMA model. If the observed stock series $y(t)$, $1 \leq t \leq T$ has a holiday effect, but $Y(t) = \log y(t)$ is the modeled series, then $y(t)$ will induce a holiday effect in $X(t) = Y(t) - Y(t-1) = \log(y(t)/y(t-1))$ for $t > 1$. The series $X(t)$ is a flow series in the log domain. Because $Y(t) = Y(1) + \sum_{u=2}^{t} X(u)$, if $\tilde{H}(t)$ is a good regressor for estimating the holiday effects of $X(t)$, then $\tilde{H}_S(t)$ defined by (12) can be an effective regressor for estimating the holiday effects of $Y(t)$. It can then provide useful approximating holiday effect factors for $y(t)$ of the form $\exp(\beta \tilde{H}_S(t))$, as the forecasting results of the empirical studies will show.

3.3 Adjustment Factors and Difficulty of Coefficient Interpretation

As just explained, in case the data are log-transformed for regARIMA modeling, the holiday's effect is taken to be a multiplicative factor estimated by $\exp(\hat{\beta} \tilde{H}_S(t))$. Holiday adjustment consists of division of the data $y(t)$ by the positive factor $\exp(\hat{\beta} \tilde{H}_S(t))$, which is often multiplied by 100 to describe the holiday's effects on various months in percents without reference to the units of $y(t)$. In the somewhat less common case in which a regARIMA model is fit directly to the $y(t)$, the holiday's effect on a month is taken as an additive factor estimated by $\hat{\beta} \tilde{H}_S(t)$ in the units of $y(t)$. Holiday adjustment consists of subtracting $\hat{\beta} \tilde{H}_S(t)$ from $y(t)$.

It would be helpful if the value of $\hat{\beta}$ conveyed information about the size and direction of the holiday's effect in a simple way, but this is not to be expected. The property (16) has the consequence that in any calendar month j in which $\tilde{H}_S(j + 12(M-1))$ has a non-zero value, it must take on both positive and negative values as M varies. Even when $\tilde{H}_S(j + 12(M-1))$ has only two distinct values, as in the example of (20) below, the values will generally differ in magnitude as well as sign. For any coefficient estimate $\hat{\beta} \neq 0$, the same will be true of $\hat{\beta} \tilde{H}_S(j + 12(M-1))$. Consequently, the value of $\hat{\beta}$ will not have a simple interpretation. Because of their lack of utility, we will provide values of $\hat{\beta}$ and of its estimated standard error $\hat{\sigma}_\beta$ only for the Easter holiday regressor empirical study, where all regressors are univariate. As will be explained in Subsection 4.1, we use a likelihood ratio test, instead of one involving $\hat{\sigma}_\beta$, to decide when the coefficient (scalar or vector) of the preferred holiday regressor is statistically significant.

3.4 Vector Regressors

For simplicity, the preceding derivations and discussion were given for scalar regressors, but they apply when the regressors are column vectors and their coefficients are conforming row vectors. For example, regressors of the form (5) are the basic regressors of Bell and Hillmer (1983), but they also considered the case in which the holiday's effect is different across several non-overlapping intervals while constant within each interval. In this case, the regressors for the different intervals are the components of a vector regressor intended to provide a more flexible step function approximation to the holiday's effect. Such vector regressors are used to estimate stock Chinese New Year effects for more than a third of the series considered in Section 7 where such effects were found.

4. THE BASIC MODEL SELECTION PROCEDURE AND THE FORECAST COMPARISON DIAGNOSTICS

4.1 Model Selection Involving AICC

The estimation of holiday effects, and also trading day effects for a time series Y_t is done through the estimation of regARIMA models for the series $y_t = f(Y_t)$ where either the natural log transformation $f(Y) = \log Y$ is used, or no transformation, $f(Y) = Y$. A regARIMA model has the form

$$y_t = \sum_i \beta_i x_{it} + z_t,$$

where the x_{it} are regressors for trading day, holiday, outlier, or other relevant effects and z_t the regression residual series $z_t = y_t - \sum_i \beta_i x_{it}$ is generally assumed to be a non-stationary series that is transformed to stationarity by a differencing operator of the form $\delta(B) = (1-B)^d(1-B^s)^D$, where B denotes the backshift operator ($Bz_t = z_{t-1}$), the integers d and D, satisfy $0 \leq d \leq 2$, and $0 \leq D \leq 1$, and $s = 4, 12$ according to whether the data are quarterly or monthly. The differenced series $w_t = \delta(B)z_t$ is assumed to follow a seasonal ARIMA model of the form

$$\phi(B)\Phi\left(B^s\right)w_t = \theta(B)\Theta\left(B^s\right)a_t, \tag{19}$$

where, with z denoting a complex variable, $\phi(z)$ and $\Phi(z)$ are polynomials that are nonzero when $|z| \leq 1$, $\theta(z)$ and $\Theta(z)$ are nonzero for $|z| < 1$ and $\phi(0) = \Phi(0) = \theta(0) = \Theta(0) = 1$. The estimation of the coefficients of

$$\delta(B)y_t = \sum_i \beta_i \delta(B)x_{it} + w_t,$$

and of (19) is done by iterated generalized least squares treating the a_t as independent Gaussian variates with mean zero and constant variance σ_a^2. For more information, see Chapter 4 of U.S. Census Bureau (2009) and its references for more details.

To detail the model selection procedure used for the empirical studies, let L_N denote the log of the maximized likelihood of the regARIMA model with no holiday effect regressor and let h denote its total number of regression and ARMA parameters, estimated from N successive data points obtained by applying the differencing operator of the ARIMA model to the available observations. (For a monthly time series of length T and a differencing operator $\delta(B) = (1-B)^d(1-B^{12})^D$, one has $N = T - d - 12D$.) Let $L_N^{\tilde{H}_S}$ and $h^{\tilde{H}_S}$ denote the corresponding quantities for a model with a holiday regressor vector $\tilde{H}_S$ with dim $\tilde{H}_S \geq 1$, perhaps one of several holiday regressor vectors under consideration. Our basic model selection procedure is a variant of the Minimum AIC criterion of Akaike (1973). We use the sample-size adjusted AICC of Hurvich and Tsai (1989) in place of AIC, as X-12-ARIMA does. The AICC values of these competing models are given by

$$\text{AICC} = -2L_N + 2h\left(1 - \frac{h+1}{N}\right)^{-1}; \tag{20}$$

$$\text{AICC}^{\tilde{H}_S} = -2L_N^{\tilde{H}_S} + 2h^{\tilde{H}_S}\left(1 - \frac{h^{\tilde{H}_S}+1}{N}\right)^{-1}.$$

When $N \to \infty$, the factors multiplying $2h$ and $2h^{\tilde{H}_S}$ decrease to 1 and the AIC values result. For the series and models of the empirical studies we present, h and $h^{\tilde{H}_S}$ are small enough relative to N that the differences between the AIC and AICC values do not affect the choice of model. To cover the case in which several holiday regressors $\tilde{H}_S$ are considered, we define

$$\begin{aligned} \text{AICC}^* &= \min_{\tilde{H}_S} \text{AICC}^{\tilde{H}_S}, \\ \Delta\text{AICC}^* &= \text{AICC} - \text{AICC}^*, \end{aligned} \tag{21}$$

and we use $\tilde{H}_S^*$ to designate the $\tilde{H}_S$ associated with AICC*. When only one $\tilde{H}_S$ is considered, then $\tilde{H}_S^* = \tilde{H}_S$ and $\text{AICC}^* = \text{AICC}^{\tilde{H}_S}$. Holiday effect estimation with any of the $\tilde{H}_S$ is rejected if $\Delta\text{AICC}^* \leq 0$. When $\Delta\text{AICC}^* > 0$ and only one $\tilde{H}_S$ is considered, then holiday effects are assumed to be present and the regARIMA model with this $\tilde{H}_S$ is used to estimate them (unless a relevant diagnostic compellingly contradicts this decision). For our empirical studies, always several $\tilde{H}_S$ are considered. In this case, when $\Delta\text{AICC}^* > 0$, then a log-likelihood ratio test of the significance of the coefficient $\hat{\beta}$ of $\tilde{H}_S^*$ is done, with the null hypothesis of no holiday effect, $\hat{\beta} = 0$, as a crude way to compensate for the multiplicity of comparisons involved. For the modeling with $\tilde{H}_S^*$ of the holiday effect to be accepted, the value of the likelihood ratio statistic $LR_n^* = -2(L_N^{\tilde{H}_S^*} - L_N)$ must be significant in reference to its asymptotic $\chi^2_{h^{\tilde{H}_S^*} - h}$ null-hypothesis distribution (see Taniguchi and Kakizawa (2000, p. 61)) at a specified level α of significance. When $\alpha = 0.05$ and $h_{\tilde{H}_{S^*}} - h = 1$, as in the Easter regressor study below, significance means $LR_n^* \geq 3.84$ (or, for N large enough, $\Delta\text{AICC}^* \geq 1.84$). For $h_{\tilde{H}_{S^*}} - h = 2$, resp. $h_{\tilde{H}_{S^*}} - h = 3$, which occur in the CNY regressor study, the corresponding values are $LR_n^* \geq 5.99$ ($\Delta\text{AICC}^* \geq 1.99$), resp. $LR_n^* \geq 7.82$ ($\Delta\text{AICC}^* \geq 1.82$). Any single one of these thresholds can be implemented in X-12/13-ARIMA by using the `aicdiff` argument (e.g. `aicdiff=1.84`) in the `regression` spec, along with an appropriate `aictest` specification (e.g. `aictest=easterstock[31]`).

Remark 1 Although we do not use their rules explicitly, we note that Burnham and Anderson (2004, p. 271) offers rough rules of thumb for interpreting

AIC differences, based on experience and on limited simulation support. We formulate the rules with AICC instead of AIC to offer the reader some perspective on the AICC differences in Tables 2 and 6 below. With AICC_{min} denoting the minimum AICC value and AICC_{alt} denoting the second smallest AICC value, or the AICC value of some similarly competitive alternative model, set $\Delta\text{AICC} = \text{AICC}_{alt} - \text{AICC}_{min}$. If $\Delta\text{AICC} < 2$, there is substantial support for the alternative model, considerably less if $4 \leq \Delta\text{AICC} \leq 7$, and essentially no support if $\Delta\text{AICC} > 10$.

