Estimation of Prior Correctons due to Removal of SNA in LPI Series

Version 2.0

Contents of this document:

1. Goals

To predict the impact of Safety Net Adjustment (SNA) removal on the seasonal pattern in Labour Price Index (LPI) series. Complete removal of SNA from LPI collections is expected towards end of Dec quarter 2006. Our goal is to arrive at seasonal break (and possible trend break) prior factors for 2005/2006 using exclusively, the contribution of SNA based jobs to the total period-to-period movements over the last three years [Subject: LPI extended Safety Net Adjustment data; Database: Time Series Analysis WDB; Author: Antoinette Beckwith; Created: 10/07/2006; Doc Ref: NACT-6RK2ZU] . This will enable us to perform a reliable seasonal adjustment of LPI series.

Schematics in terms of actual series and S*I chart representations are shown in **Figure 1**. Note that these are not realistic. The magnitudes of the seasonality and trend levels for the different components are shown exagerated.

The problem reduces to estimating the seasonal factor ratio for a quarter *t* (also known as the seasonal break prior factor "SB") in the current (or forthcoming) year(s): [i.e. >=2006] and previous years [i.e. <=2005]:

$$SB_t = \frac{S_{t \in \{\geq 2006\}}}{S_{t \in \{\leq 2005\}}} \qquad (1)$$

We assume this ratio can be estimated (hence 'predicted') from the contribution to LPI of 'Non Safety Net' (NSN) jobs during the period in which Saftey Net Adustment is present, i.e:

$$SB_t \approx \frac{S^{NSN}_{t \in \{\leq 2005\}}}{S_{t \in \{\leq 2005\}}} \qquad (2)$$

The schematic "S*I" chart for SEP quarter in **Figure 1** neatly illustrates this estimate. The reliability and/or validity of the assumption in (2) can be assessed once actual LPI data becomes available for remaining quarters in 2006 and beyond.

Note that there could also be a possible trend break (level shift) following the removal of SNA. This is shown in the first schematic of **Figure 1** where the 'NSN' series may be at a different level from the original (total) series which includes SNAs. Note that the incidence of a trend break will be <u>independent</u> of estimates for the seasonal factors for each of the total and NSN series components, and hence independent of the ratio in eqn (2). This is because the seasonal factors for each series are estimated with respect to their own underlying trends and have nothing to do with the location and magnitude of a trend break. Estimation methods for a possible trend break are discussed in section 5 below.

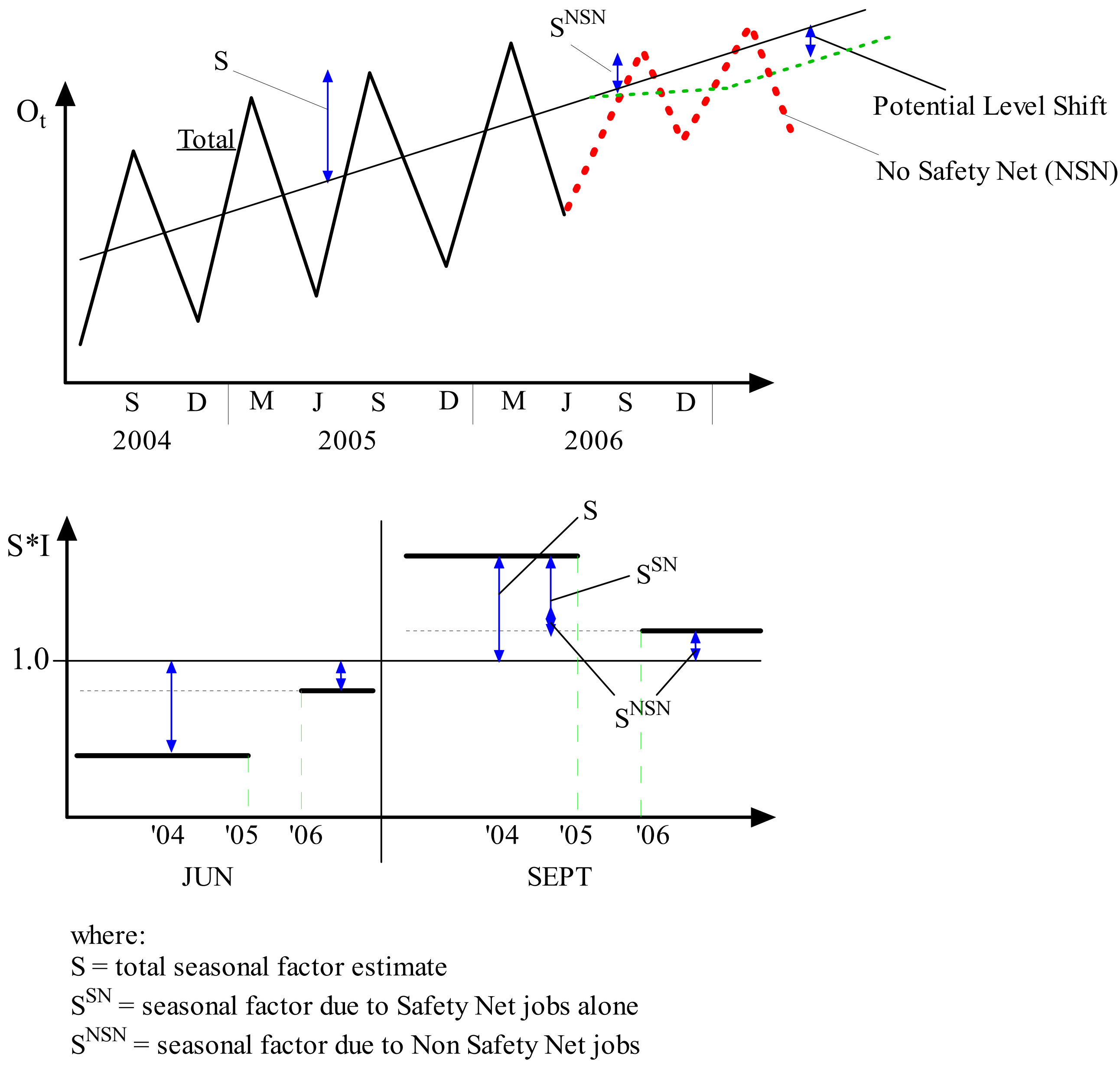

Figure 1: schematic of seasonal factor ratio (seasonal break) estimation.

