Australian Bureau of Statistics

1351.0.55.159

Research Paper

Predicting Survey Estimates by State Space Models Using Multiple Data Sources

Australia

2017

AUSTRALIAN BUREAU OF STATISTICS

EMBARGO: 11.30AM (CANBERRA TIME) THU 10 AUGUST 2017

Research paper

Predicting Survey Estimates by State Space Models Using Multiple Data Sources

Xichuan (Mark) Zhang and Oksana Honchar

Methodology Division

Methodology Advisory Committee

30 June 2016, Canberra

ABS Catalogue No. 1351.0.55.159

Produced by the Australian Bureau of Statistics.

INQUIRIES

For further information about these and related statistics, contact the National Information and Referral Service on 1300 135 070.

CONTENTS

PREDICTING SURVEY ESTIMATES BY STATE SPACE MODELS USING MULTIPLE DATA SOURCES

Xichuan (Mark) Zhang and Oksana Honchar
Methodology Division

ABSTRACT

The Australian Bureau of Statistics (ABS) is embarking on a transformation program, which includes, amongst other things, re-engineering, using different collection modes for survey data, and using different, but more efficient, sampling frames and estimation methods for official statistics. Whilst this transformation is expected to bring about positive changes to official statistics, there is a risk that such changes could induce statistical impacts in some ABS time series. Such impacts can be misinterpreted as real world changes. The challenge for Methodology Division is to develop methodologies to monitor, measure and, where needed, adjust for the impacts for any affected ABS time series.

In this research, a methodology to measure such statistical impact in time series is proposed. To estimate the change that occurs on the target survey variable, the method uses related data series, which measure a similar concept to the target survey variable, but which are not subject to measurement change. Under this method, the statistical impact can be assessed by intervention analysis, taking advantage of the cross-correlations and leading properties between the target survey variable and the other related series. We illustrate the power of this method by estimating supplementary survey effects using Australian Labour Force Survey data as an example.

This research can also be extended to provide additional benefits in statistical estimation. By exploiting the cross-correlations between the target survey variable and the other related series, we can potentially significantly improve the precision of survey variable estimates, and maintain a high level of coherence between the series.

1. INTRODUCTION

Many surveys conducted by national statistical offices are repeated. This enables estimation of changes for the total aggregate (or population) as well as cross-sectional estimates. The time series produced by such repeated surveys over time create a basis for social, economic and environmental analysis and policy making.

Any changes in survey methodology might affect the continuity of the estimated time series, and this creates difficulties for users in interpreting movements in data and making policy decisions. It is not always clear if the unusual movements in the estimates represent real world changes or if they are measurement changes introduced by new or alternative methodological approaches. Therefore any changes in survey methodology have to be well managed, i.e. the impact of methodological change has to be identified, measured and adjusted, if necessary, to mitigate the risk of misinterpretation of the changes by providing a coherent picture before and after the change.

The Australian Bureau of Statistics (ABS) is embarking on a transformation program, which includes, amongst other things, re-engineering, using different collection modes for survey data and using different, but more efficient, sampling frames and estimation methods for official statistics. Whilst this transformation is expected to bring about positive changes to official statistics, there is a risk that such changes could induce statistical impacts in some ABS time series. Such impacts can be misinterpreted as real world changes. The challenge for Methodology Division is to develop methodologies to monitor, measure and, where needed, adjust for the impacts for the affected ABS time series.

The first and the most straightforward approach to assess impact of survey changes is to conduct a parallel run, i.e. to conduct the survey under the old and new approach simultaneously (see, for example, Van den Brakel, 2008). The current and the proposed survey designs are run in parallel for a period of time in order to collect information about the impact of the change. This approach presents a big challenge for an official statistical office due to the high cost and / or low power under a small sample size, and the complicated logistics of a parallel run operation.

Survey budgets often have strong limitations that make parallel runs impossible. In such cases, a time series modelling approach can be considered as an alternative option to the parallel run. Time series models without overlapping periods have been proposed and applied in the literature[1]. Van den Brakel and Roels (2010) also presented an application to percentage estimates of categorical variables as a special case. In general, this time series intervention approach relies on a time series model which includes a dummy variable that incorporates auxiliary information on the time and duration of the survey change. The time series model is assumed to describe the underlying behaviours of the series effectively. However, such an assumption may not be appropriate when a substantive real world change occurs while a survey is in transition to a new design. Another related series that is not subject to measurement change could assist to distinguish the measurement change from the real world change. We can borrow the idea of using related series to improve a survey estimate for this purpose.

1 Section 6.3, Van den Brakel, Smith and Compton (2008) provides a good overview.

Harvey and Chung (2000) proposed a bivariate structural time series model in state space form for estimating the underlying change in unemployment in the UK using information on unemployment benefits claimant counts. Van den Brakel and Krieg (2015, 2016) used a multivariate structural time series model in a state space form for small area estimation for the Dutch Labour Force Survey using information on the number of people who receive unemployment benefits. The above-mentioned investigations used multivariate time series modelling with series that were strongly related to the target series, i.e. the claimant count series and the number of people who receive unemployment benefits were strongly related to the LFS unemployment series. However, it is not always possible to find such good examples of related series in practice.

This paper presents an extension of a multivariate structural time series model application to handle the following situations by using other data sources, which are not subject to the measurement change, to:

- measure the statistical impact of changes in methodology and other transformation processes;
- use model predictions for quality assessment;
- ensure coherent estimates from other sources of information; and
- further refine survey estimates which are subject to sampling and non-sampling errors.

Section 2 provides a summary of findings from the current study. Section 3 describes methods used for investigation of the potential options for predicting survey statistics using information from multiple sources. Measurement of statistical impact of changes on time series consistency is also investigated in this section. The Australian LFS is presented as a case study in Section 4. Section 5 provides an evaluation of the study.

All the calculations reported in this paper were carried out with programs written in STAMP (see Koopman *et al*, 2009) and SSM procedure in SAS.

2. MAIN RESULTS

A special multiple time series model called a Seemingly Unrelated Time Series Equation (SUTSE) model is investigated as a basis for predicting a target survey estimate using multiple data sources.

Firstly, a case study presented in this paper shows that a standard bivariate SUTSE model, with the ABS LFS total unemployment estimates as the target series and the unemployment benefit claimant counts data as related series, can provide a valuable tool for detecting outliers and structural changes, thus enhancing the quality of the LFS unemployment estimates.

However, available multiple data sources may not have appropriate properties for applying a standard SUTSE model to predict survey estimates efficiently. With a good understanding of the SUTSE model's implied assumptions and limitations, we also present a strategy to select valuable data sources and adjust the way a SUTSE model is applied to take advantage of SUTSE modelling strength.

Another case study of ABS LFS total Australian employed persons estimates demonstrates such a strategy works much better than a univariate structural time series model by borrowing strength from multiple source data in an efficient way. Once again, this could improve prediction accuracy and outlier detection for LFS survey estimates.

3. METHODS

3.1 STATE SPACE MODEL (SSM) FORMULATION

Structural time series models (STMs) are formulated in terms of unobserved components, such as trends and cycles, that have a direct interpretation (Harvey, 1989). The key to handling structural time series models is the state space form (SSF), with the state of the system representing the various unobserved components such as trends and seasonals. Once in state space form, the Kalman filter provides the means of estimating the initial values of the states and updating the state as new observations become available.

Firstly, we will consider univariate structural time series models and methods of modelling unobserved components for those models. Then we will describe how a sampling error component can be incorporated into the model using the example of Australian LFS. Methods of intervention analysis will be described in Section 3.1.3. In Section 3.1.4 we will consider multivariate structural time series models, namely seemingly unrelated time series equations models (SUTSE), that under some assumptions give gains in accuracy of predictions for target series using related series from multiple sources of information. Finally, the state space formulation is given for the structural time series models.

3.1.1 Univariate structural time series model

The common univariate structural time series model for the observed variable y_t in case when it has been obtained from a sample survey is defined as

$$\hat{y}_t = \mu_t + \gamma_t + \varphi_t + \varepsilon_t + e_t, \quad \varepsilon_t \cong NID(0, \sigma_\varepsilon^2), \tag{3.1}$$

where μ_t, γ_t and φ_t are unobserved trend, seasonal and cyclical components, respectively, ε_t is a disturbance term that is normally and independently distributed with zero mean and variance σ_ε^2 and e_t is a sampling error. The unobserved trend, seasonal and cyclical components in the structural time series model can be time-varying and therefore treated as stochastic variables. The components are modelled using state equations.

The trend component from the observation equation (3.1) in general case is modelled as

$$\mu_t = \mu_{t-1} + \upsilon_{t-1} + \xi_t, \quad \xi_t \cong NID(0, \sigma_\xi^2), \tag{3.2}$$

$$\upsilon_t = \upsilon_{t-1} + \zeta_t, \quad \zeta_t \cong NID(0, \sigma_\zeta^2), (3.3)$$

where μ_t is the unobserved time series trend level at time t, υ_t is trend slope that is also called a drift or a movement, and ξ_t and ζ_t are the level and the slope disturbances at time t that are normally and independently distributed with zero mean and variances σ_ξ^2 and σ_ζ^2 respectively. If variance of one of the disturbance terms (or both) in the trend state equations is close to zero then the respective disturbance term also can be put equal to zero and the respective component in the model can be treated as deterministic. A particular version of the model is called the smoothed trend model when $\sigma_\xi^2 = 0$ and $\sigma_\zeta^2 > 0$. If the structural time series model includes only the trend component that is modelled as in (3.2)–(3.3) then the model is called a local linear trend model.

The seasonal component[2] can be modelled using the following simple autoregressive model

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j} + \omega_t\,, \quad \omega_t \cong NID(0, \sigma_\omega^2), \tag{3.4}$$

2 There are several alternative models for seasonal patterns. See the details in Harvey (1989, pp. 40-43)

where s is the periodicity of the seasonal. $\sigma_\omega^2 > 0$ allows the seasonality to evolve over time.

The cyclical component[3] can be modelled using a restricted form of autoregressive model of order two (see Harvey, 1985):

$$\varphi_t = \Phi_1\varphi_{t-1} + \Phi_2\varphi_{t-2} + \kappa_t, \quad \kappa_t \cong NID(0, \sigma_\kappa^2), \tag{3.5}$$

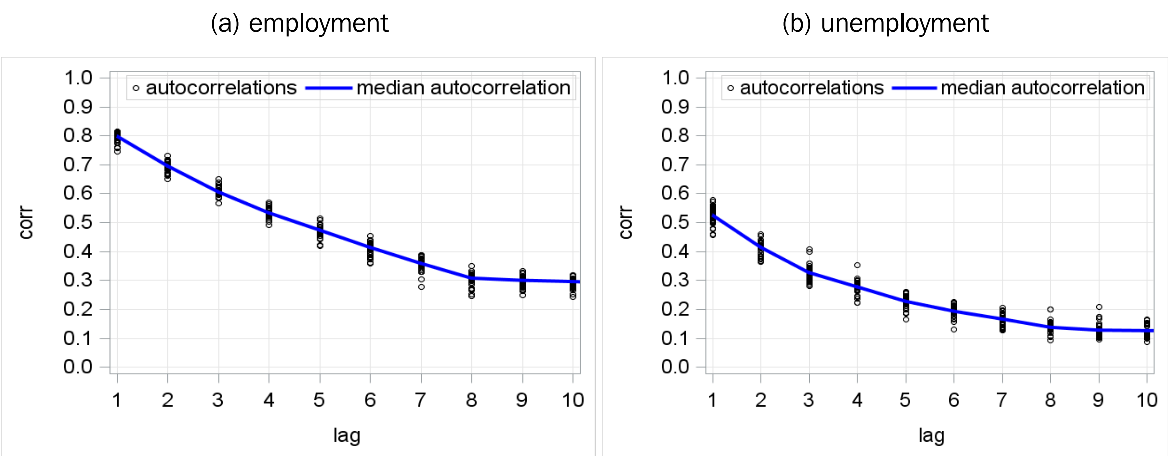
where κ_t is a cycle disturbance term with zero mean and variance σ_κ^2, $\Phi_2 < 0$ and $|\Phi_1(1-\Phi_2)/(4\Phi_2)| < 1$. The cycle peak is at period $2\pi/\cos^{-1}\left(-\Phi_1(1-\Phi_2)/(4\Phi_2)\right)$ (see Priestley, 1981, pp 241). Again, the cyclical component is allowed to change stochastically over time, unless the variance of the disturbance term is equal to zero.