4.2 The Out-of-Sample Forecast Error Diagnostics

Let $y(t)$, $1 \leq t \leq T$ denote the observed time series data. Given a forecast lead $l \geq 1$ and forecast origin $1 \leq \tau \leq T - l$, let $y(\tau + l|\tau)$ denote the forecast of $y(\tau + l)$ obtained from $y(t)$, $1 \leq t \leq \tau$ that is provided by the regARIMA model with no stock holiday regressor when its parameters are estimated from $y(t)$, $1 \leq t \leq \tau$. With τ_0 denoting the index of the chosen initial forecast origin, the empirical root mean square lead l out-of-sample forecast error at lead l is $\text{RMSE}_l = \{(T - l - \tau_0 + 1)^{-1} \sum_{\tau=\tau_0}^{T-l} (y(\tau + l) - y(\tau + l|\tau))^2\}^{1/2}$. Let RMSE_l^* denote the analogous value for the model with the selected holiday regressor. When one of the ratios

$$\text{RMSE}_l/\text{RMSE}_l^*, \quad l = 1, 12; \tag{22}$$

is greater than one, then we conclude that use of the holiday regressor has, improved the out-of-sample forecasting at lead l on average over the time span from τ_0 to $T - l$.

In the empirical studies, we will also show values of the analogous ratios obtained when only forecasts of months for which the stock holiday regressor can be non-zero are considered. These are the months for which the holiday regressor should be most helpful for forecasting, on average. When larger than 1.00, these analogous ratios tend to be substantially larger than the ratios (22). This is natural, because significant improvement of forecasts of $y(\tau + l)$ from use of the regressors would not be expected in months $\tau + l$ in which the regressor is zero. (If having the regressor in the model improves other regARIMA model parameter estimates, a small forecast improvement some of these months could be expected.) The regressors $\tilde{H}_S^*(t)$ are zero except in March in the Easter effect study and are zero except in January, or January and February, in the CNY effect study.

Remark 2 The software's maximum log-likelihoods in the AICC criteria are associated with parameters that minimize in-sample, average one-step-ahead square error (in a somewhat weighted sense over the full time series). There is no direct link of AICC with mean square forecast performance at lags $l > 1$ in general, see Findley (2005b, 2007) and (c2) of Theorem 5.1 of Findley et al. (2004). Thus, in empirical studies, one can expect frequent conformity between AICC preference and the corresponding full-sample RMSE ratios for $l = 1$ being larger than 1.0, and less conformity with $l = 12$. This happens in our studies. The $l = 12$ ratios for the months where the holiday regressors are non-zero are natural criteria for the holidays we consider. However, we have followed the guidelines arising from the unpublished simulation studies behind the default values of τ_0 for X-12-ARIMA and X-13-AS. These conservatively prescribe a value close to 96 (eight years of monthly data). We used $\tau_0 = 97$ (January, 2003) for the Easter study and $\tau_0 = 96$ (December, 2007) for the CNY study. As a result the sums of 12-step-ahead forecast errors over holiday-effect months involve few forecasts. So in our empirical studies, their averages and their ratios in tables below are highly variable. In spite of this, we will use them to illustrate how these ratios can provide a useful alternative perspective on the contribution of the holiday-effect estimates for adjustments of individual series.

4.3 Flow versus Stock Regressors for Stock Series

A referee called our attention to a series of five papers by distinguished economists, in volume 18 of Econometrica (Klein,1950a; Fellner and Somers,1950a; Klein, 1950b; Brunner, 1950; Fellner and Somers,1950b), which debate inconclusively the role of flow variables in models for stock series. Stochastic economic variables are their focus, rather than deterministic regressors like the holiday effect regressors considered here. For our empirical studies, the referee advised "Let the data do the talking $\cdots$". Accordingly, for all of the series for which stock holiday effects were found to be present by the criteria of Subsection 4.1, we also investigated whether the model selection procedure preferred the flow holiday regressor analogues of the stock holiday regressors initially selected. As Tables 2 and 6 below show, this happened for 1 of 13 series in the Easter regressor study and for 3 of 18 series in the CNY study. Also for these series, the flow estimates provide improved forecasts on average in holiday months at one or both of the forecast lags. But there was only one series, from the CNY study, for which flow regressor almost always provided greater smoothing around holiday months than the stock regressor. For this series the differences were quite small. Additional details are given below.

5. STOCK EASTER MODELING

The X-12-ARIMA holiday regressors, all of which are described in Table 4.1 of the X-12-ARIMA Reference Manual (U.S. Census Bureau, 2009), have annual sums of zero, and all but one have the level and seasonally adjusted form (7) of $\tilde{H}(t)$, derived from $H(t)$ of the form (5). The exception is the Statistics Canada Easter regressor, denoted `sceaster[w]` in Table 4.1, which will be discussed in more detail in Subsection 8.3. First we specialize the general formula (1) to describe the stock Easter holiday regressor generated by the principal flow series Easter regressors, which are designated as `easter[w]` in Table 4.1.

5.1 Monthly Stock Easter Regressors from easter[w]

The regressors $H(t)$ underlying the flow series Easter-effect regressors of X-12-ARIMA (and of TRAMO-SEATS, see Gómez and Maravall (1997)) have the form (5) with interval lengths $1 \leq w \leq 25$. For a given w, the interval consists of the w consecutive days up through the day before Easter. The dates of Easter vary between March 22 and April 25. Therefore, (4) holds with $K = 1$ for $H(t)$. For each w, the calendar month averages $\bar{H}_1, \cdots, \bar{H}_{12}$ of (6) are given in Table 7.30 of U.S. Census Bureau (2009),[3] and the resulting $\tilde{H}(t)$ is the regressor

[3] The period P of the current Easter calendar is 5,700,000 years, see Montes (1998). A good approximation to the frequency distribution of the dates of Easter over this long period

specified by the variable `easter[w]` of the `regression` spec of X-12-ARIMA. Because $1 \leq w \leq 25$, the regressors $H(t)$ and $\tilde{H}(t)$ are zero except in February, March and April.

Hence, by (13), for month $t = j + 12(M-1)$, the value $\tilde{H}_S(t)$ of the stock series regressor generated by $\tilde{H}(t)$ has the formula

$$\tilde{H}_S(t) = \begin{cases} 0, & j = 1; \\ \tilde{H}(2 + 12(M-1)), & j = 2; \\ \tilde{H}(2 + 12(M-1)) + \tilde{H}(3 + 12(M-1)), & j = 3; \\ 0, & 4 \leq j \leq 12. \end{cases} \tag{23}$$

The final value 0 results from (14).

For $1 \leq w \leq 21$, the regressors $H(t)$, $\tilde{H}(t)$ and $\tilde{H}_S(t)$ are zero in February and $\tilde{H}_S(t)$ is nonzero only in March, with $\tilde{H}_S(3 + 12(M-1)) = \tilde{H}(3 + 12(M-1))$. So the annual sum formula (18) yields $\sum_{j=1}^{12} \tilde{H}_S(j + 12(M-1)) = 9\tilde{H}(3 + 12(M-1))$.

The value of $\tilde{H}(3 + 12(M-1))$ changes sign from year to year, depending on the date of Easter. With $w = 1$, for example, Table 7.30 reveals that $\bar{H}_3 = 0.2350$ to the precision shown. To this accuracy, $\tilde{H}_S(3 + 12(M-1))$ has the two values given by

$$\tilde{H}_S(3 + 12(M-1)) = \begin{cases} 1 - 0.2350 = 0.7650, \\ \qquad\qquad \text{Easter before April 2;} \\ 0 - 0.2350 = -0.2350, \\ \qquad\qquad \text{Easter on April } k,\ 2 \leq k \leq 25. \end{cases} \tag{24}$$

For any $1 < w \leq 21$, it is easy to see that $\tilde{H}_S(3 + 12(M-1))$ has more than two values. For example, for $w = 15$, for which Table 7.30 gives $\bar{H}_3 = 0.4695$,

---

is obtained from the dates of Easter for the years 1600–2099 given in Bednarek (2007). The values of $\bar{H}_1, \cdots, \bar{H}_{12}$ given in Table 7.30 of U.S. Census Bureau (2011) are calculated from this approximate distribution. As long as $\sum_{j=1,12} \bar{H}_j = 1$ and a seasonal differencing is used in the regARIMA model (or fixed seasonal regressors), the choice of these values will not change the Easter effect regressor coefficient estimate, because it is obtained from the fully differenced regressor. Moderately different choices of the $\bar{H}_j$ will result in slightly different seasonal factors being calculated from the holiday-effect adjusted series, see Findley and Soukup (2000) but the seasonal and holiday combined factors will usually change very little.

we have

$$\tilde{H}_S(3+12(M-1)) = \begin{cases} 1-0.4695 = 0.5305, \\ \qquad \text{Easter before April 2;} \\ \frac{1}{15}\max(16-k,0)-0.4695, \\ \qquad \text{Easter on April } k,\ 2 \le k \le 25. \end{cases}$$

These monthly stock Easter regressors and their quarterly analogues are implemented as the variables `easterstock[w]` of the `regression` spec of X-13ARIMA-SEATS (X-13A-S).[4] This is an enhanced revision of X-12-ARIMA with an implementation of SEATS, so that the option of ARIMA model-based seasonal adjustment is available. Many features of X-13A-S are described in Findley (2005a) and Monsell (2007, 2009). In analogy with what X-12-ARIMA and X-13A-S do with flow series regressors, which are designated `easter[w]`, the specification `aictest=easterstock` causes the regARIMA model specified and fit to the data with no Easter effect regressor to be augmented with an `easterstock[w]` regressor and refit to data, with each of the three lengths $w = 1$, 8 and 15 being separately tried.

5.2 Stock Easter Results: U.S. Manufacturers' Inventories

The AICC model selection procedure described in Subsection 4.1 was applied with the chi-square test done at the 0.05 level of significance. This is X-13A-S's `aictest=easterstock` procedure. In the case of series identified as having a stock trading day effect, the AICC and forecast comparison was always between the model with both trading day and Easter effect regressors and the model with only trading day regressors. Whenever outlier regressors occurred in the regARIMA model without holiday day regressors, the same outlier regressors (not shown) were included in the model with holiday regressors.

Here we present results for the 13 series out of 122 in the U.S. Census Bureau's monthly U.S. Manufacturers' Shipments, Inventories and Orders Survey

[4] These regressors are not avaible in the regression spec of X-12-ARIMA, but they can be generated for input as user-defined regressors by the GENHOL utility we used to obtain CNY regressors. For more information, see Monsell (2011).

(the M3 Survey) that were determined to have stock Easter effects by the procedure just described. For consistency with our CNY regressor study presented below, the computer runs were done with the software's automatic choice between log transformation and no transformation (with one exception noted below) and with automatic regARIMA modeling for the data specified by the transformation choice. Our results do not reproduce results published by U.S. Census Bureau. For the published results, the log transformation was always used in modeling the series, and no stock Easter effects were estimated for these series.