2. Method

First, some notation:

O_t = Original LPI level series

O_t^{NSN} = No Saftety Net (NSN) component of original series

O_t^{SN} = Saftety Net (SN) component of original series

m_t^O = Movement in original LPI series from period $t-1$ to t

m_t^{NSN} = Movement in NSN component from period $t-1$ to t

m_t^{SN} = Movement in SN component from period $t-1$ to t

m_t^{TNSN} = Movement in trend component from period $t-1$ to t for NSN series

m_t^T = Movement in trend component from period $t-1$ to t for original LPI series

m_t^{INSN} = Movement in irregular component from period $t-1$ to t for NSN series

m_t^I = Movement in irregular component from period $t-1$ to t for original LPI series

T_t^O = Trend component in original LPI series

T_t^{NSN} = Trend component in underlying NSN series

I_t^O = Irregular component in original LPI series

I_t^{NSN} = Irregular component in underlying NSN series

S_t = Seasonal factor component in original LPI series

S_t^{NSN} = Seasonal factor component in underlying NSN series

SB_t = Seasonal break factor $= S_t^{\mathrm{NSN}} / S_t$

$o_t = \log\left(O_t\right); \quad o_t^{NSN} = \log\left(O_t^{NSN}\right)$

$t_t = \log\left(T_t\right); \quad t_t^{NSN} = \log\left(T_t^{NSN}\right)$

$s_t = \log\left(S_t\right); \quad s_t^{NSN} = \log\left(S_t^{NSN}\right)$

$i_t = \log\left(I_t\right); \quad i_t^{NSN} = \log\left(I_t^{NSN}\right)$

The seasonal break priors [i.e. the SB_t in eqn (2)] were estimated using the following steps:

(1) Given the SN-based jobs contribution to LPI movements, m_t^{SN} from the document: (Subject: LPI extended Safety Net Adjustment data; Database: Time Series Analysis WDB; Author: Antoinette Beckwith; Created: 10/07/2006; Doc Ref: NACT-6RK2ZU), the contribution of Non-SN (NSN) based jobs to the total movement is simply given by:

$$m_t^{NSN} = m_t^O - m_t^{SN} \qquad (3)$$

All movements are shown in **Figure 2**:

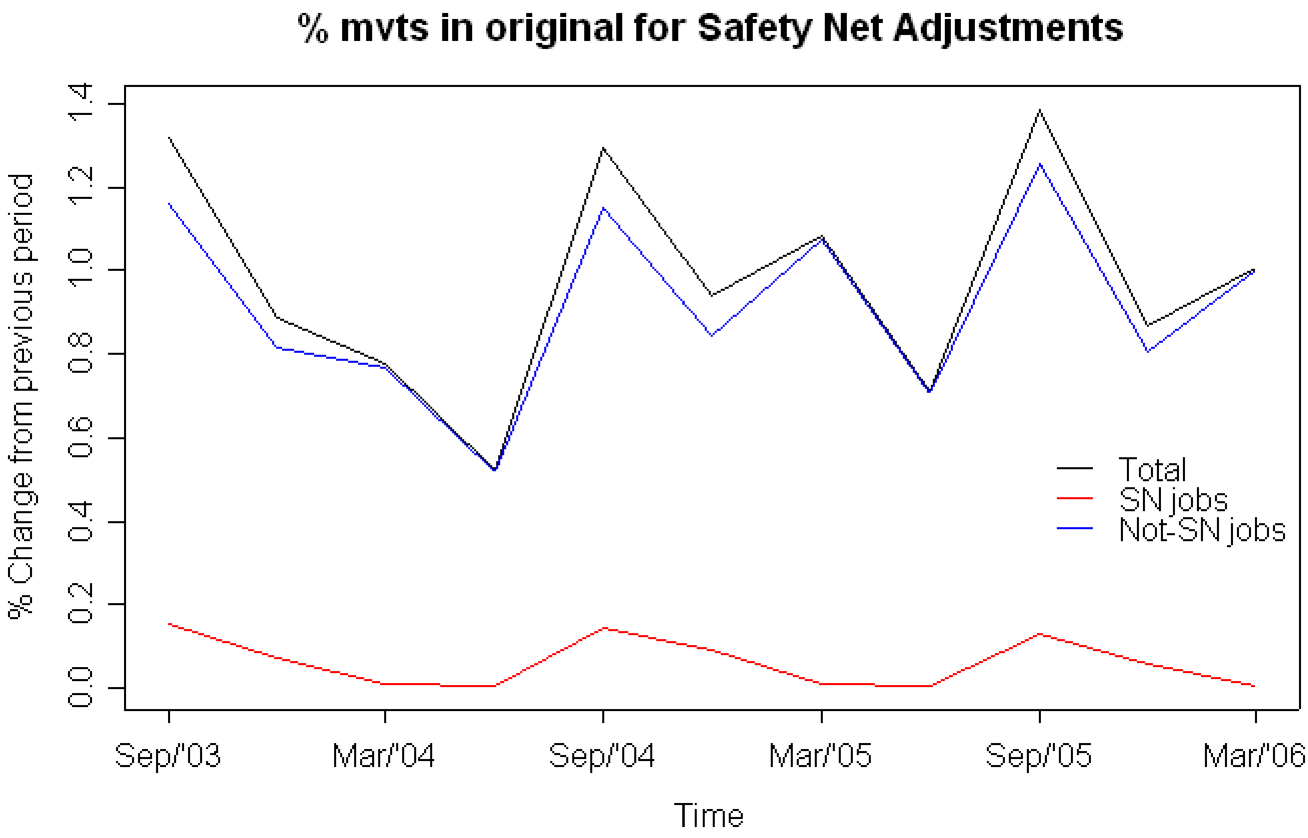

Figure 2: period-to period movements in LPI series over span where SN contributions are available.

(2) The 'unknown' NSN level can be reconstructed from the movements using:

$$O_t^{NSN} = O_1^{NSN} \prod_{i=2}^{t} \left(1 + m_i^{NSN}\right), \qquad (4)$$

where O_1^{NSN} is an 'arbitrary' starting level which will cancel out in the seasonal factor estimation below. Taking logs, we have equivalently:

$$o_t^{NSN} = o_1^{NSN} + \sum_{i=2}^{t} \log\left(1 + m_i^{NSN}\right) \qquad (5)$$

and since movements are small, the following approximation holds to good accuracy:

$$o_t^{NSN} \approx o_1^{NSN} + \sum_{i=2}^{t} m_i^{NSN} \qquad (6)$$

The log[level] series in NSN, o_t^{NSN}, is reconstructed using equation (6) with some 'arbitrary' starting level o_1^{NSN}. The specific value assumed for o_1^{NSN} shall not concern us in the seasonal factor estimation procedure below.