3.1.2 Survey error treatment

In the case of modelling time series that come from sample surveys with rotation panels, the sampling error can be also incorporated into the structural time series model. Sampling error variance, and covariance structure across time, needs to be pre-defined by prior knowledge or can be estimated from the survey using a replicate method.

Let us consider survey error treatment for the Australian LFS. For simplicity we use estimates based on the standard GREG estimator (Särndal, Swensson and Wretman, 1992) applied to each month's data, which gives estimates very close to the somewhat more complex composite estimator that is actually implemented. The variance (and covariances) of the GREG estimator is then calculated by applying a jack-knife approach (Wolter, 2003) within strata to the (GREG) weighted residuals (Särndal, Swensson and Wretman, 1992) for the number of employed and the number of unemployed people. The residuals are the result of using a linear model to incorporate auxiliary information into the production of the survey estimates. These were calculated from the monthly LFS data records files for the period between June 2010 and April 2013. This period of time (between two redesigns) was used because otherwise changes in the survey design create problems for calculation of weighted residuals by primary sampling units (PSUs), as these might be different for two successive survey designs. After that, for each pair of months within the time period correlations had to be calculated at the various lags (1–10). Then the correlations for each lag were averaged thus ten autocorrelations were obtained for each LFS estimate (employed and unemployed) (see figure 3.1).

3.1 Autocorrelations for number of employed (on the left) and unemployed (on the right) people



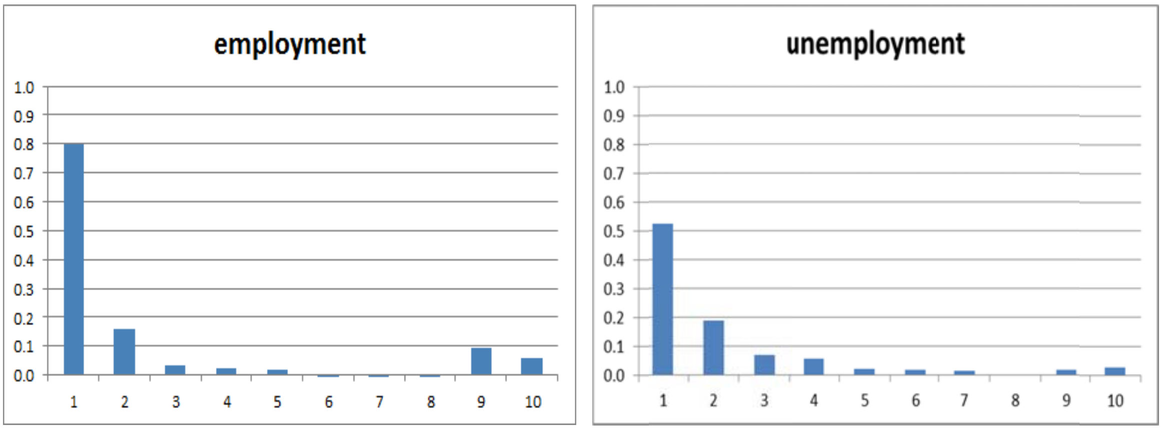
3 There is also an alternative model in trigonometric form. See the details in Harvey (1989, pp. 45-46)

The next step is to solve the Yule-Walker equations using autocorrelations from the previous step as an input to get Auto-Regressive coefficients (see Box and Jenkins, 1970). Partial autocorrelations for the number of employed and unemployed people are presented in figure 3.2. It is clear that only those at lag 1 and 2 are significant; implying that an AR model of order two can be used for modelling the sampling error component for the number of employed and unemployed people:

$$e_t = \Psi_1 e_{t-1} + \Psi_2 e_{t-2} + \delta_t, \quad \delta_t \cong NID(0, \sigma_\delta^2). \tag{3.6}$$

where $\Psi_1 = 0.67, \Psi_2 = 0.16,$ and $\sigma_\delta^2 = 4.7957E\text{-}\ 6$ for the (logarithm transformed) LFS number of employed persons, and $\Psi_1 = 0.4247, \Psi_2 = 0.19,$ and $\sigma_\delta^2 = 4.75E\text{-}\ 4$ for the (logarithm transformed) LFS number of unemployed persons respectively.

3.2 Partial autocorrelations for number of employed (on the left) and unemployed (on the right) people



3.1.3 Intervention analysis

Changes in survey methodology or data collection and processing of data can have a few different effects on time series. The first and most common effect is *a level shift*, where the value of the level in a time series suddenly changes at the point where the intervention was made, and then continues permanently after the intervention. The second possible effect is *an additive outlier*, where an effect is detected only in the time period when the intervention was introduced. Another possible effect may be a significant and permanent *change in the seasonal pattern* as the result of an intervention. It is also quite likely that an intervention can result in more than one of the above-mentioned effects.

The intervention effects can be measured by including intervention variables in a structural time series model. There are two possibilities. The first one is to incorporate the intervention dummy variable w_t into the observation equation: $y_t = \mu_t + \gamma_t + \varphi_t + \lambda_t w_t + \varepsilon_t + e_t$, where λ_t is regression coefficient. Then the state equation for the intervention variable coefficient will be following:

$$\lambda_t = \lambda_{t-1} + \eta_t, \quad \eta_t \cong NID(0, \sigma_\eta^2), \quad t = 1, \ldots, T, \tag{3.7}$$

The form in (3.7) is the most general situation, but conceptually it usually makes sense that σ_η^2 is zero and, therefore, disturbances η_t are fixed to zero. In such case, λ_t is treated as a fixed regression coefficient. However in some cases λ_t is allowed to be time-varying with σ_η^2>0. This would be appropriate when the impact of an ongoing intervention, such as the introduction of a revised questionnaire, is not stable due to interviewers adjusting to the change across time.

The definition of the intervention dummy variable w_t depends on the form which the intervention effect is assumed to take. For example, if an additive outlier is assumed, then w_t is a pulse variable, which takes unity for the intervention time period and zero for other time periods; while a shift in the level of the series can be captured by a step variable.

It might sometimes happen that the seasonal pattern changes as the result of an intervention. Modelling this kind of an effect requires the introduction of $s-1$ dummy variables from time τ onwards, the effects of which are constrained to be zero over s consecutive time periods.

In the case when it is assumed a few effects form the intervention, an appropriate number of intervention variables have to be introduced into the model.

3.1.4 State space representation

Using matrix algebra, the univariate structural time series model can be written in the state space form (SSF):

$$\mathrm{y_t}=z_t'\alpha_t+\varepsilon_t,\quad \varepsilon_t\cong NID(0,\sigma_\varepsilon^2) \tag{3.8}$$

$$\alpha_t=T_t\alpha_{t-1}+R_t\eta_t,\quad \eta_t\cong NID(0,Q_t)$$

where the term y_t and ε_t are scalars (i.e. of order 1×1), z_t is an $m\times 1$ observation (design) vector, T_t is an $m\times m$ transition matrix, α_t is an $m\times 1$ state vector (m – the number of elements in the state vector), R_t is an $m\times r$ selection matrix with $r\le m$ number of non-zero disturbance terms, and η_t is the $r\times 1$ vector of the r state disturbances with zero means and unknown variances collected in an $r\times r$ diagonal matrix Q_t.

For example, SSF for the local linear trend model (see Section 3.1.1) is

$$\mathrm{y_t}=(1\quad 0)\alpha_t+\varepsilon_t, \tag{3.9}$$

$$\alpha_t=\begin{pmatrix}\mu_t\\ \upsilon_t\end{pmatrix}=\begin{pmatrix}1&1\\0&1\end{pmatrix}\begin{pmatrix}\mu_{t-1}\\ \upsilon_{t-1}\end{pmatrix}+\begin{pmatrix}\xi_t\\ \zeta_t\end{pmatrix}$$

The state space form (SSF) allows a general treatment of virtually any linear time series models through the general algorithms of the Kalman filter and the associated smoother (Harvey, 1989). The Kalman filter is used for minimum mean-square estimation of the state vector, based on current and past observations, together with variance matrices.

3.1.5 Seemingly unrelated time series equation (SUTSE) model

A multivariate structural time series model, the so-called Seemingly Unrelated Time Series Equations (SUTSE) model, can be used to improve the accuracy of survey estimates (see Harvey and Chung, 2000). In the SUTSE model, each series is modelled as in the univariate case, but the disturbances may be correlated across series (see Harvey and Koopman, 1997). Related series can improve accuracy of the unobserved components in a target series and decrease its prediction error when forecasting.

For example, suppose that a bivariate local linear trend model is appropriate for two time series. Then it can be written as follows:

$$\boldsymbol{y_t}=\boldsymbol{\mu_t}+\boldsymbol{\varepsilon_t},\quad \boldsymbol{\varepsilon_t}\cong \boldsymbol{NID}(\boldsymbol{0},\boldsymbol{\Sigma_\varepsilon}),$$

$$\boldsymbol{\mu_t}=\boldsymbol{\mu_{t-1}}+\boldsymbol{\upsilon_{t-1}}+\boldsymbol{\xi_t},\quad \boldsymbol{\xi_t}\cong \boldsymbol{NID}(\boldsymbol{0},\boldsymbol{\Sigma_\xi}), \tag{3.10}$$

$$\boldsymbol{\upsilon_t}=\boldsymbol{\upsilon_{t-1}}+\boldsymbol{\zeta_t},\quad \boldsymbol{\zeta_t}\cong \boldsymbol{NID}(\boldsymbol{0},\boldsymbol{\Sigma_\zeta}),$$

where $\boldsymbol{y_t}$ and all the other vectors are of order 2×1, Σ_ε, Σ_ξ and Σ_ζ are covariance matrices of order 2×2 for the irregular disturbance ε_t and level and slope disturbances ξ_t and ζ_t respectively.

The covariance matrices for level and slope disturbances ξ_t and ζ_t are following:

$$\Sigma_\xi = \begin{pmatrix} \sigma_{1\xi}^2 & \rho_\xi \sigma_{1\xi}\sigma_{2\xi} \\ \rho_\xi \sigma_{1\xi}\sigma_{2\xi} & \sigma_{2\xi}^2 \end{pmatrix}, \tag{3.11}$$

$$\Sigma_\zeta = \begin{pmatrix} \sigma_{1\zeta}^2 & \rho_\zeta \sigma_{1\zeta}\sigma_{2\zeta} \\ \rho_\zeta \sigma_{1\zeta}\sigma_{2\zeta} & \sigma_{2\zeta}^2 \end{pmatrix}. \tag{3.12}$$

where ρ_ξ and ρ_ζ are correlations between respective disturbance terms. In the case where the correlations ρ_ξ and ρ_ζ are close to ± 1, the trends of the two series are similar.