The series, as used here, end in October 2008, when the current recession was starting. Use of more recent data eliminated one series and produced mostly worse results, especially for out-of-sample forecasting, as would be expected. The series starting dates vary from January 1992 to January 1995 according to the choice made for the regARIMA modeling of each series at the Census Bureau. These are end-of-month inventory series, with the qualification that adjustments are made to produce approximate end-of-calendar-month values for reporters to the M3 Survey who provide end-of-report-period values for four- or five-week periods instead of for calendar months. For details, see M3 (2008). Revised data for these series are available from http://www.census.gov/econ/currentdata/.

The effects are multiplicative for the 8 series whose model included a log transformation and additive for the remaining 5. The 13 series are identified in Table 1. A Total Inventory series is usually the sum of three component inventories series: Materials and Supplies, Work-in-Progress and Finished Goods. Although it was not the automatic choice, the log transformation was used for the Total Inventory series 31ATI because it was the automatic choice for the component series 31SFI.

Table 2 first shows the value w of the regressor chosen for each series and its associated ΔAICC* as defined in (21), followed by the estimated coefficient $\hat{\beta}$ of $\tilde{H}_S(t)$ and its estimated standard error $\hat{\sigma}_\beta$. One can note that the $\hat{\beta}$ are all comfortably more than $2\hat{\sigma}_\beta$ units away from zero, but it is difficult to obtain other information from the $\hat{\beta}$, see Subsection 3.3.

The last two columns of Table 2 show ratios (22) of empirical root mean square out-of-sample forecast error at leads $l = 1, 12$, starting from $l = 1$

Table 1 M3 inventory series with significant Easter holiday effects

11SFI	Finished Goods Inventories of Food Products
21SFI	Finished Goods Inventories of Wood Products
22BTI	Total Inventories of Paperboard Container Manufacturing
24ATI	Total Inventories of Petroleum Refineries
24SWI	Work-in-Progress Inventories of Petroleum and Coal Products
25CTI	Total Inventories of Paint, Coating and Adhesive Manufacturing
31ATI	Total Inventories of Iron and Steel Mills and Ferroalloy and Steel Products
31SFI	Finished Goods Inventories of Primary Metals
32SFI	Finished Goods Inventories of Fabricated Metal Products
34ATI	Total Inventories of Electronic Computer Manufacturing
35SFI	Finished Goods of Electrical, Equipment, Appliances and Components
37SFI	Finished Goods Inventories of Furniture and Related Products
39SMI	Materials-and-Supplies Inventories of Miscellaneous Manufacturing

forecasts of January 2003. Next to them, in parentheses, are the corresponding ratios $\text{RMSE}_l^{Mar}/\text{RMSE}_l^{*Mar}$ for just the March forecasts, which could be the more revealing quantities, as is explained in Subsection 4.2, perhaps somewhat compromised because the number of Marches in the forecast interval is small. Ratios greater than 1.0 favor use of the holiday regressor under consideration.

As the Table 2 shows, the RMSE values[5] RMSE_l^* at $l = 1$ for the models with an Easter regressor are smaller than the RMSE_1 values of the models without holiday regressor for 10 of the 11 series. Also, the ratio values in parentheses show that 7 of these 10 series experienced even greater forecast improvements in March from the use of holiday regressor.

At $l = 12$, only 8 of the 11 series have equal or improved forecasts with the holiday regressor. Among these 8 series, only 25CTI experiences worse March forecasting from use of the Easter regressor. The use of a flow Easter regressor with a smaller AICC for 21SFI yielded equivalent or slightly worse forecast

[5] The mean square error values for (22) can be obtained from X-12-ARIMA and X-13A-S (`save = fce` in the `history` spec) as can the forecast error values for each month (`save = fch` in the `history` spec). From the latter, the ratios $\text{RMSE}_l^{Mar}/\text{RMSE}_l^{*Mar}$, $l = 1, 12$ for March forecasts can be computed. X-12-ARIMA can be downloaded from http://www.census.gov/srd/www/x12a/, as can the GENHOL program referenced in the preceding footnote and below.

Table 2 The selected Easter interval length w, the associated ΔAICC*, the Easter regressor's coefficient and its standard error, and the ratios $\text{RMSE}_l/\text{RMSE}_l^*$ (and $\text{RMSE}_l^{Mar}/\text{RMSE}_l^{*Mar}$) $l = 1, 12$ for each series of Table 1

Series	w	ΔAICC*	$\hat{\beta}$	$\hat{\sigma}_\beta$	$l = 1$	$l = 12$
11SFI	15	5.6	−0.0133	0.0046	1.03 (1.02)	1.00 (1.06)
22BTI	1	8.4	0.0172	0.0050	0.97 (0.95)	0.97 (0.88)
24ATI	8	4.4	0.0267	0.0102	1.02 (1.21)	1.00 (1.03)
24SWI	15	7.1	0.0656	0.0207	1.01 (0.82)	1.01 (1.05)
25CTI	8	5.5	0.0116	0.0042	1.02 (1.14)	1.00 (0.97)
(2)⊠31ATI	15	8.4	0.0088	0.0026	1.00 (1.14)	1.00 (1.06)
31SFI	1	12.0	0.0214	0.0055	1.05 (1.19)	1.00 (1.02)
(1)⊠34ATI	8	3.4	0.0296	0.0123	0.99 (1.17)	0.99 (1.34)
(1)⊠35SFI	8	10.7	−0.0168	0.0045	1.02 (1.37)	1.00 (1.02)
21SFI	15	3.5	103.3300	41.8800	1.01 (1.10)	1.00 (1.02)
21SFI#	15	4.9	65.1100	23.8400	1.02 (1.12)	1.00 (1.02)
31ATI	15	9.1	117.0200	34.0100	1.02 (1.11)	1.00 (1.03)
32SFI	1	10.1	−162.9800	40.3300	1.03 (1.18)	1.00 (1.00)
(1)⊠37SFI	1	2.4	−44.8600	20.1300	1.01 (1.29)	1.04 (1.21)
39SMI	8	2.9	61.0400	26.4300	1.01 (1.12)	1.00 (1.04)

Note: The superscript # indicates a row comparing the flow Easter regressor with the stock Easter regressor for a series where the flow regressor has a smaller AICC by the amount shown. Ratios in this case are flow RMSEs divided by stock RMSEs. For the last five series, automatic modeling rejected log transformation. The symbols (1)⊠ and (2)⊠ indicate that the Easter factors too often worsen or fail to improve the seasonal adjustment around holiday months, see Section 6.

performance than the stock Easter regressor, as the row values for 21SFI# show. The numerators of the $l = 1, 12$ ratios in this row are the RMSE values for the model with the flow regressor.

Finally, we present information regarding the ranges of the seasonal, trading day (from the 1-coefficent model of Findley and Monsell (2009)), and Easter effect adjustment factors for these series. We refer to these factors generically as S, TD, and E, respectively. These are multiplicative factors when the series are log-transformed for modeling. Otherwise they are additive. Table 3

Table 3 Minima and maxima of the seasonal, trading day and Easter effect adjustment factors

Series	min S	max S	min TD	max TD	min E	max E
11SFI	0.935	1.065	0.997	1.003	0.993	1.007
22BTI	0.971	1.021	—	—	0.995	1.013
24ATI	0.903	1.070	0.996	1.004	0.990	1.017
24SWI	0.875	1.073	—	—	0.968	1.034
25CTI	0.943	1.036	—	—	0.996	1.007
31ATI	0.977	1.026	0.996	1.004	0.996	1.004
31SFI	0.970	1.027	0.993	1.007	0.994	1.016
34ATI	0.921	1.105	—	—	0.989	1.018
35SFI	0.913	1.070	—	—	0.990	1.006
21SFI	−354.30	367.84	—	—	−51.39	51.94
21SFI#	−360.10	391.07	—	—	−32.73	32.73
34ATI	−369.43	453.36	−43.38	43.38	−58.20	58.82
32SFI	−528.75	455.28	−15.03	15.03	−119.73	43.35
37SFI	−161.52	132.11	—	—	−32.92	11.93
39SMI	−130.67	119.88	—	—	−23.42	37.72

Note: The last six series have additive adjustment factors and hence negative minima. A# on a series code indicates a row of values from a flow Easter regressor.

reveals that the ranges of the holiday factors (calculated as $\max_t\{\exp(\beta \tilde{H}_S(t))\} - \min_t\{\exp(\beta \tilde{H}_S(t))\}$ in the multiplicative case) are generally larger than the ranges of the trading day factors and smaller than the ranges of the seasonal factors. This is consistent with what is typically found for flow series.

Titova and Monsell (2009) present results for other Census Bureau inventory series found to have statistically significant stock Easter holiday effects in a slightly shorter span of data.

6. EVALUATION BASED ON SMOOTHNESS

Sufficiently large AICC differences, as described in Subsection 4.1, identified the candidate series for Easter effect adjustment listed above in Table 1 for U.S.

Manufacturing inventories and also candidate Taiwan stock series for CNY adjustment of listed below in Table 5. The average out-of-sample forecast error ratios support these preferences more often than not (less well for the U.S. series). But smoothing is what most users want holiday effect adjustment to achieve, although this is a difficult property to formulate and to compellingly relate to the mathematics of adjustment.

We visually analyzed overlay graphs of the competing seasonal adjustments of the series, for example seasonal-only adjustment versus stock holiday combined factor adjustment, or flow combined factor versus stock combined factor adjustment. From one year to the next, each holiday's main effects occur around the same month or two. So we examined the extent to which holiday adjustment improved or worsened smoothness around these months, or had no easily visible effect. A few of these graphs are shown for the CNY study, which has larger holiday adjustment factors, in Figures 1, 5, 6, 12 and 14 below.

Based on this analysis, in Tables 2 and 6, we recommend seasonal adjustment with no holiday adjustment for some series. We also found one flow series for which some seasonal adjusters or data users might slightly prefer seasonal adjustment with flow CNY factors in place of stock CNY factors, see Figure 14.

There are two main reasons for rejecting a holiday effect adjustment based on smoothness properties: (1) When the holiday adjustment makes a visible difference in smoothness but, at least as often as not, it yields a less smooth series around the holiday months, also in more recent years; see Figure 5. (2) The adjustments are so small that they are not of practical interest. Such rejections are indicated by (1)⊠ and (2)⊠ respectively in Tables 2 and 6. Otherwise, holiday adjustment is recommended.

There can be ambiguous situations. For example, (1) can hold early in the series but in the more recent years of the series, holiday adjustment can almost always increases smoothness. Or, adjustment effects can be mostly very small but some in recent years provide smoothing great enough to have practical value. In the few ambiguous cases, encountered, we favored holiday adjustment.

A comment on 21SFI is needed to conclude the Easter effect study. This is the series for which AICC preferred flow Easter adjustment over stock Easter adjustment. An overlay graph (not presented) shows that the only conspicuous (but not large) smoothness difference occurs around Easter of the final year 2008, where the flow adjustment is somewhat smoother than the stock adjustment. This is not enough to justify flow adjustment of a stock series.

