## ADJUSTING FOR A CALENDAR EFFECT IN EMPLOYMENT TIME SERIES

**Stephanie Cano, Patricia Getz, Jurgen Kropf, Stuart Scott and George Stamas, Bureau of Labor Statistics**
**George Stamas, BLS, 2 Massachusetts Ave. NE, Room 4985, Washington, DC 20212**

**Key Words: Regression, Seasonal Adjustment**

### 1. INTRODUCTION

The Current Employment Statistics (CES) program is a survey of nearly 400,000 business establishments nationwide, which provides monthly estimates of nonfarm payroll jobs and the hours and earnings of workers. The month-to-month movements in these series are closely followed by policy makers and forecasters as timely indicators of the overall strength and direction of the nation's economy. Over-the-month changes in CES series are nearly always analyzed on a seasonally adjusted basis, but historically a calendar-related limitation in the CES seasonal adjustment process complicated the interpretation of month-to-month movements in the series. While the CES survey is referenced to a consistent concept, the pay period including the 12th of each month, inconsistencies arose in the seasonal adjustment process because there are sometimes 4 and sometimes 5 weeks between the weeks including the 12th in a given pair of months. In highly seasonal industries, this variation can be an important determinant of the magnitude of seasonal hires or layoffs that have occurred at the time the survey is taken, thereby complicating seasonal adjustment.

Standard seasonal adjustment methodology relies heavily on the experience of the most recent three years to determine the expected seasonal change in employment for each month of the current year. Because the previous methodology did not distinguish between 4 and 5 week survey intervals, the accuracy of the seasonal expectation depended on how well the current year's survey interval corresponded with those from the previous three years. All else the same, the greatest potential for distortion when applying projected factors occurred when the current month being estimated had a 5-week interval but the three years preceding it were all 4-week intervals, or conversely, when the current month had a 4-week interval but the three years preceding it were all 5-week intervals. In the first case, for a month in which seasonal growth typically occurs, the seasonal expectation was too low and the seasonal employment gain for the current month often exceeded the expectation, thus exaggerating the strength of job growth. In the second case, again for a month in which seasonal growth typically occurs, the seasonal expectation was too high and the resultant employment series risked presenting a weaker employment picture than genuinely existed. A recent example of this latter situation occurred with April 1995: There were 4 weeks between the March and April surveys in 1995, while each of the three preceding years had 5-week intervals. When the April 1995 survey registered a very weak employment gain, concerns were raised as to whether this calendar effect had significantly dampened the published over-the-month change.

Recent availability of X-12-ARIMA seasonal adjustment software developed by the Bureau of the Census enabled the Bureau of Labor Statistics (BLS) to conduct detailed research into refining the CES seasonal adjustment process to remove this calendar effect. Initial research on a calendar effect in CES series was conducted at the Federal Reserve Board. Researchers there utilized time series modeling techniques to identify and remove the varying interval effect before seasonally adjusting CES series. BLS adopted the basic method used by the Federal Reserve Board researchers, using a technique known in X-12-ARIMA software as REGARIMA modeling to identify the estimated size and significance of the calendar effect. REGARIMA modeling combines standard regression analysis with ARIMA modeling. The REGARIMA models evaluate the variation in employment levels attributable to 11 separate survey interval variables, one specified for each month except March, which always has a 4-week reporting interval from February.

Results obtained from a joint chi-square test that examines statistical significance across the 11 monthly variables, as well as those from t-tests on individual coefficients, provide evidence supporting the presence of this interval effect in most CES employment series. As expected, controlling for the 4- vs. 5-week calendar effect produced smoother seasonally adjusted series, as exaggerated movements caused by the less precise capture of seasonal components were reduced by the X-12-based procedure. The interval modeling may

The views expressed here are those of the authors and do not necessarily reflect those of the Bureau of Labor Statistics.

introduce a little instability, as measured by revisions between estimates for a given month derived from different overlapping spans.