If $\rho_\zeta = \pm 1$ then there is only one source of stochastic movement in the two slopes and one slope is a linear combination of the other slope. In this case, the rank of the covariance matrix Σ_ζ equals unity and the model is called a common slope model. Such series are co-integrated of order (2,1), denoted CI(2,1), implying both series require second differencing to be stationary, and a linear combination of first differences is stationary.

If correlations for both disturbance terms $\rho_\zeta = \pm 1$ and $\rho_\xi = \pm 1$ then there is an additional linear combination of levels which becomes stationary. The rank of the covariance matrixes Σ_ζ and Σ_ξ equals unity. The model with such properties is called a common trends model. Such series are co-integrated of order (2,2), denoted CI(2,2), implying that there is a linear combination of the observations themselves that is stationary.

In the general case, there are more than two time series in the structural time series model. The covariance matrices for level and slope disturbances are symmetric and, in the case where common factors are present, are less than full rank. The presence of common factors implies co-integration of the series.

The principle of the above bivariate SUTSE local linear model can be extended to other unobserved components such as seasonal factors, cycles and survey errors. There can be a common factor for each component. Recognition of common factors yields models which provide more efficient inferences and predictions. Multivariate SUTSE models are often over parameterised. Common factor models are also a way to reduce this problem.

3.2 AN EXTENSION TO THE SUTSE MODEL

Harvey and Chung (2000) and Harvey (2006) proved that the application of a standard SUTSE model to conceptually similar series can improve the prediction of a survey estimate. In practice, however, such conceptually similar series are not always available. We often have some leading or coincident (composite) indicators, which are related to the target series. The question to be asked is "can a SUTSE model be applied to improve a prediction?" To answer this question we need to examine what are the implied assumptions/conditions a standard SUTSE model makes.

The definition of a SUTSE model is:

> a set of same form univariate linear (component) models linked only by their disturbance, which may be correlated.

The greater the correlation, the greater the efficiency gain in estimation using this approach. Unlike a general vector autoregressive (VAR) model, the SUTSE model cannot link a direct leading and lagging relationship between the same components among the multivariate series. In other words, the SUTSE model is most efficient if the maximum correlation of a same component of the target series and a related series is coincidental.

This implied assumption/condition may not be necessarily satisfied for the series involved in a multivariate SUTSE model. Thus, the application of a SUTSE model may not gain anything or, at least, may not be efficient. In order to best utilise a SUTSE model to gain predicting precision efficiently, we propose the following adjustment strategy for selecting relevant series and SUTSE model building.

1. Selecting relevant series which lead, or are at least coincident with, the "business cycle" of the target series (see Section 3.3 for details).

2. Aligning (synchronising) the "business cycle" with the target series by shifting the relevant series forward by the leading periods of the relevant series.

3. Constructing a more flexible SUTSE model, which allows each univariate model to have its own different composition of components but has at least one key component in common with the target series – such as the slope or cyclical component. The disturbances of key components are linked by the component disturbance covariance matrix.

With the above treatments, we ensure that an improvement in prediction of the target series can be achieved because the extended SUTSE model is in the most efficient form to utilise the information of the target series in the relevant series.

3.3 CRITERIA FOR MULTIPLE SERIES SELECTION

There are different criteria for selection of suitable candidates for SUTSE modelling. First of all, the selected series have to be *conceptually related* to the target series.

The other desired feature for selected series is *leading properties*. If disturbances for unobserved components of a target series are correlated with a lagged related series then the variables for the lagged series are called leading indicators. The presence of leading properties for related series implies that the prediction for the target series can be obtained at least a few months in advance.

Non-stationary properties of series (*unit roots and co-integration*) are also considered as criteria for related time series selection. If a set of time series are cross sectional, and assuming that the different series are not subject to any cause-and-effect relationship between them but are subject to the same social-economic environment, we can link them together under the same structure and allow the various state components to be contemporaneously correlated. For non-stationary multivariate time series, co-integration is a necessary condition to model their "long" relationships and get efficiency for including relevant time series to improve prediction power. If there is no correlation between respective disturbance terms, then there is no reason to involve the additional time series since the multivariate model does not gain anything from separated univariate models for prediction. For testing the correlation between cyclical components of target and related series, business cycles analysis can be conducted using a Hodrick-Prescott filter (1997). Here the cyclical (or "business cycle") components are defined as deviation from the trend derived from a suitable Hodrick-Prescott filter.

Higher priority is given to *ABS series* rather than external series for a number of reasons. The first one is guarantee of high accuracy in the data and known sampling errors for the ABS time series. Other reasons include easy access to ABS data, the opportunity to get time series for any area (state, region) or domain of interest, the timeliness of the most recent estimates in a related time series, and documentation of changes. In some external data sources there may be changes (a series may even be discontinued in an extreme case) and users may, or may not be aware of such changes, or able to adjust for them.

A higher priority is also placed on *real value series* rather than business cycle index series that have no trend, and therefore cannot be co-integrated with the target series. However, in some cases, such series might have common cyclical or seasonal components with target series and thus give some efficiency gains for predicting the target series.

Time series length and periodicity are also important criteria for selection of suitable candidates for state space modelling. Series with length less than ten years might not give very accurate predictions and hence such series were excluded from consideration in our case studies. Also, higher priority is given to the series that have the same periodicity as a target series. For example, if the target series are monthly (for example, LFS employment and unemployment) then it is preferable to have related series at the monthly basis as well, rather than quarterly series.

3.4 MODEL FIT AND SELECTION STRATEGY

Having chosen related series as outlined above, several criteria were used for selection of a good structural state space model.

1. The first criterion was the accuracy of prediction performance by borrowing strength from other series against univariate model prediction. Statistical measures for assessment against this criterion were prediction error variance and prediction mean deviation.

2. The second criterion was an earlier detection of unusual estimates from the perspective of coherence with other series.

3. A good SUTSE model was one which reduced false alarms against univariate STM.

4. Comparison of model performance was done using information criteria such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) etc.

5. Finally, the assumptions underlying the state space model were evaluated by testing whether the standardized disturbances were normally and independently distributed. The tests on normality, heteroscedasticity and independence were used to check that these assumptions were not violated.

4. CASE STUDIES

4.1 ABS LABOUR FORCE SURVEY METHODOLOGY

The Labour Force Survey (LFS) is based on a multi-stage area sample about 30000 dwellings per month and covers approximately 0.32% of the civilian population of Australia aged 15 years and over (ABS, 2016). Households selected for the LFS are interviewed face-to-face, by phone or web form each month for eight consecutive months, with one-eighth of the sample being replaced each month. This high overlap of respondents from month-to-month induces a strong serial correlation into the sampling errors as already estimated in Section 3.1.2.

The estimation method used in the LFS is composite estimation, which was introduced in May 2007. Composite estimation combines data collected in the previous six months with the current month's data to produce the current month’s estimates, thereby exploiting the high correlation between overlapping samples across months in the LFS. The composite estimator combines the previous and current months' data by applying different factors according to length of time in the survey. After these factors are applied, the seven months of data are weighted to align with current month population benchmarks. In January 2014 composite estimation was applied to all estimates from July 1991 as part of the 2011 Census rebenchmarking.

There were also some other major measurement changes for LFS unemployment estimates. For example, the unemployment duration definition was changed in 2001. See details in ABS (2009, 2011).

The ABS implemented a LFS redesign in 2013 that included a consolidated supplementary survey program (see the details in ABS, 2013). This change also resulted in some changes to ABS LFS estimates, which were more significant than anticipated.

4.2 MULTIPLE DATA SOURCE SELECTION FOR UNEMPLOYMENT AND EMPLOYMENT

4.2.1 Time series selection for modelling of unemployment

The Department of Human Services (DHS), on behalf of the Department of Social Services (DSS), publishes statistical information on a monthly basis for the various types of labour market payments delivered.[4] The total unemployment benefit claimant counts (CC) are comprised of new start allowance (NSA) job seekers and youth allowance (other) job seekers. The relationship and differences between the ABS LFS unemployment estimates and CC are explained in ABS (2014). The CC monthly data are available from December 1995 to March 2016 (DSS 2016) for this study while ABS monthly unemployment estimates are available from February 1978 to March 2016.

The CC series has no leading properties, however, they are available before LFS estimates.

There have been several administrative and policy changes for the CC collection over time. The main changes were:

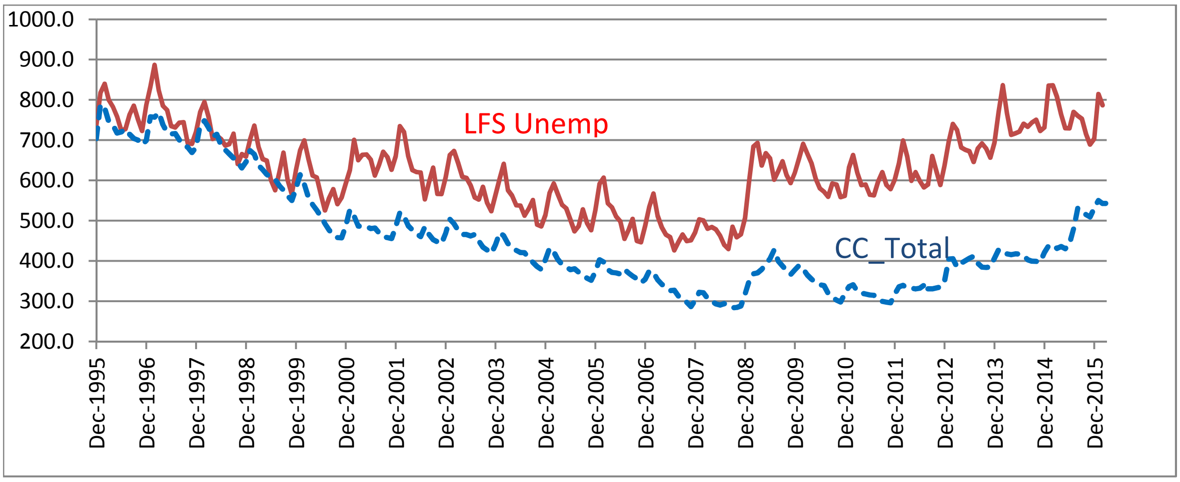
- the method of counting recipients;
- the inclusion of some CDEP recipients in the total recipient numbers;
- the introduction of Youth Allowance in July 1998;
- the way 'job seeker' is defined;
- the way duration is calculated;
- the eligibility for Newstart Allowance and Youth Allowance (other) from July 2012;
- the cessation of grandfathered Parenting Payment provisions, which saw an increase in the number of Newstart recipients in January 2013; and
- the introduction of *Jobactive*, an employment services model with a stronger focus on job search, which replaced Job Services Australia on 1 July 2015.

As the result of these changes, the time series of the published CC data may have significant structural breaks, which may have profound effects if they are not treated appropriately to create consistent measures.

Figure 4.1 shows the original estimates of LFS unemployment and CC in thousands. The two series appear to be diverging over time at first glance. However, such divergence may not necessarily mean the CC series does not contain useful information about LFS unemployment. Since both of them conceptually measure the unemployment phenomenon and are subject to the same economic environment, it is plausible that their underlying changes move together despite divergence in levels. For example, around the start of 2009 both series experienced a shock and level shift in relation to the global financial crisis.