7. STOCK CHINESE NEW YEAR MODELING

Lin and Liu (2003) used combinations of flow series regressors of the form (7), derived from interval-proportion regressors (5) to model and adjust for the effects of several Chinese lunar calendar holidays for a variety of monthly flow series. The most important of these holidays is the Chinese New Year (CNY), whose dates fall between January 21 and February 21 through 2644. It has approximately a 60 year cycle. The actual cycle length is significantly longer, see Aslaksen (2010). Lin and Liu found its effects occurring in different ways in as many as three intervals, a "before" interval of varying length w leading up through the day before the New Year's date, a week-long "after" interval starting on the holiday, and a week-long "recovery" interval starting a week after the holiday. For most of the series analyzed by Lin and Liu, the significant effects leading up to the holiday occurred in intervals of length not exceeding 20 days. For these intervals, the associated regressors (5) sum to 1 over all calendar years, so (4) is satisfied. (See Subsection 8.1 for a way to accommodate intervals which include days in the preceding December.) For the level plus seasonal adjustment factors (6), we considered both 60 year and 150 year averages, but the resulting flow regressors (7) differed in value by less than 10^{-4}. Therefore, following Lin and Liu, we used 60 year averages to define the flow regressors (7) from which the stock CNY regressors of our empirical study were constructed. Table 4 describes the regressors considered and the codes we use for them.

With $\tilde{H}_S^{\backslash 1c}$ denoting a stock CNY regressor with a code different from 1c and with $\tilde{H}^{\backslash 1c}$ denoting the corresponding flow regressor, (11) and (14) yield

$$\tilde{H}_S^{\backslash 1c}(j + 12(M-1)) = \begin{cases} \tilde{H}^{\backslash 1c}(1 + 12(M-1)), & j = 1; \\ 0, & 2 \leq j \leq 12. \end{cases} \tag{25}$$

Table 4 Codes for Chinese New Year regressors used

Regressor's Interval	Regressor Code
7 days before CNY	1b
14 days before CNY	2b
20 days before CNY	3b
7 days starting from CNY	1a
7 days starting a week after CNY	1c

For the 1c regressors, denoted $\tilde{H}^{1c}$ and $\tilde{H}_S^{1c}$, the flow regressor is identically 0 only for April and later months. Thus, from (11) and (14), for any year $M \geq M_0$ and $t = j + 12(M-1)$

$$\tilde{H}_S^{1c}(t) = \begin{cases} \tilde{H}^{1c}(1 + 12(M-1), & j = 1; \\ \tilde{H}^{1c}(1 + 12(M-1)) + \tilde{H}^{1c}(2 + 12(M-1)), & j = 2; \\ 0, & 3 \leq j \leq 12. \end{cases} \quad (26)$$

7.1 CNY Results for Taiwan Indicator Inventory Series

We now present CNY modeling results for 18 monthly Taiwan economic indicator inventory series published by the Directorate General of Budget, Accounting and Statistics and listed in Table 5. These are the series, from an initial set of 25, for which the minimum AICC criterion-based procedure, augmented with likelihood ratio tests as described in Subsection 4.1, selected models with one or more CNY regressors for the data from January 2000 to September 2010. In these years, the CNY dates ranged between January 22 (in 2004) and February 18 (in 2007). The CNY regressors $\tilde{H}_S$ considered are given by (12) with $\tilde{H}$ denoting CNY flow regressors like those used by Lin and Liu for the intervals shown in Table 4. The regressors $\tilde{H}_S$ (and $\tilde{H}$ for the comparison of flow with stock regressors, see Subsection 4.3) were produced by the downloadable GENHOL program from a file of CNY dates. GENHOL also produces the spec file text required to have X-12-ARIMA or X-13A-S read in the regressor values generated and add the regression vector to the regARIMA model specified; see Monsell (2011).

Table 5 Inventory Ratio and Index of Producers Inventory (IPI) series for which automatic modeling chose CNY regressors

Series Code	Series Title (Type)
EA0802	Inventory Ratio Manufacturing of Taiwan
QI02	IPI Foods
QI03	IPI Beverages
QI04	IPI Tobacco
QI05	IPI Textile Mills
QI06	IPI Wearing Apparel and Clothing Accessories
QI11	IPI Petroleum and Coal Products
QI12	IPI Chemical Material
QI13	IPI Chemical Products
QI14	IPI Medical Goods
QI15	IPI Rubber Manufacturing
QI18	IPI Non-Metallic Mineral Products
QI19	IPI Basic Metal Manufacturing
QI21	IPI Electronic Parts and Components Manufacturing
QI22	IPI Computer, Electronic and Optical Products Manufacturing
QI25	IPI Motor Vehicles and Parts
QI26	IPI Other Transport Equipment
QI27	IPI Furniture

Table 6 below uses the regressor codes of Table 4 to show the CNY regressors chosen for each series. In addition, the codes *tdstock* and *tdstock1* are used to indicate the presence in the regARIMA model of the 6-coefficient or the 1-coefficient stock trading day regressor, respectively. Both are discussed in Findley and Monsell (2009). The effects are multiplicative for the 13 series whose model included a log transformation. They are additive for the remaining 5, whose results appear in the last 6 rows of Tables 6 and 7. Coefficient estimates are not presented due to their limited utility, see Subsection 3.3.

Table 6's AICC values and RMSE ratios (22) compare the models with CNY regressors to the models without these holiday, analogously to the comparisons done for Easter regressors in Subsection 5.2. The forecasts considered are for the interval from January 2008 to September 2010. Again, RMSEs are considered with averages over all months and also only over CNY months. the

Table 6 CNY and TD regressor choices, and values of ΔAICC* and $\text{RMSE}_l/\text{RMSE}^*_l$ (and $\text{RMSE}_l^{Jan\&Feb}/\text{RMSE}_l^{*Jan\&Feb}$) $l = 1, 12$

Series	Regressors	ΔAICC*	$l = 1$ Ratios	$l = 12$ Ratios
QI02	1b	11.6	1.10 (1.26)	1.03 (1.32)
QI03	1b, 1a, 1c	25.3	1.12 (2.31)	1.06 (1.47)
QI05	2b, 1a, 1c, tdstock1	20.0	1.15 (1.04)	1.05 (1.00)
QI11	3b	4.5	1.03 (3.10)	1.02 (1.47)
QI12	1b	9.7	1.07 (0.83)	1.01 (1.07)
QI12#	1b	4.3	0.97 (0.91)	1.02 (1.05)
QI13	1b, 1a	4.7	1.01 (1.06)	0.97 (0.92)
QI15	1b, tdstock1	18.9	1.07 (1.08)	0.98 (1.00)
QI18	1b, 1a, tdstock1	19.7	1.13 (0.97)	1.05 (1.00)
(1)⊠QI19	2b, tdstock1	8.3	1.07 (1.01)	1.01 (1.00)
(1)⊠QI21	3b	3.8	0.96 (0.86)	0.98 (0.89)
(1)⊠QI22	2b	7.4	0.97 (0.85)	0.92 (0.50)
QI25	1b	7.9	1.08 (1.18)	1.00 (1.11)
QI25#	1b	2.3	1.00 (1.03)	1.02 (1.15)
QI27	1b, 1a	2.5	1.02 (1.16)	1.00 (1.01)
EA0802	2b, 1a, 1c, tdstock1	48.3	1.23 (3.33)	0.85 (0.90)
QI04	2b	32.4	1.09 (1.41)	0.85 (1.52)
QI06	1b	22.2	1.06 (1.12)	1.02 (1.00)
QI14	3b	10.0	1.02 (1.22)	1.06 (1.51)
QI14#	3b	4.3	0.91 (0.67)	1.04 (1.27)
(1)⊠QI26	1b, 1a, tdstock	2.8	0.99 (0.95)	0.97 (0.89)

Note: The superscript # indicates a row comparing the flow CNY regressor with the stock CNY regressor for a series where the flow regressor has a smaller AICC by the amount shown. Ratios in this case are flow RMSEs divided by stock RMSEs. For the last five series, the log transformation was not used. The symbol (1)⊠ indicates that the CNY factors too often worsen the seasonal adjustment around holiday months, see Section 6.

latter RMSEs have the superscript $^{Jan\&Feb}$. There are three series, QI21, QI22 and QI26, for which all lead 1 and 12 forecast RMSEs of the model with CNY regressors are larger than the RMSEs of the models without CNY regressors. Thus one might prefer models with no CNY regressor for these series, a decision supported by smoothing considerations, see Section 6, as Table 6 indicates. (Note also that QI21 and QI26 have the AICC differences least supportive of

CNY regressors.) For the other 15 series, our initial decision was to do CNY adjustment with regressors shown in Table 6. This was contradicted by the graphical smoothness analysis only for QI19.

As the table shows, the lead $l = 1$ RMSE values RMSE_1^* for the models with stock CNY regressors are smaller than the RMSE_1 values of the models without stock holiday regressors for all 15 series. Also, the ratio values in parentheses show that 11 of these 15 series experienced even greater average forecast improvements in months in which the CNY regressors were nonzero.

At $l = 12$, among the 15 series, 11 have equal or improved forecasts on average over all months when the model has a holiday regressor. This holds for the January and February forecasts with 12 series. In Table 6, with few exceptions, the series with AICC differences $\Delta\mathrm{AICC}^*$ less than 8 are associated with $l = 1$ ratios closest to 1.0, especially for January and February forecasts.

As the row values for series codes with a $^{\#}$ show, use of the flow analogue of the stock CNY regressor results in better $l = 1$ forecast performance for QI12 and QI14 but worse $l = 12$ forecast performance, also for QI25, the other series for which the flow CNY regressor is preferred by AICC.

Table 7 presents the ranges of the multiplicative holiday factors for series that are log-transformed for modeling, given by $\max_t\{\exp(\beta\tilde{H}_S(t))\} - \min_t\{\exp(\beta\tilde{H}_S(t))\}$, and the ranges of the additive factors for series that are not transformed, given by $\max_t\{\beta\tilde{H}_S(t)\} - \min_t\{\beta\tilde{H}_S(t)\}$. These ranges are larger than the ranges of the trading day factors and smaller than the ranges of the seasonal factors. This is consistent with what is typically found for flow series.

Figure 1 shows the overlay of the seasonally adjusted series of QI03 obtained without CNY effect estimation with the combined seasonal and CNY effect adjusted series. There are many years in which the combined adjustment provides greater smoothing around the holiday. Figure 2 shows the January and February CNY factors. Figure 3 shows the January seasonal factors and the combined factors, i.e., the products of the seasonal and CNY factors. Figure 4 is the February analogue of Figure 3. Table 7 reveals that QI03 and the series QI25 considered in Subsection 7.2 have the greatest multiplicative seasonal factor ranges in our study.