(3) Next, trend components are estimated for the observed total t_t and inferred

NSN componenent t_t^{NSN} using linear least squares fits to o_t and o_t^{NSN} respectively. Due to the relatively short span over which SN contributions are available (i.e. ~2.5 years), it is inappropriate to apply the X11 procedure to arrive at reliable trend estimates. Even though a reliable X11 trend is available for the original series o_t, we want to use exactly the same trend estimation method for original and NSN components. **Figure 3** shows the fitted trends overlayed on the originals. The existing X11 trend for the original series is also shown.

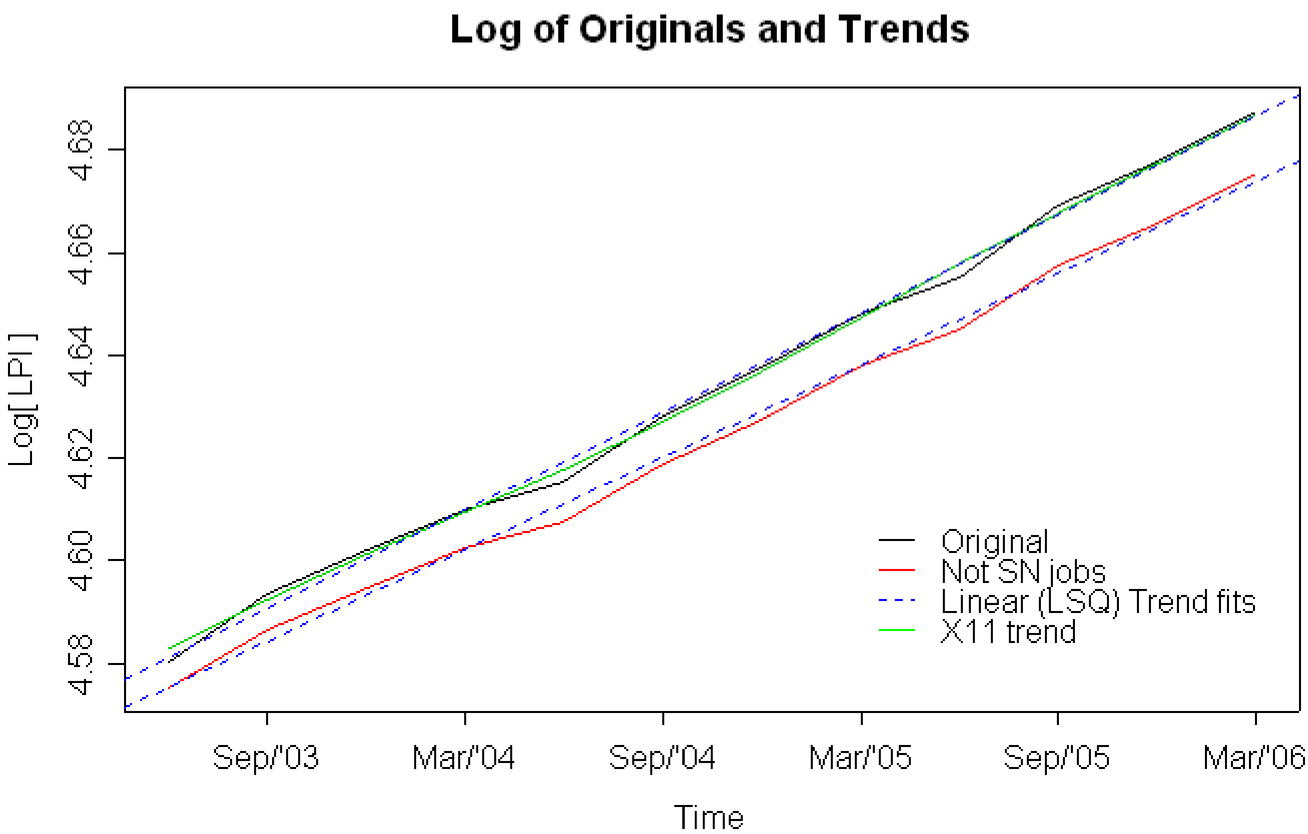

Figure 3: Original LPI series (black), reconstructed NSN series (red), linear trend fits (blue dashed) and available X11 trend for original LPI series (green).

(4) Next we assume a multiplicative decomposition model for the observed total and inferred NSN component levels:

$$O_t = T_t S_t I_t$$
$$O_t^{NSN} = T_t^{NSN} S_t^{NSN} I_t^{NSN} \qquad (7)$$

then after taking logs:

$$o_t = t_t + s_t + i_t$$
$$o_t^{NSN} = t_t^{NSN} + s_t^{NSN} + i_t^{NSN} \qquad (8)$$

It is observed that the degree of volatility in all LPI series is tiny (e.g. I/C ratio in Australia total series is ~0.02). This is further confirmed by the observation that X11 seasonally adjusted estimates are very nearly equal to X11 trend estimates.

Therefore we can safely assume:

$$I_t \approx 1 \Rightarrow \; i_t \approx 0. \qquad (9)$$

Combining (7), (8) and (9), the residuals beween original values and fitted (linear) trends actually represent the log of the seasonal factors:

$$s_t = o_t - t_t \qquad (10)$$
$$s_t^{NSN} = o_t^{NSN} - t_t^{NSN} \qquad (11)$$

The arbitraryness in the starting value o_1^{NSN} for reconstructing o_t^{NSN} (in step 2 above) should now become apparent: the seasonal factor estimates (in log space) only depend of the differences of the original and trend estimates. The starting value o_1^{NSN} is implicitly present in t_t^{NSN} so that it effectively cancels out when differenced against the original. We checked that the seasonal factor estimate s_t^{NSN} is indeed independent of this assumed starting level.

(5) The ratio of actual seasonal factors (in the original multiplicative space) at some timepoint *t* can be computed from:

$$SB_t = \frac{S_t^{NSN}}{S_t} = \exp\left[s_t^{NSN} - s_t \right]. \qquad (12)$$

This is the seasonal break prior factor sought for at some timepoint *t* , (i.e. eqn 2 above).