## 2. MODELING AND DIAGNOSTICS

### 2.1 The Model

Consider the multiplicative time series decomposition $Y = T \cdot S \cdot I \cdot P$, where $P$ denotes a prior adjustment factor, and has the decomposition $P = P_T \cdot P_S \cdot P_I$. In our application, the interval effect is month-specific, and is estimated as the factor $P_S$. For seasonal adjustment, it is combined with the seasonal factor, and the seasonally adjusted value becomes

$$\frac{Y}{S \cdot P_S} = T \cdot I \cdot P_T \cdot P_I .$$

As with other interventions and calendar effects, we use extended ARIMA models to estimate the interval effect. We write

$$\log y_t - \sum a_j M_{jt} - \sum b_j X_{jt} = \Psi\left(B, B^{12}\right) a_t$$

where $y_t$ is the observed series, the $M_j$'s represent the month variables, the $X_j$'s represent outliers or other interventions, $a_t$ represents the noise term and $\Psi$ denotes a seasonal ARIMA model. In other words, after accounting for certain identifiable effects, the series follows an ARIMA model. On the log scale, the interval effect of month $j$ at time $t$ is

$$-a_j M_{jt}, \qquad M_{jt} = \begin{cases} 1, & t = j (\mathrm{mod}\ 12),\ 5\text{-week month} \\ -.6, & t = j (\mathrm{mod}\ 12),\ 4\text{-week month} \\ 0, & \text{otherwise} \end{cases}$$

Notice that the interval adjustment is sometimes positive and sometimes negative. Since there are more instances of 4-week intervals, the factor -0.6 helps achieve a balance in these effects. This is analogous to the property that the mean of the seasonally adjusted series should be close to the mean of the unadjusted series.

### 2.2 Model Estimation

The model is estimated using the REGARIMA procedure in X-12-ARIMA software. A REGARIMA model is a regression model whose error component is assumed to follow an ARIMA model. X-12-ARIMA estimates the REGARIMA model by iterating on two steps until convergence: A generalized least squares (GLS) estimate of the regression coefficients is estimated, and then an ARIMA model is fit to the regression errors using exact maximum likelihood. The ARIMA model provides the covariance structure for the next GLS.

The automatic model selection process of X-12-ARIMA does not both perform outlier detection and test final model estimation for each model considered for selection. To this end, a modified automatic selection procedure was developed to identify models for estimation with the interval effect. The modification resulted in more and better model fits, as well as increased model selection consistency across three time spans (59 vs. 11). In addition, the revised model selection procedure provided more consistency in the identification of particular observations as outliers in successive estimates.

This research is based on the modified approach, which tests five ARIMA models: (011)(011)s, (012)(011)s, (022)(011)s, (210)(011)s and (110)(011)s. The method screens each series for additive outliers and level shifts, testing at the 3.5 sigma level, and estimates replacement values. We do not currently test for ramp effects. Models are evaluated on normality of residuals, forecast error, and evidence of over-differencing, similar to the X-12-ARIMA automatic model selection. The model best meeting the criteria is selected with a preference for the model that had been selected in the previous span. If none of the five ARIMA models meets the criteria for selection, analysts review the autocorrelation functions and attempt to find a model that meets the criteria. If all modeling attempts fail, no model is used for seasonal adjustment. Of 75 employment series directly adjusted for CES, 74 could be conveniently analyzed. Due to time limitations, implementation required the use of X-12-ARIMA's automatic model selection procedure, and not the modified approach used in the research discussed here.

## 3. SLIDING SPAN RESULTS

### 3.1 Analysis Across Overlapping Spans

The 74 employment series were estimated with the X-12-ARIMA software for three different spans with the specified REGARIMA model. The programs included prior adjustments, primarily for strikes, that have been identified and are used in current production estimates. The spans analyzed were January 1983--

March 1993, January 1984--March 1994, and January 1985--March 1995. Results were reviewed across the three spans for model selection consistency, individual t-statistics and a joint test of significance for including the monthly interval effect variables, the difference in estimated levels between each span, and the smoothness of the time series.

### 3.2 Tests for Significance of the Interval Effect Variable

Chi-square and t-statistics were observed for testing the significance of the joint contribution and coefficients for each of the 11 monthly interval variables. Of the 74 series fitted with models using the explanatory variables, 59 had t-statistics equal to or greater than 2 for the last span estimated (January 1985--March 1995); 46 series had at least one month with a t-statistic greater than 2 for all three spans. This t-value corresponds roughly to a .05 test of significance. These results are summarized by industry division in Table 1.