4 The relevant data is available from www.data.gov.au

4.1 LFS unemployment and DSS claimant counts

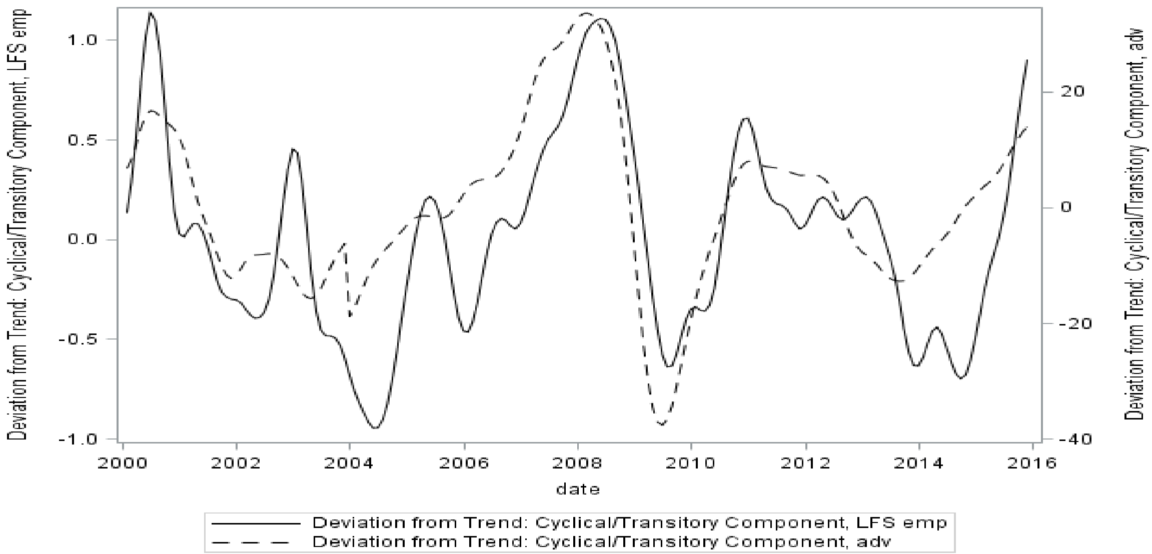


4.2.2 Time series selection for modelling of employment

The successful series candidates for predicting the number of employed people are not as clear as for number of unemployed people. 26 candidate series were tested from both ABS and external data sources (see Appendix A for details).

Based on the selection criteria established in Section 3.3, the most suitable related series for the ABS LFS number of employed persons was the ANZ job advertisements series. It has monthly periodicity, over 15 years length, is non-stationary and co-integrated with the LFS employment series. The business cycles of the ABS LFS employment and the ANZ job advertisements are shown in figure 4.2. From the business cycle perspective[5], the ANZ job advertisement leads two months over the ABS LFS employment with a high cross correlation (0.78).

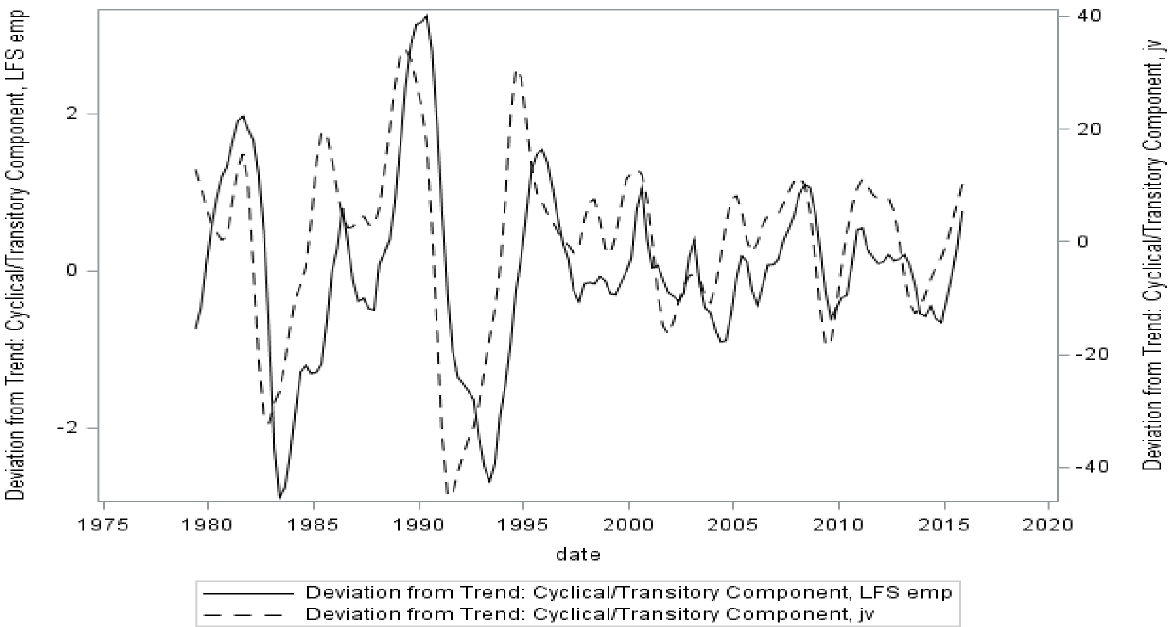
4.2 Business cycle of LFS employment and ANZ job advertisements



5 The business cycles are produced as percentage deviation from the long term trend derived from applying Hodrick-Prescott filter with smoothing parameter 129,600 to trend-cycle or seasonally adjusted estimates from seasonal adjustment process such as X-12.

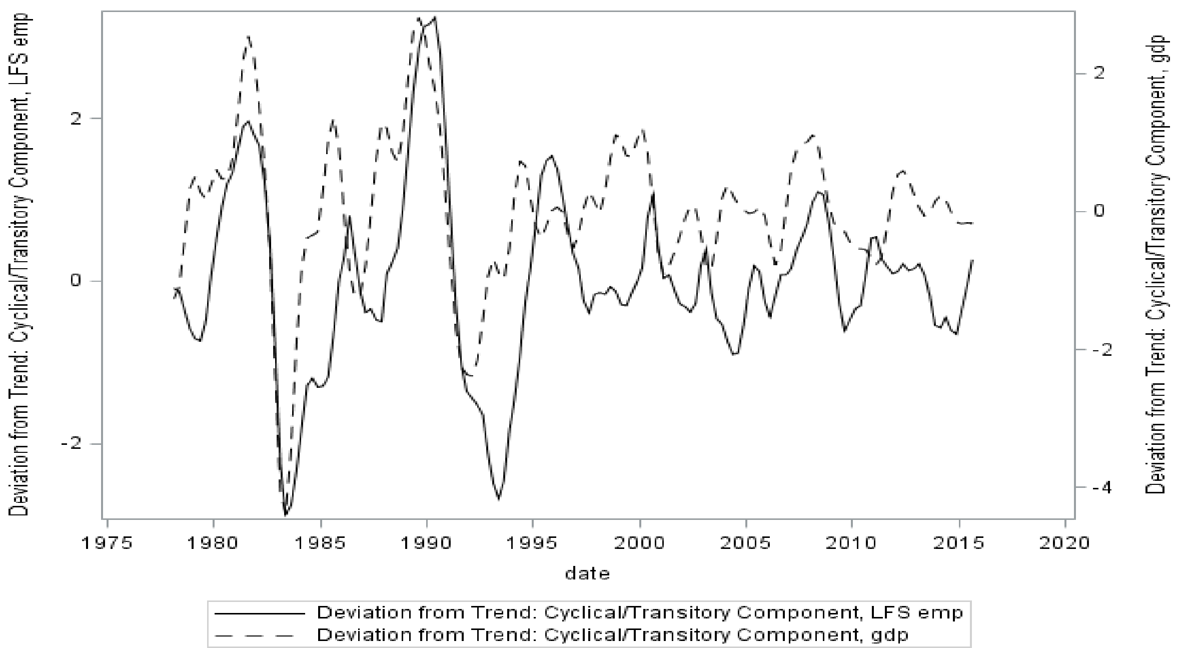
The ABS job vacancies series is the next most successful candidate for modelling LFS employment. Although this series is quarterly, it non-stationary and co-integrated with the employment series, leads three quarters over the ABS LFS employment with the highest correlation between the business cycles (0.83) among other tested series. The business cycles of LFS employment and ABS job vacancies are shown in figure 4.3.

4.3 Business cycle of LFS employment and ABS job vacancies



The ABS GDP series was also found to be suitable, although it is quarterly. This series has the same length as the LFS employment series; is non-stationary and co-integrated with the LFS employment series at 10% of confident level. The business cycles of the ABS LFS employment and GDP are shown in figure 4.4. From the business cycle perspective, the GDP leads two quarters over the ABS LFS employment with a high cross correlation (0.77).

4.4 Business cycle of LFS employment and GDP



There were also two series, i.e. ANZ newspaper advertisements and internet advertisements, that were found to be highly suitable, however, because they are two components of the ANZ job advertisements series, it was decided to only include the full series in the model.

Additionally, there were some employment business cycle index series, i.e. NAB Employment Index, DoE Leading indicator of employment, and DoE internet vacancy index that had nice properties. All those series are monthly, have leading properties and they are correlated with the business cycles of the LFS employment series. It was decided to test those series in the modelling process for further refinement.

4.3 CASE STUDY OF UNEMPLOYMENT – BIVARIATE MODEL WITH UNEMPLOYMENT BENEFIT CLAIMANT COUNTS

We implement one of the model parameterisations used in Harvey and Chung (2000), applying a standard bivariate SUTSE model with a smooth trend, correlated slope disturbances and independent seasonal and irregular components, with a predefined LFS unemployment survey error (see Section 3.1.2 for details), to logarithm transformed LFS unemployment and CC series with the model specification as listed in table 4.5.[6] and data span from January 1996 to December 2015. In the table 'in' and 'out' mean the corresponding component is included and excluded respectively.

4.5 Bivariate SSM for LFS unemployment and CC series

Components / Source	*Unemployment*	*Claimant Counts*	*Disturbance variance / covariance*
Level	In	In	$\Sigma_{\xi} = \mathbf{0}$ (Fixed)
Slope	In	In	Σ_{ζ} = General Symmetric
Seasonal	In	In	Σ_{ω} = Diagonal
Survey error	In (AR(2): $\Psi_1 = 0.425$, $\Psi_2 = 0.19$)	Out	$\sigma_{\delta}^2 = 4.75E\text{-}04$
Irregular	In	In	Σ_{ε} = Diagonal

A set of known changes in the LFS unemployment and CC series are also modelled by intervention analysis with designed dummy variables for the administrative and policy changes to the LFS and CC series over time (see the details in Section 4.2.1). They take into account the potential structural changes and relevant outliers as level shift (ls) and additive outlier (ao) respectively. The transitional change can be approximated by a level shift and an additive outlier present at the time of change. The modelled intervention coefficient values and t-value are listed in table 4.6.

According to the probability of test statistics in the last column (Pr $> |t|$), the hypothesis of no intervention effects is rejected at the 0.05% level for

- a level shift of LFS unemployment at April 2001 induced by the unemployment duration definition change,
- a level shift of CC at January 2013 because of the cessation of grandfathered Parenting Payment provisions, and
- a level shift and an outlier of CC at July 2015 for the introduction of *Jobactive* program. It reflects the transitional change of this government program implementation.