We should also mention here the well known bias when transforming from a logged additive model (e.g. eqns 10 and 11) back to the original multiplicative model (eqn. 12). In general, the expectation value of a random variable *S* in the multiplicative model given its estimate *s* in the additive model is: E(*S*) = exp[E(*s*) + 0.5var(*s*)]. Since the volatility (variance) in all LPI components is insignificant (e.g. eqn 9), we have E(S) = exp[E(*s*)] so that this bias is not expected to be important.

3. Preliminary Results (on total sectors series)

Using the methodology above, 'effective' seasonal break priors were computed for all quarters (and all years) with available SNA data in the Australia Total (ALLINDUSTRIES) LPI series. These are shown in **Table 1** and also graphed in **Figure 4**. Note that the individual quarter/year estimates are subject to volatility. We have therefore computed the average over all years for each quarter (last row in Table 1).

YEAR	QTR 1	QTR 2	QTR 3	QTR 4
2003		1.0006062	0.9996751	0.9995316
2004	1.0000423	1.0006028	0.9997702	0.9994388

2005	0.9999101	1.0004706	0.9997876	0.9998026
2006	1.0003631			
AVERAGE:	**1.000105**	**1.000560**	**0.9997443**	**0.999591**

Table 1: seasonal factor ratios (or seasonal break priors S_t^{NSN} / S_t) for "ALLINDUSTRIES" series using the method of section 2.

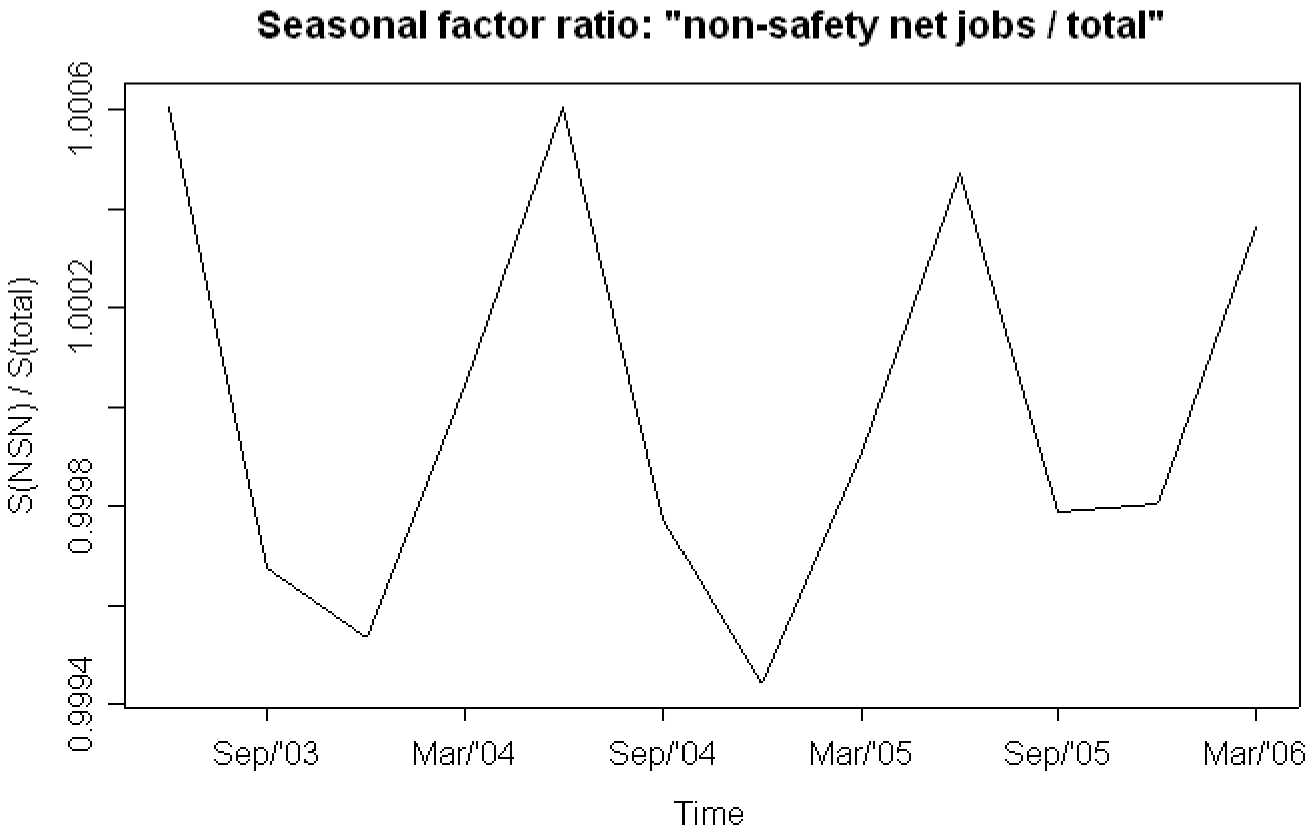

Figure 4: seasonal factor ratios (or seasonal break priors S_t^{NSN} / S_t) for "ALLINDUSTRIES" series over span where SNA contribution is available. Estimates are approximate since they include volatility (see last row in Table 1 for averages).

The seasonal factor 'decreases' are greatest for September and December as expected since these are the quarters where SNA contributiosn are the greatest. Phasing out of SNA will no doubt lead to a diminuition in relative seasonal strength in these quarters, but at the same time lead to a relative 'increase' in seasonal strength for March and even greater for June quarters. See section 4 below for an assessment of the significance of these values.

It's important to note that these results are senstive on the trend estimate (i.e. fitted or otherwise, see Fig. 3). This will be further discussed in section 6 below.

4. Sanity Check using Alternative Method

To check the appropriateness of the above methodology, we use an alternative but somewhat implcitly related method to arrive at seasonal break factors. This is based on a "global" linear least squares method to arrive at estimates for four effective seasonal break factors:

$$SB_1 = \left\langle \frac{S_1^{NSN}}{S_1} \right\rangle; \; SB_2 = \left\langle \frac{S_2^{NSN}}{S_2} \right\rangle; \; SB_3 = \left\langle \frac{S_3^{NSN}}{S_3} \right\rangle; \; SB_4 = \left\langle \frac{S_4^{NSN}}{S_4} \right\rangle \qquad (13)$$

i.e. one effective (average) value for each quarter.

