Small Area Estimation of Unemployment: From feasibility to implementation

Paper presented at the New Zealand Association of Economists Conference,
Wellington, New Zealand,
30 June 2011

Soon Song

Statistical Analyst, Statistical Methods, Statistics New Zealand
P O Box 2922
Wellington, New Zealand
info@stats.govt.nz

www.stats.govt.nz

Crown copyright ©
This work is licensed under the Creative Commons Attribution 3.0 New Zealand licence. You are free to copy, distribute, and adapt the work for non-commercial purposes, as long as you attribute the work to Statistics NZ and abide by the other licence terms. Please note you may not use any departmental or governmental emblem, logo, or coat of arms in any way that infringes any provision of the Flags, Emblems, and Names Protection Act 1981. Use the wording 'Statistics New Zealand' in your attribution, not the Statistics NZ logo.

Liability
The opinions, findings, recommendations, and conclusions expressed in this paper are those of the authors. They do not represent those of Statistics New Zealand, which takes no responsibility for any omissions or errors in the information in this paper.

Citation
Song, Soon (2011, June). *Small area estimation of unemployment: From feasibility to implementation.* Paper presented at the New Zealand Association of Economists Conference, Wellington, New Zealand.

Summary

Statistics New Zealand is exploring model-based approaches to produce unemployment rates at the territorial authority (TA) level, in response to the demand for small area statistics to support planning, decision making, and service delivery at a local area level. The Household Labour Force Survey (HLFS) is the main source of national and regional level information on the labour market. Statistics NZ does not publish unemployment-related statistics at territorial authority (TA) level using survey direct estimates due to the insufficient sample size at the TA level.

Statistics NZ has undertaken various research projects to produce TA-level unemployment rate using HLFS sample data since 2003. In 2009, we investigated the usability of a model developed for a research programme funded by Eurostat called Enhancing Small Area Estimation Techniques to meet European Needs (EURAREA). Our investigation was positive towards producing unemployment rates using HLFS sample data. In 2010, we proposed to produce an experimental series for TA-level model-based quarterly unemployment rates, using HLFS sample data and empirical best linear unbiased prediction (EBLUP) models in EURAREA.

Currently, we use quarterly population estimates at national level for the HLFS benchmarks. These benchmarks are incorporated into the weighting process system. We do not have quarterly population estimates at TA level to use as a TA-level benchmark. In this paper, we propose to produce the TA-level quarterly population estimates. This is a ratio method, which combines two sources of population estimates, **TA-level yearly** population estimates and **national-level quarterly** population estimates. Firstly, we can calculate the TA-level proportions of sex by age groups against the national-level total of sex by age groups. Secondly, we can multiply these proportions to the national-level quarterly population estimates to produce the TA-level quarterly population estimates.

With these TA-level quarterly population estimates, we propose three options for producing TA-level weights. These options are:

- using the final original weight without alteration
- by direct post stratification
- by adjusting the final weight.

We decided to use the option of adjusting the final weight. As a result of the TA-level quarterly population estimates and the adjusted final weight, we could produce estimates of count and rate statistics at TA level for unemployment, employment, and not in the labour force.

We tested all models in EURAREA in 2009 project and recommended using the EBLUP models with covariates of sex, age, and benefit recipients. Based on the recommendation, we also tested EBLUP models with the proposed covariates as well as ethnicity. In order to identify a best model, we conducted the following steps.

Firstly, we identified significant covariates for two target variables independently, unemployment and employment. We used the SAS proc mixed procedure to identify the

significant individual variables, which are sex, age, ethnicity, and benefit recipients for model covariates as EURAREA lacks this particular functionality. Secondly, we produced mean square errors (MSE) for unemployment proportions using several combinations of covariates, which were the model fit indicators for EBLUPA and EBLUPB. The combinations of covariates were 'sex and age', 'sex, age and ethnicity', and 'sex, age, ethnicity, and benefit recipients'. We found that EBLUPA produced smaller MSE than EBLUPB, which used all covariates. Note that we did not attempt using interaction terms of covariates due to the complexity of organising model input datasets.

Thirdly, based on the four significant covariates, we produced model-based estimates for EBLUPA (EBLUP unit model) and EBLUPB (EBLUP area model). Also, we produced two direct estimates using the final weight and the adjusted weight at TA level. We investigated the four estimates with a time series graph for each sampled TA. Note that we selected eight sampled TAs based on sample sizes of TAs for the purpose of presentation. The findings from the comparison of four estimates were:

- the direct estimates from the small sizes of the sampled primary sampling units (PSUs) TAs showed a greater fluctuation over time than the model-based estimates
- the estimates of EBLUPA model were slightly higher than those of EBLUPB model
- direct estimates using the final weight were not much different from those using the adjusted final weight
- as sample size increased, the gap between the model-based estimates and the direct estimates was smaller.

Fourthly, we tested the EBLUP time series model and discovered much greater model errors than EBLUPA and EBLUPB models. Twelve quarters of test data may be insufficient to test a robust time series analysis. Therefore, we did not carry out further investigation of the EBLUP time series model.