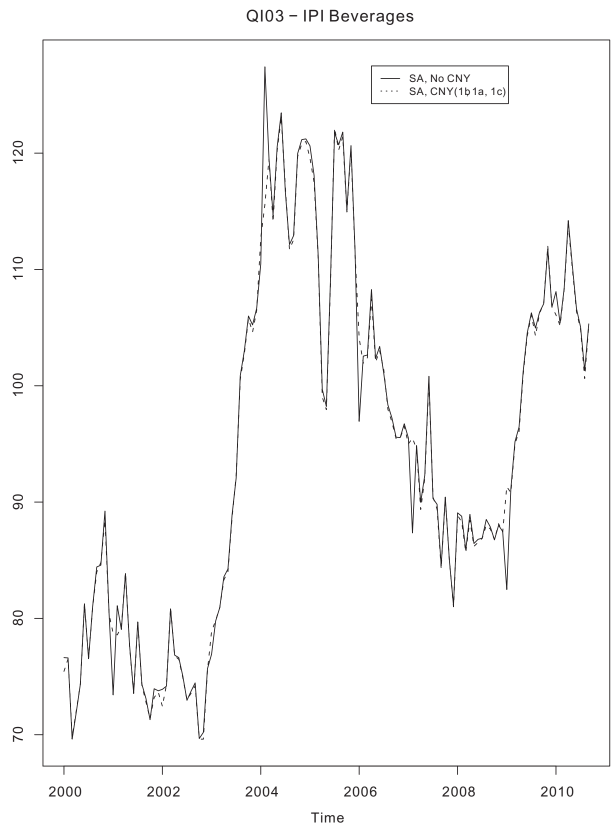
Table 7 Minima and maxima of the seasonal, trading day and CNY adjustment factors

Code	min S	max S	min TD	max TD	min CNY	max CNY
QI02	0.835	1.137	—	—	0.966	1.033
QI03	0.901	1.148	—	—	0.856	1.104
QI05	0.938	1.049	0.995	1.005	0.980	1.032
QI11	0.890	1.065	—	—	0.931	1.033
QI12	0.941	1.082	—	—	0.953	1.052
QI12#	0.943	1.088	—	—	0.969	1.032
QI13	0.933	1.074	—	—	0.978	1.023
QI15	0.939	1.085	0.993	1.007	0.958	1.042
QI18	0.962	1.040	0.992	1.007	0.983	1.037
QI19	0.945	1.078	0.993	1.007	0.984	1.017
QI21	0.956	1.053	—	—	0.983	1.038
QI22	0.920	1.060	—	—	0.975	1.040
QI25	0.635	2.566	—	—	0.892	1.114
QI25#	0.646	2.556			0.937	1.066
QI27	0.854	1.151	—	—	0.934	1.025
EA0802	−6.60	23.14	−1.61	1.61	−2.50	6.07
QI04	−43.96	43.00	—	—	−29.06	44.20
QI06	−34.77	19.62	—	—	−2.63	2.49
QI14	−5.29	5.89	—	—	−2.21	4.85
QI14#	−5.12	5.97	—	—	−2.78	2.78
QI26	−12.52	11.06	−1.89	2.35	−8.21	3.01

Note: The last five series have additive adjustment factors and hence negative minima.

7.2 Flow versus Stock Examples in Detail

Here we graphical results for some series for which AICC preferred the flow holiday over the stock holiday regressor. Table 6 identifies three such series. We consider QI25 in detail and briefly comment on QI12 and QI14. QI25 is the only multiplicatively adjusted series for which AICC preferred the flow CNY 1b regressors over the initially chosen stock CNY 1b regressor and also the flow regressor provided better average forecast performance in January and February. Figure 6 shows the overlay of its seasonal adjustment without CNY estimation



Note: One ignoring stock CNY effects (solid line), the other with estimated stock CNY effects also removed (dashed line). The combined-factor adjustment is generally as smooth or smoother around January and February, indicating that stock CNY adjustment is desirable.

Figure 1 Two seasonal adjustments for QI03

and its combined adjustment with stock CNY estimation. The January stock CNY factors are presented in Figure 7. The February factors have the value 1.0. The flow CNY factors for January and February appear in Figure 8.

Figure 9 shows QI25's January seasonal and combined factors from stock CNY estimation. No corresponding figure is given for February because the combined factors coincide with the seasonal factors (not shown), which are quite close to the seasonal factors associated with flow combined shown in Figure 11: flow CNY effect estimation has only a small impact on February sea-

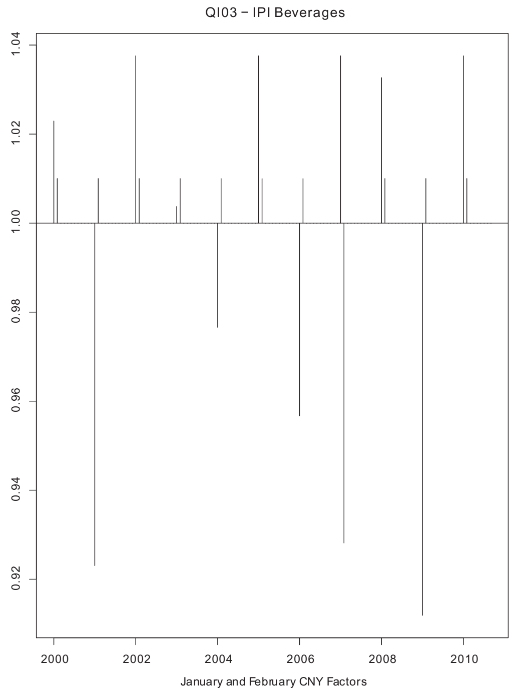
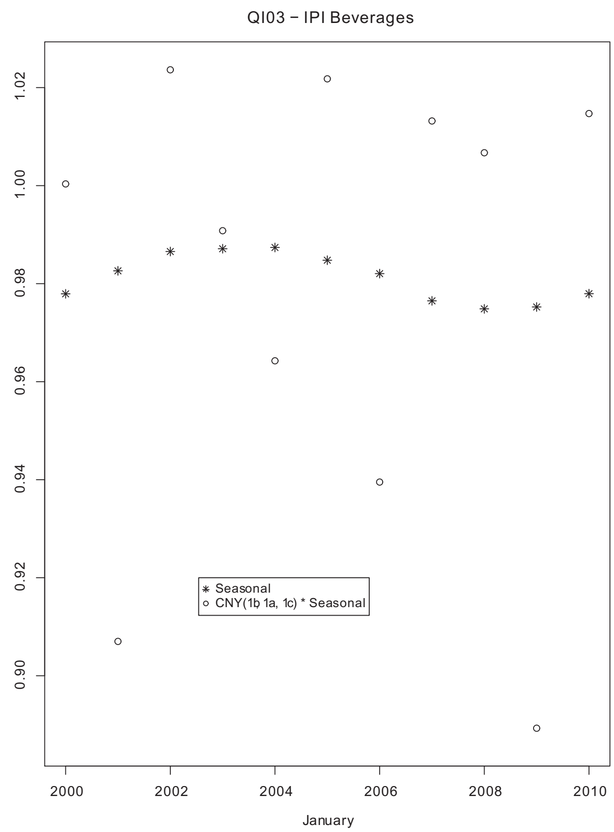


Figure 2 January and February stock CNY adjustment factors for QI03

sonal factor estimates in this case. (By contrast, the seasonal factors in Figures 10 and 11 show that the more strongly differing flow and stock January preadjustments give rise to seasonal factors that differ quite perceptibly.)

Figure 12 is the overlay of the stock CNY combined-factor adjusted series with the flow CNY combined-factor adjustment. The CNY flow factors provide a smoother seasonal adjustment around the CNY months of the first two years of the series. Thereafter the stock adjustments are smoother around CNY months more often than not. An analyst concerned with the more recent data would be likely to prefer the stock CNY adjustment. Figure 13 shows the ratio of these adjustments. This ratio is the effect on seasonally adjusted levels of changing from stock CNY adjustment to flow CNY adjustment.

We summarize our observations of the seasonal adjustment graphs (not shown) of the other two Taiwan series for which AICC preferred flow CNY estimation. For QI12, flow CNY seasonal adjustment usually yields slightly more smoothness around January and February. However, it is substantially



Note: Seasonal only (stars) and combined seasonal times stock CNY adjustment factors (circles).

Figure 3 January adjustment factors for QI03

less smooth in the one year, 2006, where the CNY adjustments differ substantially. Finally, for QI14, the additive seasonal adjustment factors are small and the CNY factors smaller still. Both CNY adjustments are acceptable and very similar. The flow adjustment is slightly smoother in three years, including 2009–10 and slightly less smooth in two. There is no strong reason to prefer the flow adjustment for these stock series.

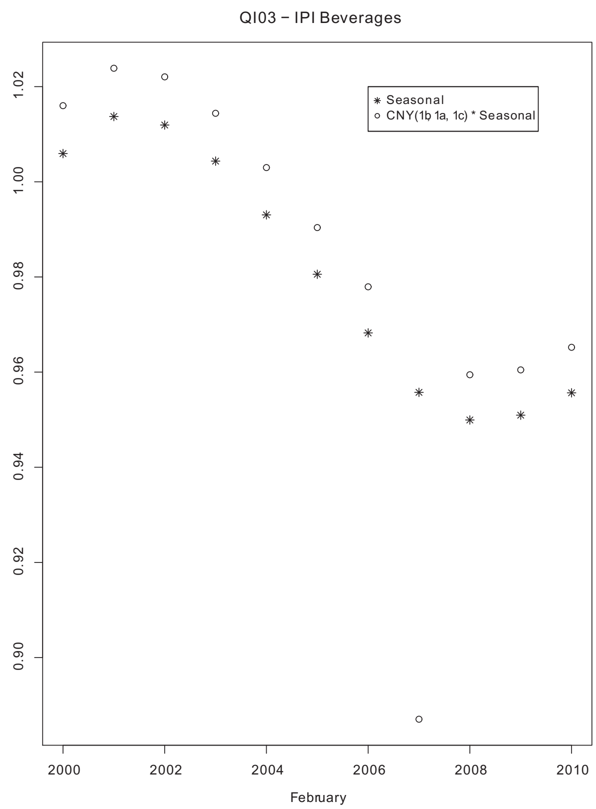
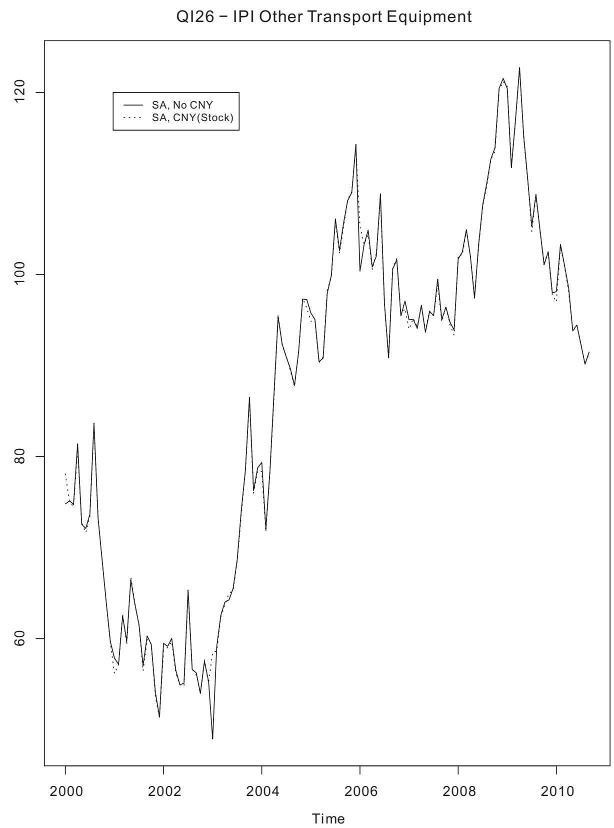