Starting with the multiplicative model assumption in eqn (7), we can write the period-to-period ratios for the original and NSN component series as follows:

$$\frac{O_t}{O_{t-1}} = \frac{T_t}{T_{t-1}} \frac{S_t}{S_{t-1}} \frac{I_t}{I_{t-1}} \qquad (14)$$

$$\frac{O_t^{NSN}}{O_{t-1}^{NSN}} = \frac{T_t^{NSN}}{T_{t-1}^{NSN}} \frac{S_t^{NSN}}{S_{t-1}^{NSN}} \frac{I_t^{NSN}}{I_{t-1}^{NSN}} \qquad (15)$$

Taking the ratio of (15) to (14) and converting the original, trend and irregular component ratios into actual period-to-period movements, we have:

$$\left(\frac{1+m_t^{NSN}}{1+m_t^{O}} \right) = \left(\frac{1+m_t^{TNSN}}{1+m_t^{T}} \right) \left(\frac{1+m_t^{INSN}}{1+m_t^{I}} \right) \left(\frac{S_t^{NSN}}{S_t} \right) \left(\frac{S_{t-1}}{S_{t-1}^{NSN}} \right) \qquad (16)$$

Taking logs and expanding eqn (16), we have:

$$r_t^{NSN} = r_t^{TNSN} + sb_t - sb_{t-1} + \varepsilon_t \qquad (17)$$

where:

$$r_t^{NSN} \equiv \log\left(\frac{1+m_t^{NSN}}{1+m_t^{O}} \right);$$

$$r_t^{TNSN} \equiv \log\left(\frac{1+m_t^{TNSN}}{1+m_t^{T}} \right);$$

$$sb_t \equiv \log(SB_t) \equiv \log\left(\frac{S_t^{NSN}}{S_t} \right);$$

$$sb_{t-1} \equiv \log(SB_{t-1}) \equiv \log\left(\frac{S_{t-1}^{NSN}}{S_{t-1}} \right);$$

$$\varepsilon_t \equiv \log\left(\frac{1+m_t^{INSN}}{1+m_t^{I}} \right)$$

As discussed above (i.e. eqn 9), the movements in the irregular components for LPI series are negligible and thus we can assume that $\varepsilon_t \sim 0$. But in general, we can attempt to estimate seasonal break factors sb_t that minimise the Mean Squared Error (MSE) in eqn (17), i.e:

$$\left\langle \varepsilon_t^2 \right\rangle = \frac{1}{N-1}\sum_{t=2}^{N}\left(d_t - sb_t + sb_{t-1}\right)^2 \qquad (18)$$

where:

$$d_t \equiv r_t^{NSN} - r_t^{TNSN}$$

Our goal is to arrive at estimates for seasonal break factors for each of the four quarters, <u>independent of the years in which they fall in</u>, i.e. the only model parameters are: sb_1 , sb_2 , sb_3 , sb_4 . The partial derivatives of the MSE (eqn 18) with respect to these parameters are expected to simultaneously vanish at the minimum MSE, i.e. we have the conditions:

$$\frac{\partial\left\langle \varepsilon_t^2 \right\rangle}{\partial sb_1} = \frac{\partial\left\langle \varepsilon_t^2 \right\rangle}{\partial sb_2} = \frac{\partial\left\langle \varepsilon_t^2 \right\rangle}{\partial sb_3} = \frac{\partial\left\langle \varepsilon_t^2 \right\rangle}{\partial sb_4} = 0\ . \qquad (19)$$

On expanding eqn (18) over the span in which SNA movement data is available (i.e. t = Dec.Qtr '03 to Mar.qtr '06) and taking derivatives, we arrive at the following simultaneous system:

$$\begin{pmatrix} 5 & -2 & 0 & -3 \\ -2 & 4 & -2 & 0 \\ 0 & -2 & 5 & -3 \\ -3 & 0 & -3 & 6 \end{pmatrix}\begin{pmatrix} sb_1 \\ sb_2 \\ sb_3 \\ sb_4 \end{pmatrix} = \begin{pmatrix} \Sigma_1 \\ \Sigma_2 \\ \Sigma_3 \\ \Sigma_4 \end{pmatrix} \qquad (20)$$

where:

$$\Sigma_1 = d_{q1'04} + d_{q1'05} + d_{q1'06} - d_{q2'04} - d_{q2'05}$$
$$\Sigma_2 = d_{q2'04} + d_{q2'05} - d_{q3'04} - d_{q3'05}$$
$$\Sigma_3 = d_{q3'04} + d_{q3'05} - d_{q4'03} - d_{q4'04} - d_{q4'05}$$
$$\Sigma_4 = d_{q4'03} + d_{q4'04} + d_{q4'05} - d_{q1'04} - d_{q1'05} - d_{q1'06}$$

The values d_t (or more precisely, r_t^{NSN} and r_t^{TNSN}) are computed using movements in the original and NSN components and corresponding <u>fitted</u> trends as performed in step 3 of Section 2 above. Note that since relative movements are involved, we do not have to deal with series components directly, and do not need to assume a starting value o_1^{NSN} for reconstructing o_t^{NSN} . Thus, this method is implicitly related to the method in section 2 since fitted (linear) trends are still assumed. However, one is not restricted to assuming fitted (linear) trends (see Section 6 for details).

Eqn (20) is of the form **A.X = B** so that one may naively assume that the solution vector is given by $\mathbf{X = A^{-1}B}$. However, the matrix **A** is singular (with rank = 3)! Singular Value Decomposition (SVD) comes to the rescue. In essence, this technique enables one to isolate the singular values of **A**, transform them, and find the 'best' solution vector **X** which minimises the least squares sum: **|A.X - B|**. In a nutshell, $\mathbf{X \sim V.D.(U^T.B)}$ where **V** and **U** are orthogonal and **D** is diagonal with singular elements replaced by 0 (for more details see *Numerical*

Recipes in C , Press et al. 1999). Using the movement data for the 'ALLINDUSTRIES' series and carrying out the SVD on eqn (20), we find that the solution vector gives a residual **|A.X - B|** ~ 10^{-19}, implying that the solution is the best that can be achieved given our machine's floating point precision of ~10^{-12}.

Having estimated the solution vector **X** = (sb_1 sb_2 sb_3 sb_4 $)^T$ in eqn (20), the actual seasonal factors for each quarter (in the original multiplicative space, i.e. eqn 13) are given by:

$$SB_t = \frac{S_t^{NSN}}{S_t} = \exp\left[\mathbf{X}\right]. \qquad (21)$$

Again, as discussed in step 5 of Section 2, the bias introduced in performing this transformation (from log-additive to multiplicative space) is insignificant. Table 2 shows some preliminary results using this method.