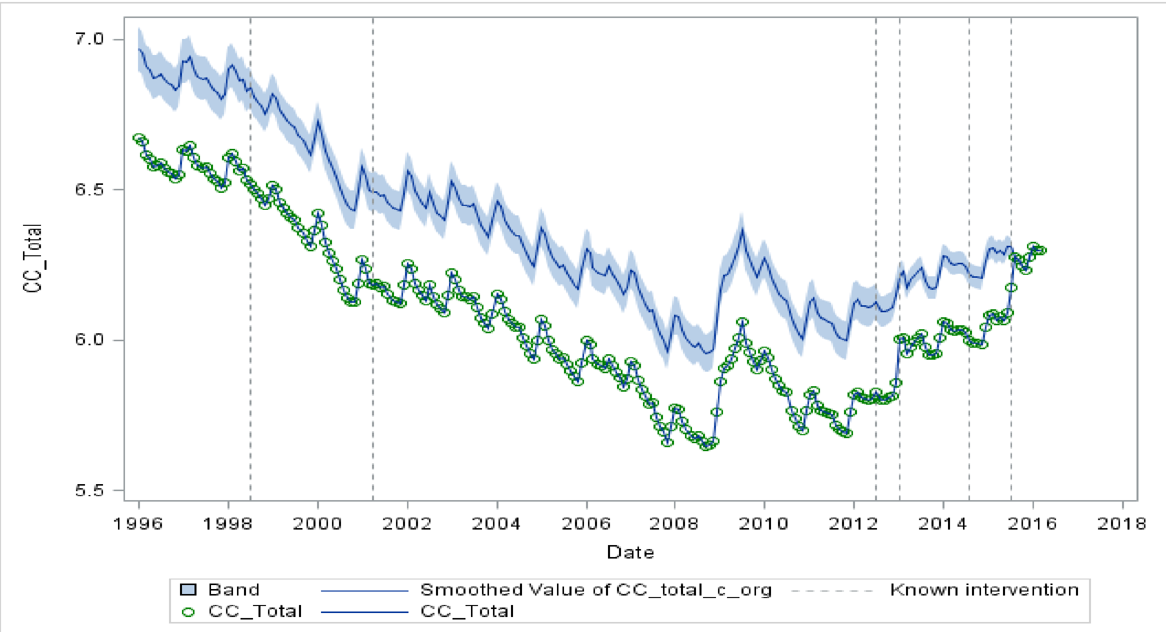
6 The two series are co-integrated C(2,1) and not CI(2,2). Various other model specifications were evaluated and tested. Although this model may not be numerically optimal in term of model selection information criteria such as Akaike Information Criteria, this model has been proved adequate from a model residual test. Details from different settings and tests are available from authors on request.

4.6 Intervention analysis of bivariate SSM for LFS unemployment and CC series

		Regression parameter estimates			
Response variable	*Regression variable*	*Estimate*	*Standard error*	*t value*	*Pr > |t|*
lfs_unemp	lfs_apr_2001_ls	**-0.09453**	**0.0286**	**-3.31**	**0.0009**
lfs_unemp	lfs_apr_2001_ao	-0.01632	0.0286	-0.57	0.5681
lfs_unemp	lfs_aug_2014_ao	0.00712	0.0255	0.28	0.7798
cc_total	cc_jul_1998_ls	0.00365	0.0175	0.21	0.8346
cc_total	cc_jul_1998_ao	-0.01878	0.0126	-1.49	0.1361
cc_total	cc_jul_2012_ls	-0.01580	0.0175	-0.90	0.3664
cc_total	cc_jul_2012_ao	-0.00706	0.0126	-0.56	0.5755
cc_total	cc_jan_2013_ls	**-0.07378**	**0.0175**	**-4.22**	**<.0001**
cc_total	cc_jan_2013_ao	0.01215	0.0126	0.96	0.3349
cc_total	cc_jul_2015_ls	**-0.22394**	**0.0192**	**-11.68**	**<.0001**
cc_total	cc_jul_2015_ao	**-0.14053**	**0.0141**	**-10.00**	**<.0001**

The smoothing is conducted with the estimated intervention effects removed. The smoothed values (or backcasts) are consistent measures over time for both the LFS unemployment and CC series. Figure 4.7 illustrates the backcasted CC estimates (with a legend of CC_total_c_org) and its 95% confidence range in comparison with the observed original series (with a legend of CC_total and circle marks). The vertical reference lines indicate the known intervention dates of interests.

4.7 Corrected original: CC total with 95% confidence band (bivariate SUTSE)



The estimated bivariate SUTSE model parameters are listed in table 4.8. The high correlation (0.97) of disturbance of slope components implies that both LFS unemployment and CC have similar sources of stochastic movement.

Figure 4.9 shows smoothed values of the slope components of LFS unemployment and CC. It is obvious that they have a very similar shape/pattern with the same phase (the timing of turning points or peaks and troughs), which reflects the cyclical nature of the economy.[7] This style of presentation can be useful to identify potential statistical impact by examining inconsistent patterns between the two slope components. The high correlation also implies that a gain in predictive precision can be achieved.

4.8 Estimated bivariate model component disturbance covariance/correlation matrices

Component	*Disturbance variance* / ***correlation***
Level	$\Sigma_{\xi} = \mathbf{0}$
Slope	$\Sigma_{\zeta} = \begin{pmatrix} 2.6E\text{-}5 & \mathbf{0.97} \\ 3.6E\text{-}5 & 5.1E\text{-}5 \end{pmatrix}$
Seasonal	$\Sigma_{\omega} = \begin{pmatrix} 3.66E\text{-}7 & 0 \\ 0 & 2.61E\text{-}7 \end{pmatrix}$
Irregular	$\Sigma_{\varepsilon} = \begin{pmatrix} 1.45E\text{-}4 & 0 \\ 0 & 3.15E\text{-}5 \end{pmatrix}$

4.9 Estimated slope components of LFS unemployment and CC series

Table 4.10 shows the comparison of overall predictive accuracy measures of LFS unemployment estimates – prediction error variance (PEV) and prediction mean deviation (MD) from the bivariate and the corresponding univariate STM. The gain in predictive precision is measured by the relative improvement, which is calculated by the ratio between the predictive accuracy measures from the two models and minus one in percentage.

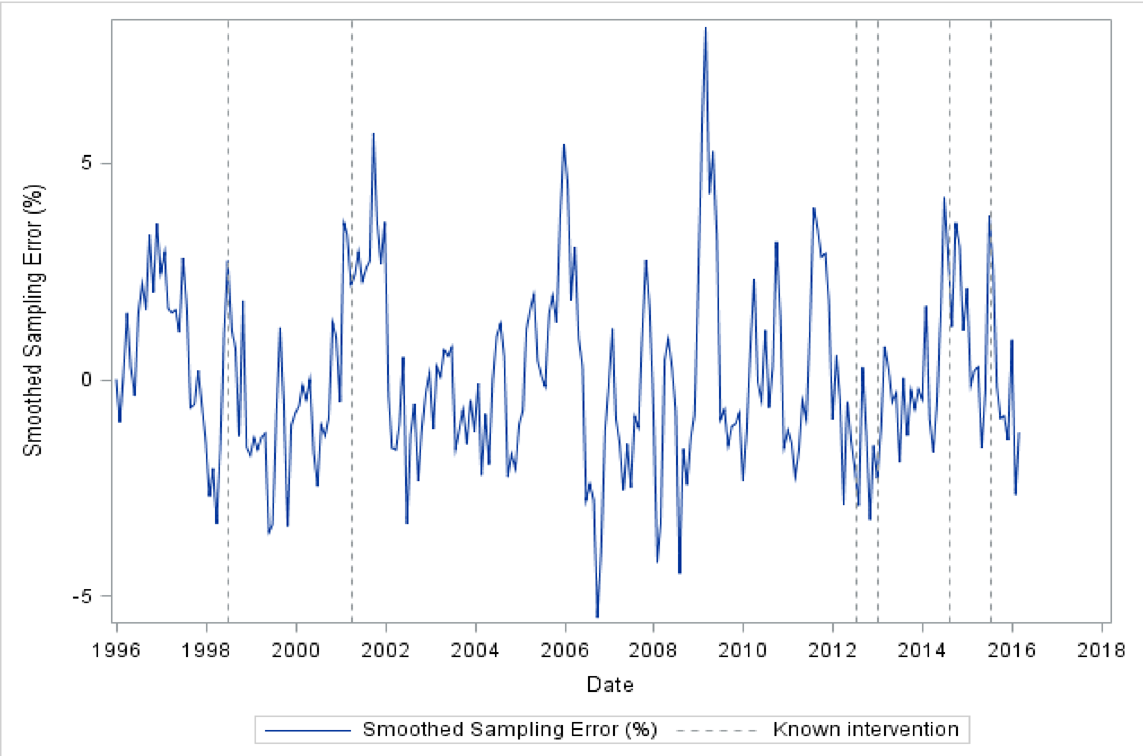
7 The slope component is modelled by a random walk process which is also be widely used for modelling business cycles. Other sophisticated cyclical component modelling is not presented here. An example is illustrated in Appendix B.

4.10 Improvement from bivariate SUTSE model

Measures/ Model	*Bivariate*	*Univariate*	*Relative improvement, %*
PEV	1.1164E-3	1.161E-3	–3.84%
MD	0.88089E-3	0.92396E-3	–4.66%

As mentioned in Section 3.1.2, the model specification and parameters for survey error stochastic processes need to be predefined before they are incorporated as a component into a structural time series model. Table 4.5 lists the survey error AR(2) model parameters estimated from the LFS survey design. Figure 4.11 shows the smoothed estimates of the LFS unemployment survey error stochastic process. Although the variance of survey error disturbance (σ_δ^2 =4.75*E*-04) is reasonably small, the estimated survey errors process, ranging from -6% to 8% of the estimated total unemployed persons, does potentially make practical differences at the total Australia level.

4.11 Estimated survey error components of LFS unemployment estimates



To demonstrate a live application in a real value scale, an experimental study was conducted to predict February 2016 LFS unemployment estimates using known CC values. The February 2016 LFS unemployment estimate and the bivariate model predicted value are 786.7K and 830.2K respectively, with relative standard error of 3.1% and a 95% confidence range from 781.9K to 884.8K. In other words, the LFS estimate at the time was within the predicted 95% confidence range.

This case study demonstrates that a standard bivariate SUTSE model for LFS unemployment estimates using the CC series leads to an improvement of prediction precision because of the high correlation between the slope disturbances of the two series. This result is consistent with Harvey and Chung (2000). For the ABS LFS unemployment series, the magnitude of the survey error induced variation appears relatively small at the Australian level. However, we might see a different situation at the state or small domain level because the survey error would be relatively larger. Although small domain modelling is out of the scope of this paper, the same approach is still applicable, and could be explored as an extension of this study.

4.4 CASE STUDY OF EMPLOYMENT – MULTIVARIATE MODEL WITH EXTENDED SUTSE MODEL

The case study of LFS unemployment and CC series demonstrates how a conceptually similar series can improve a survey estimates prediction. In practice, such a pair of conceptually similar series is not always available. LFS employment estimates and employer payroll data are conceptually a good pair. However, we do not have high frequency payroll data available in Australia. We do however have some employment leading indicator series (see details in Section 4.2.2).

To evaluate the strategy developed in Section 3.2, we performed an experimental study for predicting quarterly seasonally adjusted LFS total employment estimates.

The purpose of the experimental study is to prove that the strategy step (2) – *Aligning (synchronising) the "business cycle" with the target series by shifting the related series forward by the leading periods* does improve SUTSE efficiency in relation to the SUTSE model selection and evaluation. However, we note that the prediction of a quarterly series is of no practical use for monthly LFS employment estimates.