Table 1. *A summary of test statistics for inclusion of explanatory variables across three spans*.

| *Industry* | *Number of series* | *t>2 across 3 spans* | *Joint p -value < .10* |
|---|---|---|---|
| *TOTAL* | 74 | 46 | 41 |
| *TOTAL PRIVATE* | 68 | 40 | 36 |
| *Mining* | 4 | 2 | 2 |
| *Construction* | 3 | 2 | 2 |
| *Manufacturing* | 20 | 12 | 9 |
| *Transportation & Utilities* | 9 | 5 | 6 |
| *Wholesale Trade* | 2 | 0 | 0 |
| *Retail Trade* | 8 | 6 | 6 |
| *Finance, Insurance & Real Estate* | 7 | 4 | 2 |
| *Services** | 15 | 9 | 9 |
| *Government* | 6 | 6 | 5** |

* *One series in services was not modeled with explanatory variables.*
** *Two government series include an extra intervention variable accounting for nonseasonal employment events.*

Each month had an interval variable with a t-value greater than 2 across all three spans in at least one of the 74 industries. Those series with t-values of 2 or more in less than three spans generally estimated the interval effect in the same direction across all three spans. While many of the series show a significant interval effect in at least one month, some present an inconsistent picture across spans. Notably, in SIC 15, building construction, January has large t-values in the first and last span but a small value in the second span.

Table 1 also provides results on the joint test for the inclusion of all 11 interval variables given a specific ARIMA component. For a total of 51 series, p-values generated from the third span indicate rejecting the hypothesis that the variables have no effect at the .10 level of significance. Across all spans, 41 series had consistent rejecting p-values.

Individual and joint tests for inclusion of the monthly regression variables suggest that about half of the series should be corrected for the interval effect. These tests are consistent for most series. Of the 41 series with a joint test significant at the .10 level across all three spans, 34 had at least one month with a significant t-value across all three spans. Given the constraints of production under automated systems, we preferred to treat all series identically, i.e., the correction for the interval effect in all months. Modeling results suggest that this may be feasible.

### 3.3 Smoothness

Individual series and aggregates of those series were examined for evidence that the interval adjustment actually represented an improvement in portraying the underlying economic trend when compared to seasonal adjustment without the interval adjustment. This was done with calculations of revisions and smoothness statistics. The smoothness of each series for each span was calculated as the square root of the sum of the squared first differences. Ratios were formed by dividing the smoothness statistic with interval adjustment by the statistic without interval adjustment, so that a ratio less than 100% tells us that the adjusted series is smoother. The distribution of 2-digit SICs across ranges of smoothness ratios shown below suggests that interval modeling helps reveal the underlying trend in two-thirds to three-fourths of the series, depending on the span, and rarely causes a serious distortion of the series.

Table 2. *Frequencies of 2-digit SIC Smoothness Ratios (%)*

| | ***Spans*** | | |
|---|---|---|---|
| | ***1st*** | ***2nd*** | ***3rd*** |
| ***<90*** | 12 | 10 | 8 |
| ***90-100*** | 36 | 44 | 48 |
| ***100-110*** | 25 | 17 | 16 |
| ***> 110*** | 1 | 3 | 2 |

Smoothness statistics across the three estimation spans are presented by division in Table 3. Evidence supporting adjustment for the varying interval effect is not equally compelling for all series, but with few exceptions, the adjustment did not appear to do harm. It was decided that the adjustment should be made to all the series except for seven. Three of these are the construction industries, one is in transportation and public utilities, and three are in services. With the exception of construction, the series are as smooth or smoother with the adjustment for the interval effect. The overall results illustrated in total nonfarm and total private indicate a small difference in smoothness in favor of removing the interval effect. The difference in smoothness is greatest in retail trade, where 4 of 8 series appear to be substantially smoother across all three spans. If the adjustment is made in only 68 of the series the resulting aggregates are slightly smoother. The improvement to totals results primarily from the decision not to adjust construction series.

Table 3. *Ratio of square roots of the sum of squared first differences, the series with the interval effect removed to the series with the effect present, times 100, by division*

| | All Series Adjusted | | | 68 Series Adjusted | | |
|---|---|---|---|---|---|---|
| Series/Span | 1 | 2 | 3 | 1 | 2 | 3 |
| Total | 98.2 | 98.2 | 97.7 | 97.5 | 97.4 | 97.2 |
| Private | 98.0 | 98.6 | 97.9 | 97.3 | 97.6 | 97.3 |
| Mining | 99.1 | 98.4 | 97.6 | 99.0 | 98.4 | 97.6 |
| Construction | 104.3 | 107.5 | 106.8 | 100.0 | 100.0 | 100.0 |
| Manufacturing | 97.8 | 99.1 | 97.9 | 97.8 | 99.1 | 97.9 |
| Transp. & Utils. | 97.7 | 99.5 | 100.7 | 98.2 | 99.7 | 99.9 |
| Wholesale | 99.0 | 99.8 | 100.4 | 99.0 | 99.8 | 100.4 |
| Retail | 87.6 | 87.9 | 86.4 | 87.6 | 87.9 | 86.4 |
| Fin. Ins.& RE | 96.7 | 97.7 | 99.8 | 96.7 | 97.7 | 99.8 |
| Services | 98.8 | 99.1 | 99.3 | 98.7 | 99.0 | 99.1 |
| Government | 96.8 | 94.7 | 93.3 | 96.8 | 94.7 | 93.3 |