Figure 4 February seasonal factors for QI03 (stars) and multiplicatively combined seasonal and stock CNY factors (circles)

8. MODIFICATIONS FOR OTHER SITUATIONS

We now consider examples for which (4) fails to hold, or seasonal mean removal (7) is not done, or stocks are measured on a fixed day earlier than the last day of the month. For the examples considered, there are simple modifications of the approach taken in the preceding sections which yield stock regressors appropriate for moving holiday adjustment that have a simple form analogous to (13).



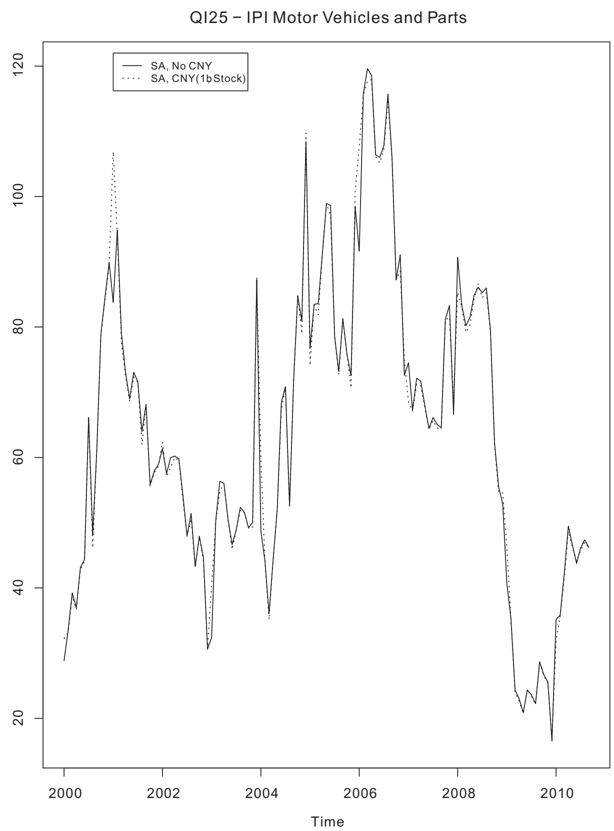
Note: This is an example of a series for which the value of CNY adjustment is not recommended: around the CNY months January and February, it provides smoother movements in 2003–6, but less smooth movements in 2000–1, 2007–8 and 2010.

Figure 5 Seasonal Adjustments of QI26

8.1 Examples in Which Flow Regressor Annual Sums Are Not Constant

We first consider an example in which the interval associated with a holiday regressor of the form (5) overlaps two different years, with the consequence that annual sums $\sum_{j=1}^{12} H(j + 12(M - 1))$ are not constant, i.e. (4) fails to hold.

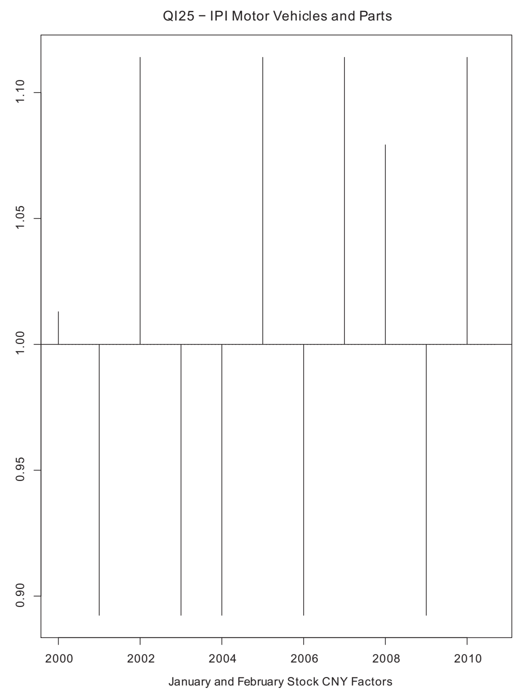
When the "before" interval associated with increased economic activity



Note: One ignoring stock CNY effects (solid line), the other with combined stock CNY and seasonal effects removed (dashes). After January 2002, the combined-factor adjustment is as smooth or smoother than the seasonal-only adjustment around January, making it desirable.

Figure 6 Two seasonal adjustments for QI25

prior to CNY has a length of 21 days or more (but less than 51 days, for simplicity), then it will include one or more days from December of the year $M-1$ for each year M in which the holiday falls on January 21. When this happens, $\sum_{j=1}^{12} H(j+12(M-1))$ is less than one. In some other years it will be equal to one. Thus neither (4) nor (11) will hold. However, the analogues of (4) and (11) will hold for 12 month sums that begin in December and end in November: $\sum_{j=0}^{11} H(j+12(M-1)) = 1$. So, if $H(t)$ has been calculated for $t = 12(M_0-1)$, one can define $\tilde{H}_S(t)$ for any $t = j + 12(M-1)$ with



Note: The February factors are 1.0.

Figure 7 January and February stock CNY factors for QI25

$0 \leq j \leq 11$ and $M \geq M_0$ by means of $\tilde{H}_S(t) = \sum_{u=12(M_0-1)}^{t} \tilde{H}(u)$ and obtain the simplified formula $\tilde{H}_S(t) = \sum_{i=0}^{j} \tilde{H}(i + 12(M-1))$ together with the properties (15) and $\sum_{m=M}^{M+P-1} \tilde{H}_S(j + 12(m-1)) = 0$.

8.2 Further Examples Requiring a Redefinition of "Months" and "Years"

The modification proposed above to accommodate the Chinese New Year effects with a long preholiday interval can be interpreted as a redefinition of "years" to denote 12-months intervals starting with December, in order to obtain regressors $H(t)$ that satisfy (4). Here we describe another useful example for which a similar strategy can be successfully employed. X-12-ARIMA and X-13A-S provide stock trading day regressors for series for which the stock is always measured on the ω-th day of the month for fixed $1 \leq \omega \leq 31$ or at

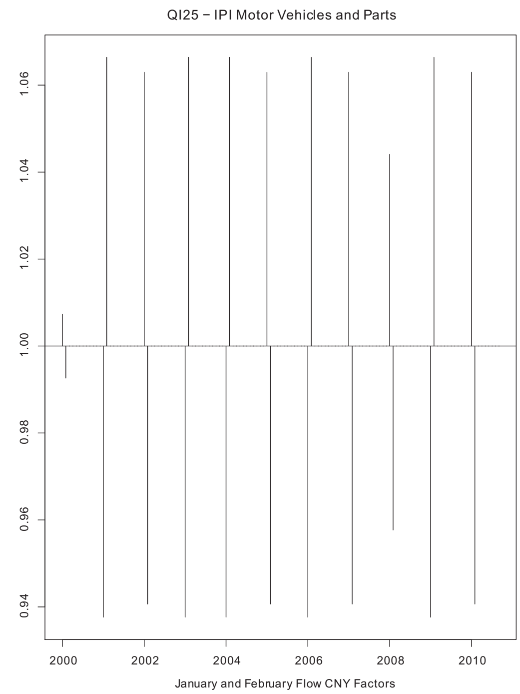
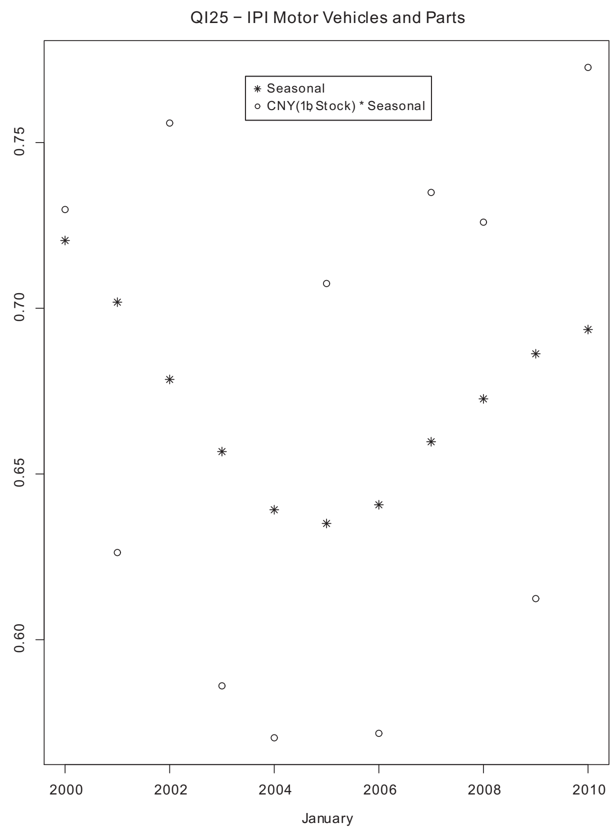


Figure 8 January and February flow CNY factors for QI25

the end of the month when the month's length is less than ω. Easter regressors with properties analogous to those of Subsection 5.1 can be obtained for such stocks by redefining the j-th month of the year to start the day after the stock day of the preceding calendar month and to end on the stock day of the j-th calendar month. For example, with $\omega = 15$, the first day of the first newly defined month of year M begins on December 16 of year $M - 1$ and this newly defined first month ends on January 15th. If Easter falls on April 17 of year M, this is the second day of the fifth newly defined month. As a consequence, for each interval length w, the values of the proportionality regressors (5) must be recalculated, as must the associated level-plus-seasonal components (6), before the desired stock regressor values (13) can be obtained.