To avoid the complication that their seasonal factors may bring, this experimental study involves three quarterly seasonally adjusted series, LFS total Australian employed persons, GDP and ABS job vacancies. The four different univariate structural time series models with different component specifications were applied to three series in a SUTSE form. The details can be found in Appendix B.

The evaluation result shows that strategy step (2) does improve SUTSE efficiency in improving LFS employment predictive precision in term of maximum likelihood and Akaike Information Criterion (AIC).

Our second experimental study aims to improve predictive precision of monthly LFS employment using a set of mixed of real value and composite index of employment leading indicator series with an extended SUTSE model from the strategy developed in Section 3.2, in particular, step (3).

Table 4.12 lists the properties of the four selected series in terms of leading and co-integration with the target series – monthly total Australian employed persons.

4.12 Selected related time series for monthly LFS employment series

Data source	*Initial leading*[8] *(month)*	*Final leading*[9] *(month)*	*Co-integration*
ANZ job advertisements (adv)	2	2	CI(2,1)
DoE internet vacancy index (doeivi)	2	2	CI(2,1)
DoE leading indicator of employment (lioe)	12	1	NA[10]
NAB employment Index (nabemp)	9	0	NA

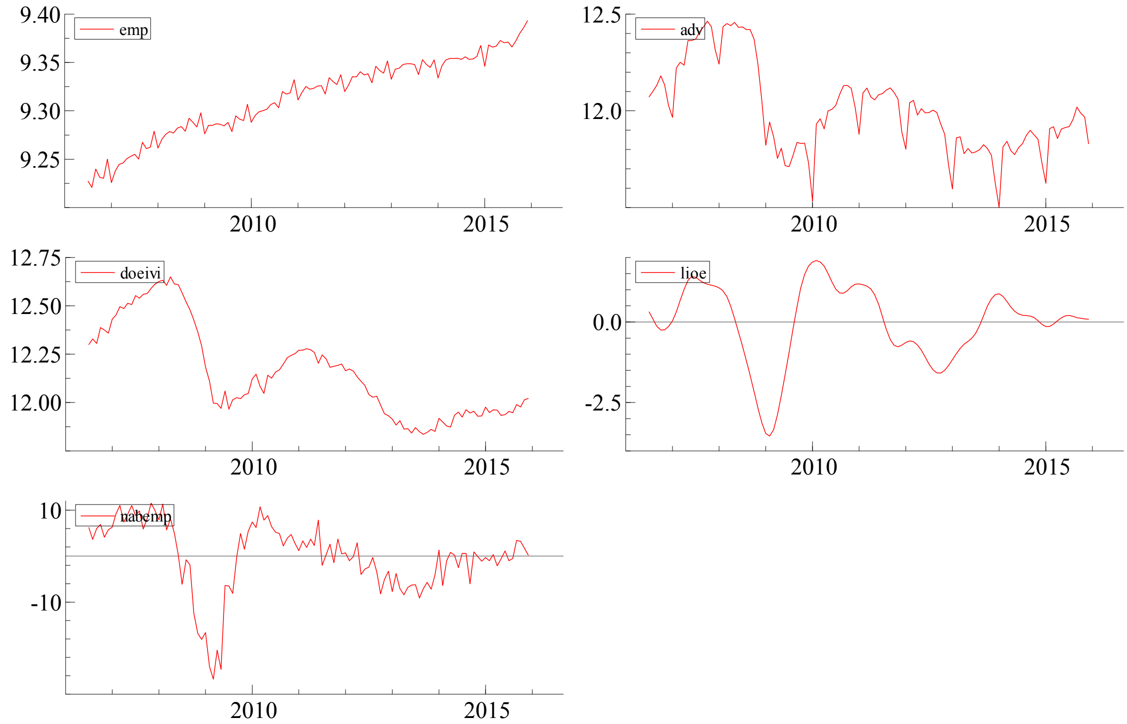
Figure 4.13 shows the series shapes and patterns. The three real value series (emp, adv and doeivi) are on logarithmic scale. Other series (lioe and nabemp) are composite cyclical index series.

8 The initial leading months are estimated from the period that the cross correlation between the cyclical component of the related series and target series reaches maximum. The cyclical components are produced as percentage deviation from the long term trend derived from applying Hodrick-Prescott filter with smoothing parameter 129,600 to trend-cycle or seasonally adjusted estimates from seasonal adjustment process such as X-12.

9 The final leading periods are estimated by fine tuning the initial leading periods in order to reach the maximum value of the cross correlation presented in the slope disturbance covariance matrix.

10 The two composite cyclical index series appear stationary component of LFS employment series and a related index series which is often produced as a composite cyclical index.

4.13 LFS employment and selected related series



At a glance, the three real value series do not share anything in common. The other two index series present similar cyclical behaviours, which relate to the business cycle of the economy. The big trough in March 2009 reflects the impact of the Global Financial Crisis on the labour market.

A standard local linear model in equations (3.2) – (3.3) (two combined random walks) is suitable for the level and slope components of the three value series. The estimated local slope can be used as a proxy of the cyclical component. However, the level components for the two composite employment business cycle index series should be modelled as a random walk equation (3.2) without slope since they do not have long term trend (or their long term trend is zero). In other words, the disturbances of slope components of the real value series are correlated to the level components of the index series. The disturbance correlation cross level and cyclical components has also been investigated by Morley, Nelson and Zivot (2003) within a univariate model, while we are dealing with the correlation between the univariate models in a SUTSE setting. Without confusing the names of the components for each series involved, it would easier to link the components by understanding the nature of the series involved in relation the to the target series. The index series can then be conceptually interpreted as "no level" but "slope" only. Therefore, the disturbances of the slope components of all the series can be correlated. An extend SUTSE can be established by linking the "slope" components based on the conceptual nature of the series involved in relation to the target series components rather than the component name literally.[11]

After aligning the series according to their leading properties in table 4.12, an extended SUTSE model is applied with the specification described in table 4.14 where 'in' and 'out' mean the corresponding component is conceptually included and excluded respectively.

---

11 An alternative standard SUTSE model can be setup suitable for the situation with an explicit cycle component for all the series involved, and with fixed level and zero slop for the three index series. We do not present in this paper because our main aim here is to demonstrate an extended SUTSE model.

4.14 An extended SUTSE model for LFS employed prediction

Data source (lead)	*emp (0)*	*adv (2)*	*doeivi (2)*	*lioe (1)*	*nabemp (0)*	*Disturbance variance / covariance*
Level	In	In	In	Out	Out	Σ_{ξ}=**0** (Fixed)
Slope	In	In	In	In	In	Σ_{ζ} = General Symmetric
Seasonal	In	In	Out	Out	Out	Σ_{ω} = Diagonal
Survey error	In (AR(2): $\Psi_1 = 0.67$, $\Psi_2 = 0.16$)	Out	Out	Out	Out	σ_{δ}^{2} =4.796*E*-06
Irregular	In	In	In	In	In	Σ_{ε} = General Symmetric

The structural time series model for each series is tailored and all of them have a conceptual slope component. The slope disturbance covariance matrix is specified as a general symmetric matrix that allows the disturbances of the slope components to be linked. The irregular disturbance covariance is also chosen to be general symmetric because the measurement of internet job vacancies come from similar sources, and the index series (DoE Leading indicator of employment and NAB Employment Index) are composite indexes including job advertisements in their composition. For simplicity, we chose the seasonal component disturbance covariance matrix as diagonal.

Figure 4.15 presents the slope components of LFS employment (*emp*), ANZ job advertisements (*adv*) and DoE internet vacancy index (*doeivi*), and the two composite index series (DoE Leading indicator of employment (*lioe*) and NAB Employment Index (*nabemp*)). It is obvious that they have a common feature in the shape/pattern. This similarity is another illustration that this extended SUTSE model has a great potential to improve prediction performance by linking their highly correlated "conceptual" slope disturbances.

4.15 The conceptual slope components of various data sources

For the monthly LFS total Australian employed persons target series, we evaluated five extended SUTSE bivariate models for each of the five related series, and a full extended SUTSE model involved all the five related series. Table 4.16 shows that the estimated disturbance correlations of the conceptual slope components.

4.16 Correlations of the conceptual slope component disturbance between the target and related series of paired bivariate and multivariate SUTSE models

Sources (leading month)	*adv (2)*	*doeivi (2)*	*lioe (1)*	*nabemp (0)*
Bivariate: Slope Corr	0.9429	0.9307	0.2229	0.01442
Multivariate: Slope Corr	0.6715	0.5910	0.001289	0.0004682

It can be seen from table 4.16 that for all the four bivariate SUTSE models, ANZ job vacancy (*adv*) series has the highest correlation with LFS employment (*emp*) (0.9429) and NAB Employment Index (*nabemp*) has the lowest correlation (0.01442). From the full multivariate model, the magnitude order of the correlations between target and related series is maintained while the values of the correlations are lower than the corresponding bivariate models. This indicates that the four related series contain complementary information about the target series. For example, Department of Employment leading indicator of employment (*lioe*) has a moderate level correlation (0.2229) with the slope component of the target series in a bivariate SUTSE model. The corresponding correlation reduces to nearly zero (0.0001289) in the full multivariate SUTSE model. This implies that *lioe* contribution to predicting the target series is insignificant because its information containing the target series can be found in other related series (*adv* or *doeivi*). Therefore, table 4.16 suggests that a multivariate SUTSE model including three series (*emp*, *adv* and *doeivi*) could be the most parsimonious model since the two index series do not contribute much to the precision of target series prediction.

The survey error stochastic process is also estimated by incorporating the predefined AR(2) model specification in table 4.14 into the SUTSE models under study. The estimated survey error stochastic processes, ranging from -0.63% to 0.42% of the estimated total employed persons, can potentially make practical difference.

A live simulation was conducted to evaluate the multivariate SUTSE model suggested above. The purpose of the simulation was to test whether the proposed model can detect an unexpected consequence to ABS LFS employed person estimates for August 2014 due to the supplementary survey change as a part of the ABS new LFS redesign implementation mentioned in Section 4.1.

Table 4.17 shows the different predictions from the multivariate SUTSE model and the univariate STM for the target series for the different scenarios at three date points for the August 2014 estimates.

4.17 Predictions and outlier detected for August 2014 LFS employed persons estimate

Date points	*Observed*	*Prediction from multi-SUTSE (RSE)*	*Prediction from uni-STM (RSE)*
July 2014	NA	11454.1 (0.226%)	11439.2 (0.272%)
August 2014	11566.6	11447.2 (0.226%)	11444.9 (0.272%)
AO (auto)		*1.040%*	*1.06%*
December 2014	11566.6	11435.8 (0.212%)	11435.8 (0.251%)
AO (intervention)		*1.14%*	*1.135%*

From table 4.17, we can make following observations:

- Using data up to July 2014, the two models predict values on the row labelled as "July 2014". It appears that the multi-SUTSE model has smaller predicting relative standard error (RSE), 0.226%, than the univariate STM's 0.272%.
- When the August data are available, both models detect an additive outlier (ao) 1.04% and 1.06% respectively. Their χ^2test statistics also confirm that the null hypothesis of no additive outlier (ao) has less than 5% significant level to be accepted.

- Using data up to and including December 2014 with the same models and an additive outlier invention dummy variable, the estimated additive outlier values are 1.14% and 1.135% respectively. Their *t* test statistics again confirm that the existence of the additive outlier for August 2014.

The multivariate SUTSE model has a much smaller RSE than the univariate STM for all three scenarios, and both models detect the additive outlier with similar values. Therefore, we can conclude that the multivariate SUTSE model gains in predicting variance, and outlier detection reliability.[12]

5. CONCLUDING REMARKS

In this paper we used a SUTSE model as a special multivariate structural time series model. We developed an extended SUTSE model by focusing on the related time series nature and behaviour in relation to the target series rather than relying on the default assumptions/conditions of a standard SUTSE model.