### 3.4 Revisions

Revisions in estimates of level and over-the-month change were calculated across the three time spans in a "sliding span" analysis for series with the adjustment and without the adjustment. Median, 85th percentile and maximum revisions were observed. Sliding spans provide three estimates for each month from January 1985--March 1993 for most series and January 1988--March 1993 for other series. At detailed and aggregate levels, the evaluation of revisions was not positive when comparing adjustments to all series to seasonal adjustment without the interval adjustment. While the series without adjustment for the interval effect appear to be more stable, the differences are under .01 percentage points for total and total, private employment series. Revision results could be a symptom of estimating the interval effect with few observations. Table 4 presents the median, 85th percentile and maximum revision, expressed in percent, between spans in estimates of levels over all of the possible months for each series.

Table 5 presents median, 85th percentile and maximum difference in percentage over-the-month changes estimated for each of the different spans. Again for total and total, private, differences in the revisions between span estimates look similar whether the interval effect is modeled or not. Series adjusted for the effect tend to have larger revisions, but not much larger.

Tables 4 and 5 show that excluding seven series from interval effect modeling does very little to the revisions in affected aggregate series, with the exception of construction.

## 4. EFFECTS ON MONTHLY EMPLOYMENT ANALYSIS

At the total nonfarm level the difference in over-the-month change between the currently published seasonally adjusted series and the X-12 based experimental series ranged from zero up to ±100,000; about two-thirds of the differences were in the 20,000 to 70,000 range. (See Table 6.) The more significant impacts generally occurred in highly seasonal months and industries, i.e., the ones in which having one more week translated into a significantly larger number of hirings or layoffs than expected. Effects were especially concentrated in July and August for manufacturing and local government, and in December and January for retail trade.

Another way to view the improvement from using the new methodology is comparison of the over-the-month changes reported for a given month under the old and new methods, for cases when the current month has a different survey interval from the three years immediately preceding it. April poses such a case in 1995; it had a 4-week interval while the Aprils of 1992 - 1994 all had 5-week intervals. In this case, the previous method produced a seasonal expectation which was too high for the 4-week situation that existed in April 1995. Because April is a strong seasonal upturn month, the potential for distortion was relatively high. The published seasonally adjusted over-the-month change based on the previous procedure was +8,000. With the new method the estimated over-the-month change would have been +97,000, a better representation of the underlying economic movement.

Another recent example occurred with November 1995 which had a 5-week interval but was preceded by three Novembers with 4-week intervals. At the total nonfarm level, November exhibits a slightly upward seasonal expectation; the previous method produced an expectation of a smaller seasonal increase than appropriate for a 5 week interval. When November 1995 employment came in stronger than the 4-week dominated factors expected, the job gain estimated for the month, 212,000, was somewhat exaggerated. Under the new method, the over-the-month job gain was estimated at 167,000.

Like all time series techniques including seasonal adjustment itself, the 4-5 week survey interval effect modeling assumes a predictable continuation of historical patterns and relationships. Thus an event like the onset of a recession after a prolonged period of growth can be problematic for both projected seasonal factors and interval effect factors. For example, when general merchandise stores (SIC 53) is modeled for the interval effect, an extra (5th) week in December is currently associated with a larger increase in hiring than a 4-week interval. If this industry went into decline, the 5th week might actually translate into an opposite effect, more layoffs and a larger net employment decline. In this case, the modeled interval effect would be in the wrong direction. A comparison of series that result from applying projected factors of each method to estimates of employment through the July 1990--March 1991 recession suggests that this is a problem with or without modeling the calendar effect. The issue deserves further research.