Titova and Monsell (2009) identify stock series for which regARIMA modeling with an Easter effect regressor obtained in this way for $\omega = 28$ is favored, by the procedure of Subsection 4.1, over modeling with any of the regressors of Subsection 5.1 ($\omega = 31$) or modeling with no Easter holiday regressor.



Note: Seasonal only (stars) and the combined stock CNY and seasonal factors (circles).

Figure 9 January adjustment factors for QI25

8.3 Deficiency of Flow Regressors with a Seasonal Component

Here we use the Statistics Canada Easter regressor `sceaster[w]` of X-12-ARIMA to demonstrate that when a flow regressor is not centered on its calendar month averages, the stock regressor it generates by accumulation can have a nonzero level-plus-seasonal component, even when the flow regressor's annual sums (and level component) are zero.

The interval of length w associated with `sceaster[w]` consists of Easter and the preceding $w-1$ days. In year M, it is defined by the number $n(M) = n(M, w)$ of days of March included in this interval. For $1 \leq w \leq 22$ and

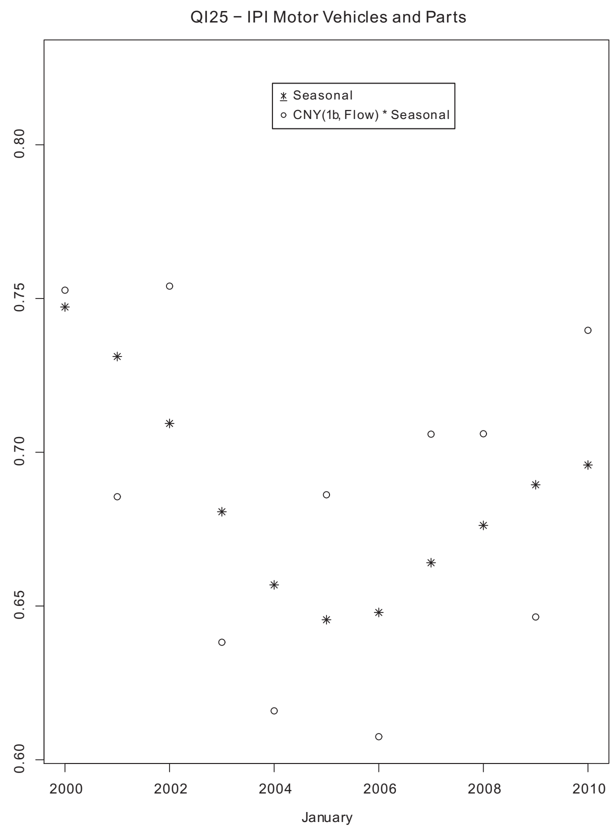


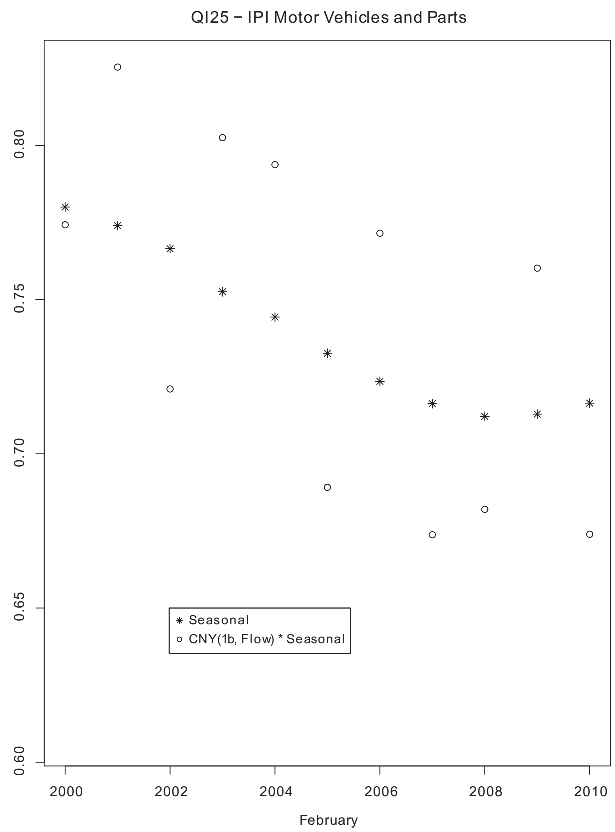
Figure 10 January seasonal factors for QI25 (stars) and the combined flow CNY and seasonal factors (circles)

$1 \leq j \leq 12$, its values are

$$H^{SC}(j + 12(M-1)) = \begin{cases} \frac{n(M)}{w}, & j = 3; \\ -\frac{n(M)}{w}, & j = 4; \\ 0, & j \neq 3, 4; \end{cases} \tag{27}$$

so its annual sums satisfy

$$\sum_{j=1}^{12} H^{SC}(j + 12(M-1)) = 0, \quad M \geq M_0. \tag{28}$$



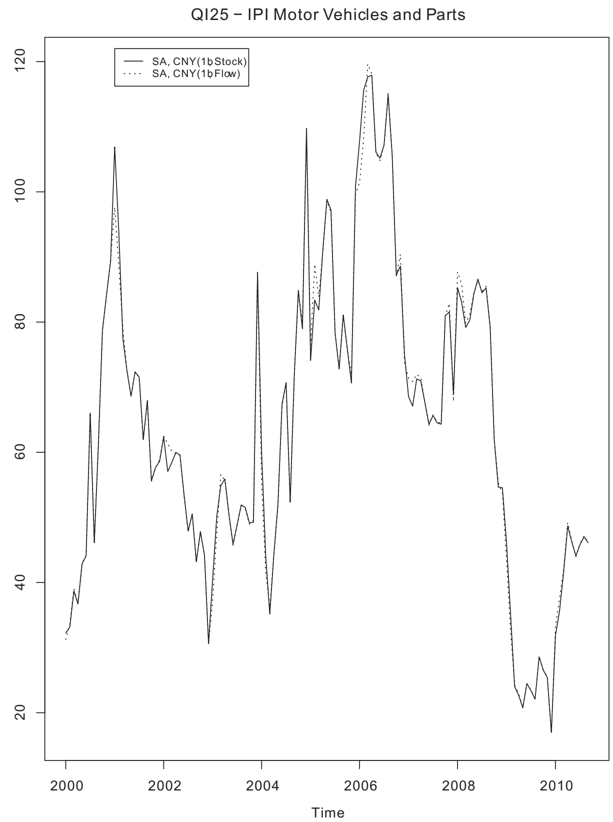
Note: Seasonal factors (stars) and combined flow CNY and seasonal factors (circles).

Figure 11 February adjustment factors for QI25

Hence its level component is zero:

$$\bar{H}^{SC} = (12P)^{-1} \sum_{t=1}^{12P} H^{SC}(t) = (12P)^{-1} \sum_{M=1}^{P} \sum_{j=1}^{12} H^{SC}(j + 12(M-1)) = 0.$$

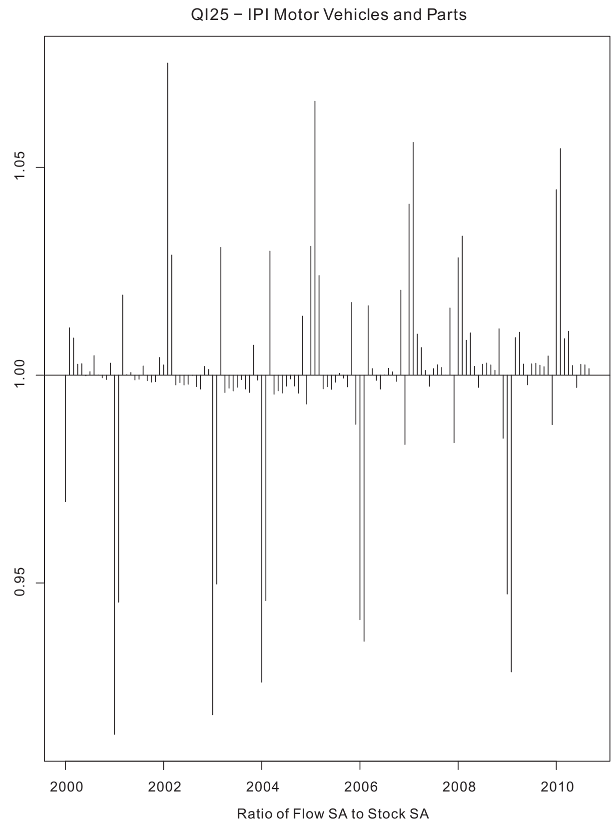
However, its seasonal component $\bar{H}_1^{SC}, \cdots, \bar{H}_{12}^{SC}$, defined in analogy with (6), is given by $\bar{H}_3^{SC} = P^{-1} \sum_{M=1}^{P}(n(M)/w) > 0$, $\bar{H}_4^{SC} = -\bar{H}_3^{SC}$ and $\bar{H}_j^{SC} = 0$, $j \neq 3, 4$. Thus $H^{SC}(t)$ has a nonzero seasonal component. Now consider the stock regressor defined by, $H_S^{SC}(t) = \sum_{u=1+12(M_0-1)}^{t} H^{SC}(u)$. It follows



Note: AICC and $l = 1$ RMSE forecast ratios favor the flow regressor. The CNY flow factors provide a smoother seasonal adjustment around the CNY months of the first two years of the series. Thereafter the stock adjustments are smoother around CNY months more often than not. An analyst concerned with the more recent data would likely prefer the stock CNY adjustment.

Figure 12 Combined-factor adjustments of QI25 obtained from flow versus stock CNY estimation

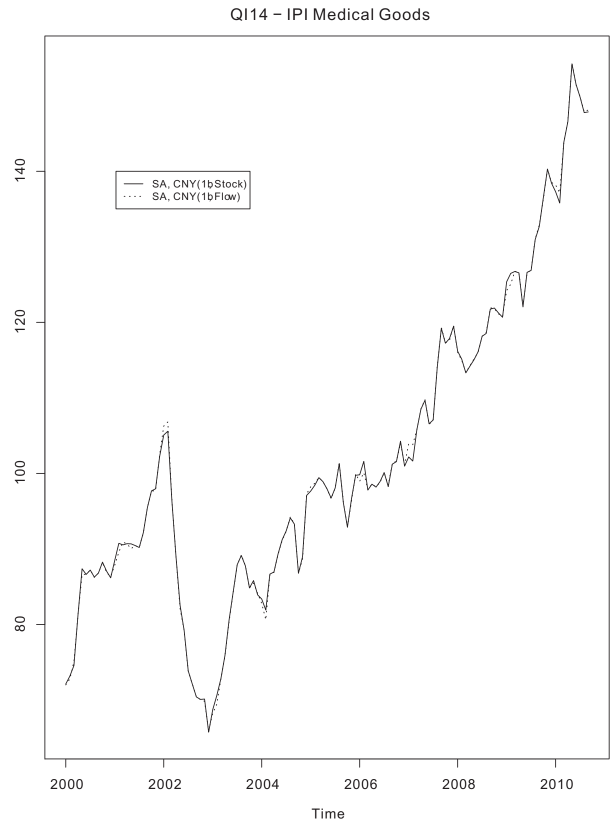
from (28) that for $t = j + 12(M - 1)$, this formula simplifies to $H_S^{SC}(t) = \sum_{i=1}^{j} H^{SC}(i + 12(M - 1))$. From (27), in year M, $H_S^{SC}(t)$ is nonzero only in March, when its value is $n(M)/w$. Hence, it has a nonzero level-plus-seasonal component, given by $\bar{H}_{S,j}^{SC} = \bar{H}_3^{SC}$ for $j = 3$ and $\bar{H}_{S,j}^{SC} = 0$ for $j \neq 3$, whose level component is positive, $\bar{H}_S^{SC} = (1/12)\sum_{j=1}^{12} \bar{H}_{S,j}^{SC} = \bar{H}_3^{SC}/12$.