Therefore, a suitable SUTSE model can be tailored to improve the model efficiency in fitting the data for predicting the target series. Our case studies for the ABS LFS total unemployment and employment estimates demonstrate how the standard and extended SUTSE model can be used to improve the precision of target series prediction.

To demonstrate effectively the idea for adopting a SUTSE model predicting survey estimates from multiple sources and the strategy to do so, we presented some simple unobserved components models and parameter setting in this paper. Our experience (see example in Appendix B) shows that many alternative models and parameter settings could improve predicting performance. Refinements need to be done on a case by case basis under our proposed strategy, and more simulations are also needed to evaluate predication power and reliability.

Since the current approach focuses on one particular target survey estimate time series only, a more holistic approach should be considered to produce a coherent and consistent prediction. For example, LFS employment, unemployment and not in the labour force should be considered as a whole. We would like to explore a constrained state space model and Kalman filter in the near future and hope they could provide a suitable methodological solution.

For some models, we experienced difficulties in achieving convergence when using the classical approach to maximum likelihood functions. Therefore, the estimated model parameters, such as the component disturbance covariance matrices, may be in question. A Bayesian estimation approach with a Gibbs sampler may be worth trying for model parameter estimation.

The SUTSE modelling presented in this paper could have multiple potential applications for the ABS. For example, it could be used as a part of toolkit for identifying and measuring any statistical impacts induced by the ABS statistical transformation program. Our proposed method takes account of real world changes as reflected in multiple data sources, and therefore augments an intervention analysis relying on the survey data alone.

Under the ABS statistical transformation program, alternative (particularly administrative) data sources are sought to reduce survey data collection costs. The SUTSE model could also be extended to form a part of survey estimates utilising alternative (external) data sources.

12 The statistical impact induced by the supplementary survey change is not a simple additive outlier in reality. How to adjust the impact is out scope of this paper.

Reliable and timely official statistics are critical for decision making. Statistical agencies are often faced with a situation that their survey estimates become available later than the other data sources. Preliminary (or flash) estimates could be produced by the SUTSE model framework to take advantage of the availability of the related data sources to improve timeliness.

The proposed SUTSE model could also be extended to a common factor model, which could then produce a composite index to track, for example, employment and unemployment conditions by blending the information from multiple data sources including the ABS LFS estimates.

REFERENCES

Australian Bureau of Statistics (ABS) (2009) *Labour Force, Australia, Historical Time Series*, cat. no. 6204.0.55.001, ABS, Canberra. <http://www.abs.gov.au/AUSSTATS/abs@.nsf/ProductsbyCatalogue/E8F82E718DA28CD1CA257871001C2B39?OpenDocument>

—— (2011) *Labour Force, Australia, February 2011*, cat. no. 6202.0, ABS, Canberra. <http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6202.0Explanatory%20Notes1Feb%202011?OpenDocument>

—— (2013) "Forthcoming Improvements to the Content of the Labour Force and Labour Supplementary Surveys" in *Labour Force, Australia, January 2013*, cat. no. 6202.0, ABS, Canberra. <http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6202.0Explanatory%20Notes1Jan%202013?OpenDocument>

—— (2014) *Australian Labour Market Statistics, July 2014*, cat. no. 6105.0, ABS, Canberra. <http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6105.0Main+Features1July%202014?OpenDocument>

—— (2016) *Labour Force, Australia, April 2016*, cat. no. 6202.0, ABS, Canberra. <http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6202.0Explanatory%20Notes1Apr%202016?OpenDocument>

Box, G.E.P. and Jensins, G.M. (1970) *Time Series Analysis, Forecasting and Control*, Holden-Day, San Francisco.

Dickey, D.A. and Fuller, W.A. (1979) "Distribution of the Estimators for Autoregressive Time Series with a Unit Root", *Journal of the American Statistical Association*, 74(366), pp. 427–431.

DSS (2016) *Department of Social Services* website at DSS - Labour Market and Related Payments Publication (http://www.dss.gov.au/lmrp).

Harvey, A.C. (1985) "Trends and Cycles in Macroeconomic Time Series", *Journal of Business & Economic Statistics*, 3(3), pp. 216–227.

Harvey, A.C. (1989) *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, Cambridge.

Harvey, A.C. (2006) "Forecast with Unobserved Components Time Series Models", Chapter 7 in G. Elliotee, C.W.J. Granger and A. Tiommermann (eds.), *Handbook of Economic Forecasting*, North-Holland.

Harvey, A.C. and Chung, C.H. (2000) "Estimating the Underlying Change in Unemployment in the U.K.", *Journal of the Royal Statistical Society, Series A*, 163, pp. 303–339.

Harvey, A.C. and Koopman, S.J. (1997) "Multivariate Structural Time Series Models, Chapter 9 in C. Heij, J.M. Schumacher, B. Hanzon and C. Praagman (eds.), *System Dynamics in Economic and Financial Models*, John Wiley & Sons Ltd.

Johansen, S. (1995) *Likelihood-based Inference in Cointegrated Vector Auto-regressive Models*, Oxford University Press Inc.

Koopman, S.J.; Harvey, A.C.; Doornik, J.A. and Shephard, N. (2009) *STAMP 8.2 Structural Time Series Analysis Modeller and Predictor*, Timberlake Consultants Ltd., London.

Morley, J.C.; Nelson, C.R. and Zivot, E. (2003) "Why are Beveridge–Nelson and Unobserved Components Decompositions of GDP so Different?", *Review of Economic and Statistics*, 85, pp. 235–244.

Priestley, M.B. (1981) *Spectral Analysis and Time Series*, Volume 1, Academic Press Inc.

Särndal, C.-E.; Swensson, B. and Wretman, J.H. (1992) *Model Assisted Survey Sampling*, Springer-Verlag, New York.

Van den Brakel, J.A. (2008) "Design-based Analysis of Embedded Experiments with Applications in the Dutch Labour Force Survey", *Journal of the Royal Statistical Society, Series A*, 171, pp. 581–613.

Van den Brakel, J.A. and Krieg, S. (2015) "Dealing with Small Sample Sizes, Rotation Group Bias and Discontinuities in a Rotating Panel Design", *Survey Methodology*, 41, pp. 267–296.

Van den Brakel, J.A. and Krieg, S. (2016) Small Area Estimation with State Space Common Factor Models for Rotating Panels", *Journal of the Royal Statistical Society, Series A*, 179, pp. 1–29.

Van den Brakel, J.A. and Roels, J. (2010) "Intervention Analysis with State-Space Models to Estimate Discontinuities due to a Survey Redesign", *Annals of Applied Statistics*, 4, pp. 1105–1138.

Van den Brakel, J.A.; Smith, P.A. and Compton, S. (2008) "Quality Procedures for Survey Transitions, Experiments, Time Series and Discontinuities", *Journal for Survey Research Methods*, 2(3), pp. 123–141.

Wolter, K.M. *Introduction to Variance Estimation*, 2nd ed., Springer-Verlag, New York.

ACKNOWLEDGEMENTS

The authors are particularly thankful to Dr. Siu-Ming Tam, Andrew Harvey, Jan A. van den Brakel, Bruce Hockman, Jacqui Jones, Paul Schubert, Kristen Stone, Ruel Abello, Julian Whiting, Peter Rossiter and the ABS Methodology Advisory Committee members, for their valuable suggestions and comments. An earlier version of this paper was presented at the Methodology Division seminar in April 2016 and the authors would like to thank the seminar participants for their helpful comments and suggestions. Remaining errors are the authors'.

APPENDIXES

A. RELATED SERIES FOR NUMBER OF EMPLOYED PEOPLE

There were 26 series tested from both ABS and external data sources as candidates for modelling the number of employed series (see table A.1). Series names are presented in the column "Series" of the table. The sources of information are shown in the column "Source". All presented series have at least ten years length except the series obtained from Australian Quarterly Business Indicators Survey (QBIS). There are two series from the QBIS measuring number of employed people with the second one including the number of employed people in public service, defence and agriculture. Both series are collected from different samples than the Australian LFS.

Most series considered were monthly, however some quarterly series were tested as well (see column "Periodicity", "M" for monthly and "Q" for quarterly series). Some series are composite index series of employment business cycle and include negative values. Such series were tested without taking logs of values. Remaining series were tested using logarithmic transformations. The next column shows the test result of unit root for the corresponding series. There is no unit root for those composite index series.

Leading properties of series are shown in the "Leading properties" column. First, leading time is presented in number of leading months or quarters; then correlation at the leading lag is presented after a coma. The next column shows at what lag the series were tested for co-integration (lag=0 or lag=leading period). Finally, results co-integration tests ("Y" for co-integrated series and "N" for non co-integration) are presented in the last column.

A.1 Related series for number of employed people

Series	*Source*	*Length*	*Perio-dicity*	*Unit root*[13]	*Leading properties*	*Co-integration*[14]	
Number of employed people (Australian LFS)	ABS	02/1978–12/2015	M	Y		lag=0	---
GDP (chain volume measures)	ABS	03/1978–09/2015	Q	Y	2 Quarters, corr=0.77	lag=0; lag=2	N (5%), Y (10%); N
Job advertisements	ANZ	08/1999–12/2015	M	Y	2 Months, corr=0.78	lag=0; lag=2	Y Y
Job vacancies	ABS	05/1979–11/2015	Q	Y	3 Quarters, corr=0.83	lag=0; lag=3	Y Y
Aggregate level of employees: 1. QBIS emp., 2. QBIS emp.+Public+Defence+Agriculture	ABS	03/2009–09/2015 short series	Q	Y	0 Quarters, corr=0.64, 0 Quarters, corr=0.64	lag=0; lag=0	N N
Employment Index, net balance	NAB	03/1997–12/2015	M	N	9 Months, corr=0.53	lag=0; lag=9	NA[15] NA
Leading indicator of employment	DoE	03/1992–01/2016	M	N	12 Months, corr=0.45	lag=0; lag=12	NA NA
Purchasing Managers' Index for Manufacturing Output in China	National Bureau of Statistics	01/2005–01/2016	M	N	10 Months, corr=0.48	lag=0; lag=10	NA NA

13 Unit root test are performed by Dickey-Fuller (1978) by varmax procedure in SAS.

14 Co-integration analysis are conducted between the related series (and shifting forward its leading period) and the target series using Johansen (1995) VAREC framework by varmax procedure in SAS.