Table 4. *Quantiles for percent revisions in estimates of levels under 3 modeling approaches*

| | ***All Series Adjusted*** | | | ***68 Series Adjusted*** | | | ***No Effect Adjustment*** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Series** | **Median** | **85%ile** | **Max** | **Median** | **85%ile** | **Max** | **Median** | **85%ile** | **Max** |
| **Total** | 0.014 | 0.036 | 0.068 | 0.014 | 0.031 | 0.072 | 0.012 | 0.024 | 0.065 |
| **Private** | 0.017 | 0.038 | 0.077 | 0.017 | 0.039 | 0.082 | 0.014 | 0.034 | 0.071 |
| **Mining** | 0.089 | 0.194 | 0.362 | 0.089 | 0.194 | 0.362 | 0.047 | 0.176 | 0.440 |
| **Construction** | 0.107 | 0.246 | 0.586 | 0.068 | 0.224 | 0.723 | 0.068 | 0.224 | 0.723 |
| **Manufacturing** | 0.034 | 0.065 | 0.184 | 0.034 | 0.065 | 0.184 | 0.023 | 0.077 | 0.194 |
| **Transp. & Utils.** | 0.052 | 0.087 | 0.148 | 0.047 | 0.096 | 0.170 | 0.021 | 0.060 | 0.178 |
| **Wholesale** | 0.021 | 0.040 | 0.129 | 0.021 | 0.040 | 0.129 | 0.014 | 0.032 | 0.089 |
| **Retail** | 0.047 | 0.091 | 0.165 | 0.047 | 0.091 | 0.165 | 0.028 | 0.069 | 0.130 |
| **Fin. Ins.& RE** | 0.025 | 0.054 | 0.100 | 0.025 | 0.054 | 0.100 | 0.019 | 0.041 | 0.082 |
| **Services** | 0.031 | 0.066 | 0.126 | 0.028 | 0.064 | 0.134 | 0.024 | 0.048 | 0.115 |
| **Government** | 0.045 | 0.084 | 0.137 | 0.045 | 0.084 | 0.137 | 0.031 | 0.074 | 0.137 |

Table 5. *Quantiles for percent revisions in estimates of over-the-month changes under 3 modeling approaches*

| | ***All Series Adjusted*** | | | ***68 Series Adjusted*** | | | ***No Effect Adjustment*** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Series** | **Median** | **85%ile** | **Max** | **Median** | **85%ile** | **Max** | **Median** | **85%ile** | **Max** |
| **Total** | 0.019 | 0.035 | 0.072 | 0.020 | 0.032 | 0.059 | 0.019 | 0.035 | 0.096 |
| **Private** | 0.024 | 0.039 | 0.092 | 0.023 | 0.039 | 0.076 | 0.018 | 0.038 | 0.112 |
| **Mining** | 0.103 | 0.162 | 0.280 | 0.103 | 0.162 | 0.280 | 0.060 | 0.159 | 0.310 |
| **Construction** | 0.158 | 0.295 | 0.625 | 0.070 | 0.250 | 0.614 | 0.070 | 0.250 | 0.614 |
| **Manufacturing** | 0.038 | 0.071 | 0.112 | 0.038 | 0.071 | 0.112 | 0.025 | 0.058 | 0.121 |
| **Transp. & Utils.** | 0.047 | 0.098 | 0.172 | 0.046 | 0.106 | 0.178 | 0.024 | 0.068 | 0.184 |
| **Wholesale** | 0.026 | 0.043 | 0.161 | 0.026 | 0.043 | 0.161 | 0.017 | 0.040 | 0.091 |
| **Retail** | 0.045 | 0.080 | 0.240 | 0.045 | 0.080 | 0.240 | 0.031 | 0.060 | 0.197 |
| **Fin. Ins.& RE** | 0.017 | 0.042 | 0.137 | 0.017 | 0.042 | 0.137 | 0.015 | 0.030 | 0.086 |
| **Services** | 0.035 | 0.068 | 0.172 | 0.034 | 0.067 | 0.166 | 0.031 | 0.060 | 0.112 |
| **Government** | 0.048 | 0.095 | 0.185 | 0.048 | 0.095 | 0.185 | 0.030 | 0.073 | 0.141 |

## 5. CONCLUSIONS

The previous CES seasonal adjustment had a calendar-related limitation which could affect the accuracy of published over-the-month changes in employment. Recently conducted research at BLS has resulted in the development of a more refined seasonal adjustment process which will mitigate the effects of varying time intervals between surveys and provide improved measurement of underlying economic trends. REGARIMA modeling techniques are used to account for the interval effect with month-specific explanatory variables. Smoothness statistics, t-statistics and joint tests for inclusion of the explanatory variables provide supporting evidence for the majority of published employment series. BLS implemented the new X-12-ARIMA-based seasonal adjustment procedures with release of May 1996 data.