	QTR 1	QTR 2	QTR 3	QTR 4
$\boldsymbol{SB_t}$ **:**	1.000066	1.000578	0.999771	0.999585

Table 2: effective seasonal factor ratios (or seasonal break priors S_t^{NSN} / S_t) for "ALLINDUSTRIES" series for each quarter using the "global linear least squares SVD" method of above.

The results in Table 2 <u>are remarkably similar</u> to the averages in Table 1!

To test the significance of the values in Table 2 (or Table 1) given the volatility in the "ALLINDUSTRIES" series (however low), we compare these to actual seasonal factor estimates derived using the X11 algorithm. To have any meaning, the new NSN seasonal factors (S_t^{NSN}) resulting from the application of the break factors in Table 2 must be significantly different from the existing factors (S_t) in the presence of volatility (I_t). The NSN seasonal factors must first be expressed in terms of equivalent factors that may result from the application of the X11 seasonal moving average filter. This is achieved by scaling from the existing 'moving averaged' factors for the total series:

$$S_t^{NSN,X11} = SB_t\, S_t^{X11} \qquad (22)$$

The 'expected' X11 NSN seasonal factors (from eqn 22) are then compared to the existing X11 factors with volatility (S_t^{X11} x I_t) to test the null hypothesis that they are consistent with a chance occurance against the alternative that they are significantly different. Rejection of H_0 implies that the removal of SNAs will result in a significant change in seasonal pattern. This is done using a chi-square test, where the null/alternative hypotheses and test statistics are defined as:

H_0 : expected $S_t^{NSN,X11} = S_t^{X11}$ given $I_t^{NSN} = I_t$ $\forall$ times t

versus

H_1 : expected $S_t^{NSN,X11} \neq S_t^{X11}$ given $I_t^{NSN} = I_t$ $\forall$ times t

$$\chi^2 = \sum_{t=1}^{N} \frac{\left(S_t^{X11} I_t - S_t^{NSN,X11}\right)^2}{\sigma_t^2(qtr)} \qquad (23)$$

where:

$$\sigma_t^2(qtr) \approx \frac{1}{N_{qtr}} \sum_{j=1}^{N_{qtr}} \left(S_j^{X11} I_j - S_j^{X11}\right)^2$$

is computed over times j corresponding to the same quarter with N_{qtr} timepoints.

In other words, we normalise the χ^2 statistic by assuming that the variance (error) at a timepoint is approximately equal to the MSE in the current X11 seasonal factors for the respective quarter.

The same volatility as that present in the original (total) series is assumed to apply in the eventual series with SNAs removed. We apply equation (23) to each separate quarter (with degrees of freedom = 9) and also across the whole series (degrees of freedom=36). Results are summarised in Table 3. H_0 is rejected at a chance probability level of <0.1% when data is combined over all quarters. This implies that overall, the removal of SNA is expected in general to lead to a significant change in the seasonal pattern. When each quarter is considered separetly, H_0 is strongly rejected for quarter 2 only, while for other quarters it is marginal. In other words, for quarters 1; 3; and 4, SNA removal is not expected to lead to a highly significant change in seasonal pattern. This is reinforced from a visual examination of Figure 5 where we plot the change in seasonal factors expected from SNA removal.

	QTR1	**QTR2**	**QTR3**	**QTR4**	**ALL QTRS**
χ^2	7.685	30.431	18.706	19.340	76.163
Pr(>χ^2) %	56.613	0.037	2.780	2.245	0.011

Table 3: results of chi-square tests for the null hypothesis of no significant difference in the seasonal factors for the "ALLINDUSTRIES" series with SNAs removed.

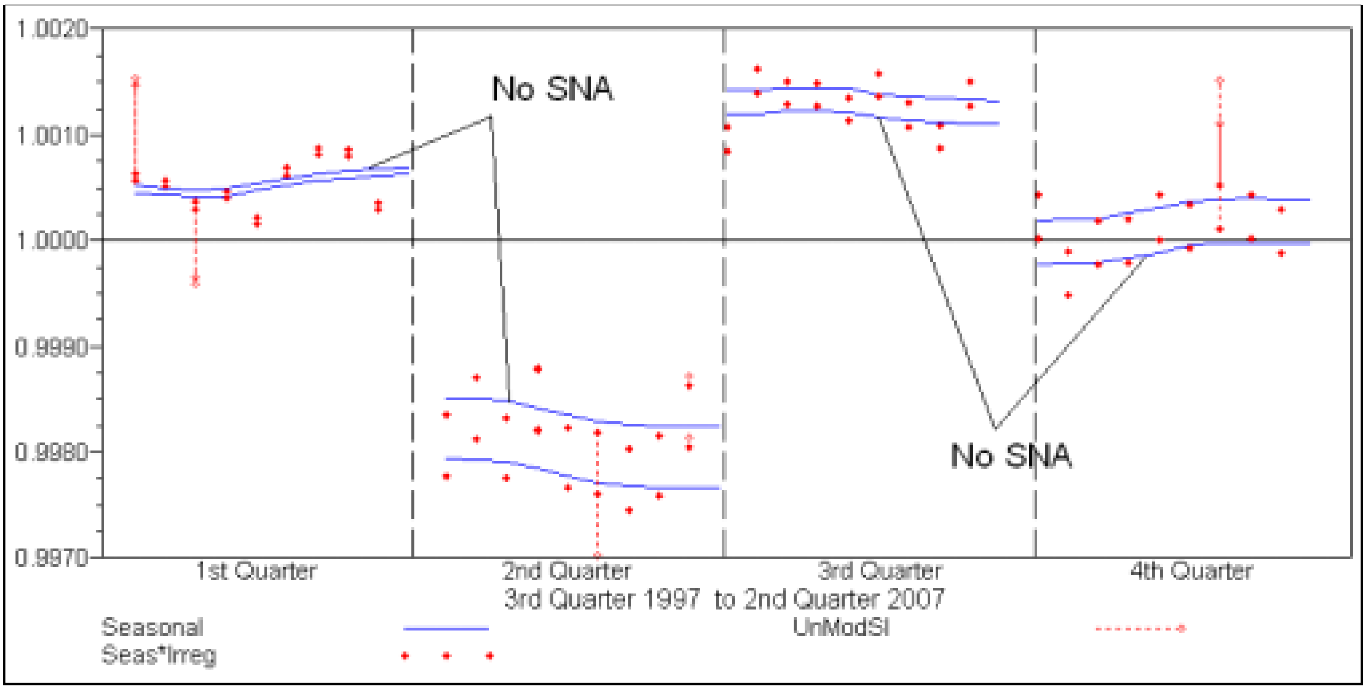

Figure 5: seasonal x irregular chart with and without application of seasonal break priors predicted from SNA removal. Note that this is crude representation of what may happen. Seasonal breaks for quarters 1, 2 were applied at years 2006/2007 and for quarters 3, 4 at 2005/2006. The most significant change in seasonal pattern is expected for quarter 2 only (see Table 3)