15 NA means 'not applicable' since the related series is stationary.

	of China						
US Yield Difference: 10–year Treasury Bond Yield 3-month Treasury Bill Interest Rate	Board of Governors of the Federal Reserve System	01/2005–01/2016	M	N Y N	12 Months, corr=–0.30; 12 Months, corr=0.29, 12 Months, corr=0.48	 lag=0; lag=12; lag=0; lag=12	NA N Y NA
Forward Orders Index	NAB	06/2004–12/2015	M	N	12 Months, corr=0.60	lag=0; lag=12;	NA
Index of economic conditions	Westpac - Melbourne Institute	02/2003–12/2015	M	N	12 Months, corr=0.40	lag=0; lag=12	NA
Consumer family finances a year ago	Westpac - Melbourne Institute	01/1996–01/2016	M	N	12 Months, corr=0.20	lag=0; lag=12	NA
Newspaper advertisements	ANZ	02/1978–12/2015	M	Y	7 Months, corr=0.84	lag=0; lag=7	N Y
Internet advertisements	ANZ	08/1999–12/2015	M	Y	2 Months, corr=0.76	lag=0; lag=2	Y Y
Internet vacancy index	DoE	01/2006–12/2015	M	N	2–3 Mths, corr=0.77	lag=0; lag=2	NA
Performance of Manufacturing Employment Index	Bloomburg	05/2001–12/2015	M	N	8 Months, corr=0.50	lag=0; lag=8	NA
Performance of Services Employment Index	Bloomburg	02/2003–12/2015	M	N	7 Months, corr=0.53	lag=0; lag=7	NA
Consumer sentiment index	Westpac - Melbourne Institute	01/1996–01/2016	M	N	12 Months, corr=0.32	lag=0; lag=12	NA
Retail trade (retail turnover)	ABS	04/1982–11/2015	M	Y	3 Months, corr=0.46	lag=0; lag=3	Y Y
Wage price index	ABS	09/1997–09/2015	Q	Y	0 Quarters, corr=0.37	lag=0	N
Average compensation per employee (in current price)	ABS	03/1978–09/2015	Q	N	4–5 Qtrs, corr=–0.53	lag=0; lag=4	Y Y
Unit labour costs	ABS	09/1985–09/2015	Q	Y	0 Quarters, corr=43.4	lag=0	N
Real unit labour cost	ABS	09/1985–09/2015	Q	Y	0 Quarters, corr=–0.15	lag=0	Y
Wages in current price	ABS	03/2001–09/2015	Q	Y	0 Quarters, corr=0.65	lag=0	N

B. EXPERIMENTAL STUDY OF QUARTERLY LFS EMPLOYMENT PREDICTION

In order to prove that the strategy developed in Section 3.2 works, we performed an experimental study for predicting quarterly seasonally adjusted LFS total employment estimates with two related series – ABS job vacancy (JV) and GDP, which measure different economic concept rather than employment.

To avoid the complication of seasonal factors may bring, seasonally adjusted series were used for the experimental study. The same univariate structural time series models with different component specifications are applied to three series in a SUTSE form.

From Section 4.2.2, the pre-screen process suggests that

- JV is an indicator of employment demand and leading approximately 2 quarters
- GDP is a status of the economy (production/income/expenditure) indicator leading employment approximately 2 quarters
- JV and GDP are CI(2,1) with the target series – ABS LFS total Australian employed persons (EMP)

Our experiment was designed in two dimensions:

1. With a SUTSE model, by varying the leading period of the related series, we prove that the strategy step (2) – *Aligning (synchronising) "business cycle" with the target series by shifting the related series forward by the leading periods* does improve the SUTSE efficiency measured by maximised likelihood (or AIC).

2. With given leading periods of the related series, varying SUTSE components specification can improve prediction efficiency measured by AIC.

Shifting a related series forward by period x is notated as (x) for example, shifting JV series forward two quarters denoted as JV(2). Four different SUTSE models are under study ranging from simple to sophisticated models. Table B.1 depicts their specifications. Model 1 is the simplest local linear model with a smooth trend. This model does not have an explicit cyclical component while the rest model have explicit cyclical component with AR(2) specification and its AR parameters need to be estimated along with all the component disturbance covariance matrices if they are predefined as non-zeros.

B.1 The four different SUTSE model specifications

Model No. (brievation)	*Interpretation*	*Specification*
Model 1 **LL:** **Level: F** **Slope: G** **Ir: D**	**Local linear model with smooth trend, linked slope and independent irregular**	$\Sigma_\xi = 0$, $\Sigma_\zeta =$ general symmetric $\Sigma_\varepsilon =$ diagonal
Model 2 **LL + AR(2)+Ir** **Level: D** **Slope: G** **AR(2): G** **Ir: D**	**Local linear model with independent level, linked slope and linked cyclical component in AR(2) model, independent irregular**	$\Sigma_\xi =$ diagonal, $\Sigma_\zeta =$ general symmetric $\Sigma\,\kappa =$ general symmetric $\Sigma_\varepsilon =$ diagonal
Model 3 **LL + AR(2)+Ir** **Level: S** **Slope: F** **AR(2): G** **Ir: D**	**Independent level with same volatility, independent deterministic slopes, linked cyclical component in AR(2) model and independent irregular**	$\Sigma_\xi = c \times I$, $\Sigma_\zeta = 0$ $\Sigma\,\kappa =$ general symmetric $\Sigma_\varepsilon =$ diagonal
Model 4 **LL+AR(2)+Ir** **Level: S** **Slope: F** **AR(2): C** **Ir: D**	**Independent level with same volatility, independent deterministic slopes, a common cyclical factor in AR(2) model and independent irregular**	$\Sigma_\xi = c \times I$, $\Sigma_\zeta = 0$ $\Sigma\,\kappa =$ reduce rank symmetric $\Sigma_\varepsilon =$ diagonal $\Sigma_\varepsilon =$diagonal

Table B.2 presents log-maximised likelihood (ML) and AIC values against the related series shifting in four different leading period combinations by column, and four SUTSE model specifications by row.

B.2 Experimental results for different leading periods and different SUTSE models

Model / Leading specs	*JV(0) GDP(0)*		*JV(2) GDP(1)*		*JV(2) GDP(2)*		*JV(3) GDP(2)*	
Model 1 **LL:** **Level: F** **Slope: G** **Ir: D**	**ML** **AIC**	**1868.8106** **–25.381**	**ML** **AIC**	**1888.8350** **–25.241**	**ML** **AIC**	**1886.1178** **–25.204**	**ML** **AIC**	**1883.7880** **–24.964**
Model 2 **LL + AR(2)+Ir** **Level: D** **Slope: G** **AR(2): G** **Ir: D**	**ML** **AIC**	**1837.8381** **–25.053**	**ML** **AIC**	**1854.8463** **–24.944**	**ML** **AIC**	**1850.5890** **–24.886**	**ML** **AIC**	**1844.1238** **–24.633**
Model 3 **LL + AR(2)+Ir** **Level: S** **Slope: F** **AR(2): G** **Ir: D**	**ML** **AIC**	**1886.3605** **–25.635**	**ML** **AIC**	**1898.8492** **–25.457**	**ML** **AIC**	**1893.2851** **–25.369**	**ML** **AIC**	**1886.0549** **–25.101**
Model 4 **LL+AR(2)+Ir** **Level: S** **Slope: F** **AR(2): C** **Ir: D**	**ML** **AIC**	**1892.0565** **–25.672**	**ML** **AIC**	**1903.2627** **–25.490**	**ML** **AIC**	**1893.2851** **–25.369**	**ML** **AIC**	**1890.7966** **–25.152**

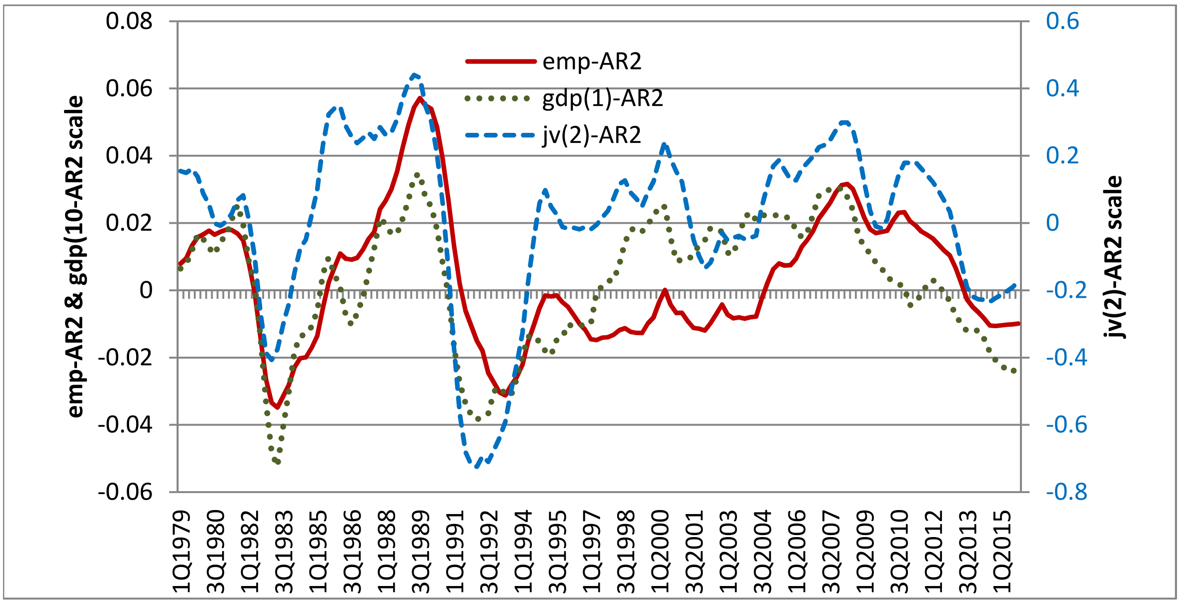
We have two observations from this table:

1. The ML values of [JV(2) GDP(1)] column are larger than the ML values on other columns for every row. This indicates that the model fitness can be improved by shifting the related series forward by the optimal leading periods.

2. The likelihood ratio test statistics range from 22.4 to 40[16]. Under the null hypothesis that there is no improvement by the shifted series JV(2) and GDP(1), the test statistic is a chi-squared distributed random variable with degree 1. As a result, this null hypothesis is rejected at p-value of 5% ($\Pr(\chi^2(1) > 22.4) = 2.2E-6$).

3. The AIC values of different models on each column appear varying. The smallest AIC value in each column is at the last row that corresponds to the SUTSE model with a common cyclical factor (model 4). This demonstrates that the co-integrated cyclical components can potentially improve model quality. The relative likelihood ratios[17] of model 4 against the simplest local linear model with smooth trend (model 1) on the top row range from 0.86 to 0.92. The relative likelihood ratio values can be interpreted as that model 1 losses relatively 8% (i.e. 1 – 0.92) to 14% (i.e. 1 – 0.86) information of model 4. Figure B.3 shows the estimated cyclical component of the three series.

B.2 Estimated cyclical components



Both the likelihood ratio test and relative likelihood value confirm that sifting the related series by the optimal leading period forward and a common cyclical factor model do improve the model fitness, quality and, therefore, predicting performance although some parts of the best model may not be easily interpreted.

The conclusions of this experimental study can be generalised whenever the related series do have optimal leading periods against the target series and one or more of their components are co-integrated.

16 Direct comparison of AIC values cross different column may not be always appropriate because the different data lengths and missing values after shifting the related series.

17 Suppose that there are two models M1 and M2, and AIC(M1) ≤ AIC(M2). Then the relative likelihood of M2 with respect to M1 is defined as exp((AIC(M1)−AIC(M2))/2). See details in Burnham K. P. & Anderson D.R. (2002). This measure is used because the competing models do not have nested relationship.

FOR MORE INFORMATION . . .

www.abs.gov.au the ABS website is the best place for data from our publications and information about the ABS.

INFORMATION AND REFERRAL SERVICE

Our consultants can help you access the full range of information published by the ABS that is available free of charge from our website. Information tailored to your needs can also be requested as a 'user pays' service. Specialists are on hand to help you with analytical or methodological advice.

POST Client Services, ABS, GPO Box 796, Sydney NSW 2001

FAX 1300 135 211

EMAIL client.services@abs.gov.au

PHONE 1300 135 070

FREE ACCESS TO STATISTICS

All ABS statistics can be downloaded free of charge from the ABS web site.

WEB ADDRESS www.abs.gov.au