## REFERENCES


Dagum, Estela Bee (1980), *The X-11-ARIMA Seasonal adjustment Method*, Catalogue 12-546E, Statistics Canada

Findley, D. F., B. C. Monsell, W. R. Bell, M. C. Otto, and B.-C. Chen (1996), *New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program*, JBES (forthcoming)

*X-12-ARIMA Reference Manual, Beta Version 1.0* (1996) Bureau of the Census



**Acknowledgments**

We are grateful to Bill Cleveland and Bill Wascher of the Federal Reserve for advice on methods and to David Findley and Brian Monsell of the Bureau of the Census for early use and support of X-12-ARIMA.


Table 6. *CES Total NonFarm Employment (in thousands), Seasonally Adjusted Over-The-Month Changes, experimental series (X-12 w/ interval effect model) vs. current published series*

| | | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OCT | NOV | DEC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1988** | experimental | | 443 | 276 | 217 | 238 | *353 | 282 | 128 | *253 | 276 | 277 | *295 |
| | published | | 470 | 286 | 262 | 183 | 362 | 241 | 152 | 240 | 281 | 330 | 303 |
| | difference | | -27 | -10 | -45 | 55 | -9 | 41 | -24 | 13 | -5 | -53 | -8 |
| **1989** | experimental | **312 | *290 | 200 | 206 | 69 | 115 | 117 | 51 | 169 | 116 | *267 | 138 |
| | published | 343 | 230 | 190 | 170 | 89 | 146 | 68 | 87 | 174 | 66 | 322 | 107 |
| | difference | -31 | 60 | 10 | 36 | -20 | -31 | 49 | -36 | -5 | 50 | -55 | 31 |
| **1990** | experimental | 221 | 350 | 201 | 46 | 252 | 100 | -151 | *-182 | -76 | -157 | -219 | -99 |
| | published | 282 | 320 | 190 | 5 | 285 | 134 | -213 | -140 | -74 | -190 | -185 | -133 |
| | difference | -61 | 30 | 11 | 41 | -33 | -34 | 62 | -42 | -2 | 33 | -34 | 34 |
| **1991** | experimental | -258 | -230 | -149 | -191 | *-37 | **59 | -50 | 67 | 15 | 11 | -128 | 19 |
| | published | -183 | -268 | -179 | -215 | 29 | 16 | -74 | 112 | 17 | -17 | -86 | -8 |
| | difference | -75 | 38 | 30 | 24 | -66 | 43 | 24 | -45 | -2 | 28 | -42 | 27 |
| **1992** | experimental | *-9 | **-35 | 66 | *156 | 187 | 32 | *68 | 136 | 66 | *146 | **175 | 170 |
| | published | -58 | -3 | 94 | 191 | 143 | 30 | 134 | 69 | 75 | 208 | 95 | 176 |
| | difference | 49 | -32 | -28 | -35 | 44 | 2 | -66 | 67 | -9 | -62 | 80 | -6 |
| **1993** | experimental | 246 | 333 | -54 | 288 | 296 | 149 | 235 | 215 | *245 | 337 | 234 | *258 |
| | published | 203 | 362 | -19 | 311 | 270 | 128 | 307 | 155 | 246 | 322 | 236 | 299 |
| | difference | 43 | -29 | -35 | -23 | 26 | 21 | -72 | 60 | -1 | 15 | -2 | -41 |
| **1994** | experimental | 194 | 331 | 473 | 270 | 303 | *268 | 300 | 308 | 252 | 200 | 457 | 171 |
| | published | 207 | 275 | 511 | 276 | 275 | 305 | 228 | 339 | 252 | 173 | 492 | 197 |
| | difference | -13 | 56 | -38 | -6 | 28 | -37 | 72 | -31 | 0 | 27 | -35 | -26 |
| **1995** | experimental | 187 | *318 | 167 | **97 | -107 | 252 | 114 | 226 | 100 | 66 | *167 | 246 |
| | published | 186 | 313 | 179 | 8 | -62 | 299 | 28 | 263 | 94 | 68 | 212 | 145 |
| | difference | 1 | 5 | -12 | 89 | -45 | -47 | 86 | -37 | 6 | -2 | -45 | 101 |
| **1996** | experimental | -186 | 653 | 109 | 22 | | | | | | | | |
| | published | -146 | 631 | 178 | 2 | | | | | | | | |
| | difference | -40 | 22 | -69 | 20 | | | | | | | | |

5 week intervals are shaded

* = a 5-week interval preceded by three 4-week intervals

** = a 4-week interval preceded by three 5-week intervals