5. Estimation of a Potential Trend Break

As discussed in section 1, estimation of a possible level shift is independent of the seasonal break prior factors estimated above. From Figures 2 or 3, there is a slight hint that the original (total) and NSN series levels have different overall movements. In fact, the difference in slope estimates from the linear fits shown in Figure 3 is significantly different from zero at the <3% chance probability level. In actual percentage movement terms, we have:

$$m_t^T - m_t^{TNSN} \sim 0.963\% - 0.903\%$$
$$\sim (0.061 \pm 0.024)\%,$$

where the error represents one standard error. If this difference is believable (as the significance claims), then a trend break is inevitable since it means that the O_t and O_t^{NSN} series must have converged in the past (i.e. had the same level). This indicates that SNA contributions must have been smaller and hence non-existent at some point in the past. The levels gradually diverge as SNA contributions increase with time. When SNAs are removed, the levels must shift and become equal again. The period over which this shift occurs may be abrupt (i.e. a genuine trend break), or gradual, depending on how long it takes SNAs to be phased out.

A question is to determine whether there was some point in the past when SNA contributions were non-existent (if ever), or expected to be insignificant. If a timepoint (or range) can be found, this will enable us to constrain a possible level shift by extrapolating the linear trends to this timepoint, i.e. where the trends become equal: $T_t^O = T_t^{NSN}$. If this point happens to fall outside the survey span, then we can still extrapolate to a time when the 'concept' of a SNA did not exist in the legislature. The problem here however is that the assumption of strict linearity in the LPI trend may not hold over a long timespan. The following schematic illustrates this concept.

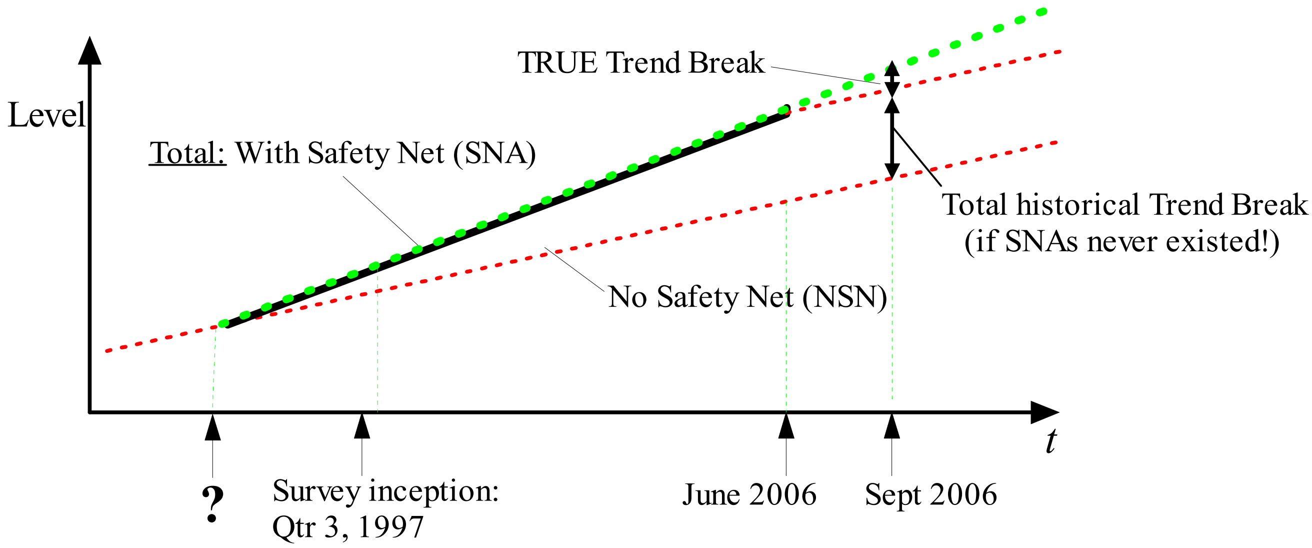

Figure 6: estimating a possible trend break using an extrapolation method

At the time of writing, the client has advised that SNAs have always existed in the surveys. This means we must look at other related sources to determine how SNA activity has contributed in the past (i.e. before the LPI-specific surveys). The only information we could find was that SNAs were introduced in 1996 but implemented in January 1997 (see: http://www.aph.gov.au/LIBRARY/intguide/ECON/safety.htm). This gives us a reference (zero) point at which the LPI did not include jobs with SNAs (i.e. quarter 3 1996). Using the above formalism, we have estimated potential trend break factors at four periods (Table 4), defined effectively as the ratio of total to no-SNA LPI trend levels:

Added 10/11/2006 following Q3'06 analysis:
Please note that the following refers to an estimate of a "total historical trend break". That is, it represents the trend break that will occur if SNAs never existed! But they do exist up to June 2006. So the "true" break due to SNA phase out over the June to Sept '06 period will be much smaller. This is indicated in Figure 6.

$$TB_t = \frac{T_t^O}{T_t^{NSN}} \qquad (24)$$

These were computed at three periods since it is unknown exactly when the (abrupt) level shift will occur, i.e. a genuine trend break from one period to the next. Note that complete phase out of SNAs is expected over quarters 3 and 4 2006 so that the level shift may not be abrupt. As expected, if SNAs continue beyond quarter 3 2006, the level shift will be larger.

We have attempted to confirm the SNA implementation date of Jan 1997 by checking if series from the 'Average Weekly Earnings' (AWE) or 'Survey of Employment & Earnings' (SEE) collections showed any change in their level around this period. No changes were apparent.

	QTR3/2006	QTR4/2006	QTR1/2007
TB_t :	1.023680	1.024294	1.024909

Table 4: effective trend break factors ($TB_t = T_t^O / T_t^{NSN}$) at three periods of interest following the expected phase out period of quarter 3 2006. These estimates are for the "ALLINDUSTRIES" series only.