Note: These show how the stock SA is altered to obtain the flow SA. The large ratios are those that involve CNY factors different from 1.0. The others reflect only the differing effects of the two CNY preadjustments on seasonal factor estimates.

Figure 13 QI25's ratios of flow combined factor adjustment values over stock combined adjustments, from Figure 12

To obtain an acceptable stock regressor, the flow regressor $H^{SC}(t)$ should be deseasonalized before generating the stock regressor. That is $H^{SC}(3+12(M-1))$ should be replaced by $(n(M)/w) - \bar{H}_3^{SC}$ and $H^{SC}(4+12(M-1))$ by $-(n(M)/w) + \bar{H}_3^{SC}$. Then $H_S^{SC}(3+12(M-1)) = (n(M)/w) - \bar{H}_3^{SC}$ sums to zero over P years, which establishes that the level plus seasonal component of this $H_S^{SC}(t)$ is zero.



Note: AICC and $l = 1$ RMSE forecast ratios favor the flow regressor. The flow adjustment is slightly smoother from 2006 on.

Figure 14 Combined-factor adjustments of QI25 obtained from flow versus stock CNY estimation

Our approach is not successful for holidays associated with Ramadan. For these holidays, the interval regressors (5) do not have constant sums over some choice of 12 month Gregorian calendar interval. Cumulative sums of deseasonalized flow regressors do not reduce to current year sums, and they do not yield regressors centered on zero.

9. CONCLUSIONS

The empirical studies presented in this paper for two economically influential holidays, Easter and Chinese New Year, validate the strategy proposed to construct regressors for estimating holiday effects in end-of-month stock series. The basic strategy is to define the regressors as sums of appropriate flow regressors from some initial time to the current times of interest. In the empirical studies, and after modifications in the supplementary cases considered in Section 8, the sum formula simplifies to sums starting at the beginning of the year of the month in question, as in (13). The same kind of simplification will occur, and similar modeling successes can be expected with other influential Chinese lunar holidays, such as the Dragon-Boat festival and Mid-Autumn holidays considered in the flow series study of Lin and Liu (2003). For these holidays, the GENHOL program (Monsell, 2011) can be used to generate the stock holiday regressors and the command file entries compatible with X-12-ARIMA or X-13A-S.

Finally, at a referee's request, we examined flow holiday regressor adjustments of the few stock series for which the flow regressor was preferred over the stock regressor by the model-selection criterion. Among these, there was one where the flow regressor adjustment provided a small amount of additional smoothing that might be useful.

REFERENCES

Akaike, H. (1973), "Information Theory and an Extension of the Likelihood Principle," in B. Petrov and F. Czaki, (eds), *Second International Symposium on Information Theory*, 267–287, Budapest: Akademia Kiado.

Aslaksen, H. (2010), "The Mathematics of the Chinese Calendar," Working Paper, Department of Mathematics, National University of Singapore.

Bednarek, M. (2007), "The Dates of Easter for 500 Years," http://mbednarek/easter.php.

Bell, W. R. (1984), "Seasonal Decomposition of Deterministic Effects," Research Report Number 84/01, Statistical Research Division, U.S. Census Bureau, Washington, DC.

Bell, W. R. (1995), "Correction to Seasonal Decomposition of Deterministic Effects," Research Report Number 95/01, Statistical Research Division, U.S. Census Bureau, Washington, DC.

Bell, W. R. and S. C. Hillmer (1983), "Modeling Time Series with Calendar Variation," *Journal of the American Statistical Association*, 78, 526–534.

Brunner, K. (1950), *Stock and Flow Analysis: Discussion*, 18(3), pp. 247–251.

Burnham, K. P. and D. R. Anderson (2004), "Multimodel Inference: Understanding AIC and BIC in Model Selection," *Sociological Methods and Research*, 33, 261–304.

Cleveland, W. P. and M. R. Grupe (1983), "Modeling Time Series When Calendar Effects Are Present," in A. Zellner, (ed.), *Applied Time Series Analysis of Economic Data*, 57–67, Washington, DC: U.S. Census Bureau.

Fellner, W. and H. M. Somers (1950a), *Stock and Flow Analysis: Comment*, 18(3), pp. 242–245.

Fellner, W. and H. M. Somers (1950b), *Stock and Flow Analysis: Note on the Discussion*, 18(3), p. 252.

Findley, D. F. (2005a), "Some Recent Developments and Directions in Seasonal Adjustment," *Journal of Official Statistics*, 21, 343–365.

Findley, D. F. (2005b), "Asymptotic Second Moment Properties of Out-of-Sample Forecast Errors of Misspecified RegARIMA Models and the Optimality of GLS," *Statistica Sinica*, 15(2), 447–476.

Findley, D. F. (2007), "Optimality of GLS for One-step-Ahead Forecasting with RegARIMA and Related Models when the Regression is Misspecified," *Econometric Theory*, 23, 1083–1107.

Findley, D. F. and B. C. Monsell (2009), "Modeling Stock Trading Day Effects Under Flow Day-of-Week Effect Constraints," *Journal of Official Statistics*, 25, 415–430.

Findley, D. F., B. M. Pötscher, and C.-Z. Wei (2004), "Modeling of Time Series Arrays by Multistep Prediction or Likelihood Methods," *Journal of Econometrics*, 118, 151–187.

Findley, D. F. and R. J. Soukup (2000), "Modeling and Model Selection for Moving Holidays," Proceedings of the Business and Economic Statistics Section of the American Statistical Association, Alexandria, VA: American Statistical Association.

Gómez, V. and A. Maravall (1997), "Programs TRAMO and SEATS: Instructions for the User," *Working Paper*, No. 97001, Ministerio de Economía y Hacienda, Direccíon General de Análisisy Programacíon Presupuestaria.

Hurvich, C. M. and C. Tsai (1989), "Regression and Time Series Model Selection in Small Samples," *Biometrika*, 76, 297–307.

Klein, L. R. (1950a), "Stock and Flow Analysis in Economics," *Econometrica*, 18(3), pp. 236–241.

Klein, L. R. (1950b), *Stock and Flow Analysis: Further Comment*, 18(3), p. 246.

Lin, J.-L. and T.-S. Liu (2003), "Modeling Lunar Calendar Holiday Effects in Taiwan," *Taiwan Economic Forecast and Policy*, 33(2), 1–37.

M3 (2008), *Instruction Manual for Reporting on the Monthly Survey M3: Manufacturers' Shipments, Inventories, and Orders*, Washington, DC: U.S. Census Bureau.

Monsell, B. C. (2007), "The X-13A-S Seasonal Adjustment Program," Proceedings of the 2007 Federal Committee on Statistical Methodology Research Conference, Washington, DC: Federal Committee on Statistical Methodology.

Monsell, B. C. (2009), "Update on the Development of X-13ARIMA-SEATS," Proceedings of the Joint Statistical Meetings, Alexandria, VA: American Statistical Association.

Monsell, B. C. (2011), "GENHOL: A Utility that Generates User-Defined Moving Holiday Regressors for X-12-ARIMA," http://www.census. gov/srd/www/genhol/ index.html.

Montes, M. J. (1998), "Calculation of the Ecclesiastical Calendar," http://www.smart.net/˜mmontes/ec-cal.html.

Taniguchi, M. and Y. Kakizawa (2000), *Asymptotic Theory of Statistical Inference of Time Series*, New York: Springer-Verlag.

Titova, N. and B. C. Monsell (2009), "Detecting Stock Calendar Effects in U.S. Census Bureau Inventory Series," Proceedings of the Joint Statistical Meetings, Alexandria, VA: American Statistical Association.

U.S. Census Bureau (2009), *X-12-ARIMA Reference Manual, Version 0.3*, Washington, DC: U.S. Census Bureau.

U.S. Census Bureau (2011), *X-12-ARIMA Reference Manual, Version 0.3*, Washington, DC: U.S. Census Bureau.

Wikipedia Contributors (2009), "Stock and Flow, Wikipedia, the Free Encyclopedia," http://en.wikipedia.org/wiki/Stock_and_flow.

存量與流量節日變數之研究

David F. Findley[*]

Center for Statistical Research and Methodology
U.S. Census Bureau

Brian C. Monsell

Center for Statistical Research and Methodology
U.S. Census Bureau

侯介澤

財務金融學系
國立東華大學

關鍵詞: 投資時間序列、季節調整、節日效果、移動節日、預測、復活節效應、中國農曆春節效應、X-12-ARIMA、X-13ARIMA-SEATS

JEL 分類代號: C82, C87

* 聯繫作者: David F. Findley, Center for Statistical Research and Methodology, U.S. Census Bureau, 4600 Silver Hill Road, Washington, DC 20233. 電話: 301-763-8773; 傳真: 301-763-8399; E-mail: david.f.findley@census.gov。

摘　　要

存量時間序列變數, 例如: 月底的庫存, 即爲每月之流入與流出量所產生之累計之加總, 亦是爲每月淨流量之累計。藉由類似存量交易日迴歸變數的計算方式, 本文介紹如何經由流量序列之節日迴歸變數的累加, 計算出存量序列之節日迴歸變數。當流量變數具有標準特性時, 則可利用本文所提出之簡單且實用的方法導出存量序列之節日迴歸變數。本文分別檢驗復活節效應對美國製造業存貨量的影響, 以及中國農曆春節效應對臺灣經濟指標存貨量的影響。本文爲了上述分析所建構的模型、預測和圖形結果, 皆顯示此方法可以有效的處理存量節日效果。亦如流量的節日變數分析, 本文的估計結果顯示, 存量的節日效果通常大於交易日效果, 但小於季節性效果。