The values in Table 4 are not sensitive to the period in which the SNA was implemented, or, at which its contribution would have become significant. Changing the SNA implementation date by ±1 year results in a deviation in the TB factors of approximately ±0.003. This is a good sign. In conclusion, if the SNA contribution has behaved according to that in Figure 3, i.e. with the LPI trends (with and without SNA) being approximately linear back to ~Jan 1997, then we would expect a level shift of ~2.4% around the SNA phase out period.

Estimate of the "TRUE" trend break due to SNA phase out over June - Sep Qtr 2006:

From Figure 6, this is given by the ratio:

$$TB(TRUE)_t = \frac{T^O_{SEP06}}{T^O_{JUN06} + \left(T^{NSN}_{SEP06} - T^{NSN}_{JUN06}\right)} \qquad (25)$$

For the ALLINDUSTRIES series, we estimare a "TRUE" SNA phase-out trend break of 1.000802 (~0.08%) at Qtr 3 2006.

Results for the private and public sectors are summarised in section 7 below.

6. Validity of Assumptions and Issues

First, here's a summary of the main underlying assumptions:

1. working hypothesis: seasonal factor changes (or seasonal break priors) due to phasing out of SNA from LPI in 2006 and beyond are assumed to be equal to the relative seasonal contributions from Non-SNA to total jobs over earlier years.
2. variance in irregular components of LPI series are tiny.
3. assumption of a multiplicative decomposition model.
4. ignorance of any bias due to transforming from a log-additive model back to original multiplicative model.
5. according to the second (alternative) method presented in section 4, the assumption is that the seasonal break priors for each quarter are independent

of the years in which they fall in, i.e. there is very little evolution in SNA activity over the three years provided.
6. for both methods above, the crucial assumption is the underlying trend component in both the original (total) and non-SNA LPI series. Here we assumed linear trends estimated using a linear least squares directly on each series.

Some justifications and proposals on how to further assess these are:

1. the validity of this hypothesis can be assessed once more data becomes available in 2006 and beyond. We will be able to tell whether the seasonal factors derived from real observations are commensurate with our predictions.
2. appropriately justified. Luckily, low volatility is a feature of all LPI series.
3. also appropriately justified since in general, the magnitude of volatility (however tiny) and seasonality do indeed increase in proportion to the trend level.
4. also appropriately justified due to justification of 2.
5. we don't have enough data to attempt to explore any instance of systematic evolution in the SNA contribution with time, even if the volatility is very low. The changes appear to be small and random over the available span and constancy of priors for each quarter is appropriate.
6. changing the underlying trend levels by different amounts in each of the original (total) and Non-SNA series will affect the seasonal factor ratio estimates of method 1 (section 2: e.g. see eqns 10, 11, 12), but, changing the trend movements (trend slopes) of any of these input series by any amount will affect the estimates of method 2 (section 4: e.g. see eqns 17). We claim that the 'best' and simplest trend estimates are just linear fits. Linearity is a very good assumption given the similarity in movement (slope) of the linear fit to the X11 trend estimate for the total series (green line in Figure 3). Also, we claim that relative trend movements are more robust to deal with than the trend levels directly. In other words, there is less room for error if relative trend movements are used (i.e. they are more easily estimated in a 'global' sense). Therefore, the second (alternative) method appears to be more robust.

Following on from point 6, it may be worth estimating standard errors on our seasonal break estimates for both methods above. These errors will effectively contain uncertainties in the linear trend fits and thus give us some indication of how sensitive we are on the assumption of the underlying trend in this work.

7. Results Summary for all sectors

For private sector total:

	QTR 1	**QTR 2**	**QTR 3**	**QTR 4**
$\boldsymbol{SB_t}$ **:**	1.0000966	1.0007652	0.9996790	0.9994598

Table 5: effective seasonal factor ratios (or seasonal break priors S_t^{NSN} / S_t) for "PRI_ALLINDUSTRIES" series for each quarter using the "global linear least squares SVD" method of above.

Added 10/11/2006: the "true" (correct) trend break due to SNA phase-out over Jun - Sep Qtrs 2006 is 1.001028 (~0.103%).

For public sector total:

	QTR 1	QTR 2	QTR 3	QTR 4
SB_t :	0.9999814	1.0000292	1.0000377	0.9999517

Table 7: effective seasonal factor ratios (or seasonal break priors S_t^{NSN} / S_t) for "PUB_ALLINDUSTRIES" series for each quarter using the "global linear least squares SVD" method of above.

Added 10/11/2006: the "true" (correct) trend break due to SNA phase-out over Jun - Sep Qtrs 2006 is 1.0000873 (~0.0087%). NEGLIGIBLE!

For all sectors (private + public):

	QTR 1	QTR 2	QTR 3	QTR 4
SB_t :	1.000066	1.000578	0.999771	0.999585

Table 9: effective seasonal factor ratios (or seasonal break priors S_t^{NSN} / S_t) for "ALLINDUSTRIES" series for each quarter using the "global linear least squares SVD" method of above.

Added 10/11/2006: the "true" (correct) trend break due to SNA phase-out over Jun - Sep Qtrs 2006 is 1.000802 (~0.080%).

8. Further Information

Talk given by Frank Masci at a TSA Research Forum:

SNRimpacts1.PRZ

(Subject: WPI September Quarter Seasonality 2006; Database: WA_LPI_WDB; Author: David Taylor; Created: 21/06/2006; Doc Ref: DTAR-6QY57Q)

(Subject: LPI extended Safety Net Adjustment data; Database: Time Series Analysis WDB; Author: Antoinette Beckwith; Created: 10/07/2006; Doc Ref: NACT-6RK2ZU)

(Subject: Fw: Seasonal adjustment of the WPI; Database: Time Series Analysis WDB; Author: Mark Zhang; Created: 02/06/2006; Doc Ref: NACT-6QCVKH)

(Subject: Paragraph for 11/2006 LPI pub..; Database: Time Series Analysis WDB; Author: Frank Masci; Created: 10/11/2006; Doc Ref: NACT-6VE455)

(Subject: Paragraph(s) for SNA impact estimation and methodology.. [SEC=IN-CONFIDENCE:STATISTICS]; Database: Time Series Analysis WDB; Author: Frank Masci; Created: 09/11/2006; Doc Ref: NACT-6VD5ML)

(Subject: Re: Workchoice/SNR impacts on LPI? [SEC=IN-CONFIDENCE:STATISTICS]; Database: Time Series Analysis WDB; Author: Frank Masci; Created: 09/02/2007; Doc Ref: NACT-6Y94LX)