Lastly, we produced two estimates: the direct estimates at regional level using the original final weight, and the estimates with summation of the TA-level model-based estimates for EBLUPA and EBLUPB separately. We compared EBLUPA estimates and EBLUPB estimates to the regional-level direct estimates separately to check if they were similar. We checked the following:

- time series of estimates for EBLUPA, EBLUPB, and direct estimate
- bias of estimates for EBLUPA and EBLUPB, based on the assumption that the regional-level direct estimates were unbiased
- coverage diagnostics for two model-based estimates against direct estimates.

We found that EBLUPB estimates were closer to the direct estimates than EBLUPA estimates.

So far, we introduced several methods to identify a suitable model: identification of significant covariates, comparison of MSE for various combinations of covariates and EBLUP time series model, and comparisons of regional level estimates. However, we were not able to decide on one conclusive model. In the end, we reached a practical conclusion of using average estimates of EBLUPA and EBLUPB as our final model.

1. Introduction

Small area estimation (SAE) is a methodology for producing estimates for a more detailed level of geography than estimates using direct survey estimation. Sometimes, we use small area estimation with small domain estimation. However, the two terms are not significantly different from applying methods. Small domain estimation is logically similar to small area estimation, which is disaggregated to a finer-level classification. For example, we produce detailed level industry statistics for business surveys and cross tabulation using detailed categorical variables.

Statistics NZ acknowledges the demand for small area statistics to support planning, decision making, and service delivery at a local area level. The HLFS is the main source of national and regional level information on the labour market. However, it is not able to give accurate direct estimates of unemployment statistics for every TA in New Zealand due to the insufficient sample size of some TAs. This research project aims to produce TA-level model-based quarterly unemployment rates using HLFS survey data with experimental series.

This report covers:

1. Introduction
2. TA level quarterly population
3. Covariate for input model
4. Test data preparation
5. HLFS sample structure
6. Weight issues
7. Overview of testing methods
8. Significant covariates
9. Output comparisons
10. Model decision
11. User validation
12. Discussions

1.1 Definition of terms, abbreviations, and acronyms

Here is a list of terms, abbreviations, and acronyms used in this paper.

- SAE: small area estimation
- EBLUP: empirical best linear unbiased predictor
- EBLUPA: unit level EBLUP model
- EBLUPB: area level EBLUP model
- EURAREA: enhancing small area estimation techniques to meet European needs, developed for a research programme funded by Eurostats
- Covariate: independent variable in model
- ONS: Office for National Statistics of United Kingdom
- ILO: International Labour Organization
- MSD: Ministry of Social Development
- Y variable: dependent variable of interest which is a reference of unemployment or employment proportion in the working-age population.

- X variable (covariate): independent variable in model; sex, age group, ethnicity, and MSD benefit recipient.
- Direct (survey) estimate: estimate using sample survey weight; this is the standard estimate method in the current HLFS sample survey
- TA-level quarterly population estimate: quarterly population estimate at TA level produced by two combined sources (TA-level yearly population estimate and national-level quarterly population estimate produced by Statistics NZ).

1.2 Small areas in New Zealand

Statistics NZ uses these geographic area codes:

- **Meshblock**: the smallest geographic unit for which statistical data is collected. Meshblocks vary in size, from part of a city block to large areas of rural land. Meshblocks aggregate to build a larger geographic area, such as an area unit, territorial authority, and regional council area. In 2011, there are 46,627 meshblocks in New Zealand.

- **Area unit:** aggregation of meshblocks. An area unit within an urban area normally has a population of 3,000–5,000,although this can vary, for example, for industrial areas, port areas, or rural areas within the urban area boundaries. In 2011, there are 2,013 area units in New Zealand.

- **Territorial authority**: aggregation of meshblocks or area units. In the testing period data, we have 74 TAs, comprising 15 cities and 59 districts. Under the Local Government Act, there are 67 TAs in 2011.

- **Regional council area:** aggregation of meshblocks and area units. In the testing period data, we have 16 regions but combined some of them to total 12 regions to match the HLFS publishing level.

Note that we can define a territorial authority or regional council area as an aggregation of meshblocks or area units, but cannot define a regional council area as an aggregation of territorial authorities.

Territorial authority is the small area examined in this report. New Zealand originally comprised 74 TAs. However, in this report we have merged the Banks Peninsula into the Christchurch district. Therefore, small areas in this report total 73 TAs including the Chatham Islands. The distribution of TAs is shown in Table 1-1. The largest TA is Auckland city with a population of 349,360, while the smallest TA is Chatham Islands with 505.

Table 1-1: Distribution of TAs by population size(1)

Population range	Number of TAs	%
-< 10,000	16	21.9
10,000 -< 20,000	12	16.4
20,000 -< 50,000	29	39.7
50,000 +	16	21.9
Total	73	100.0

1. Based on 2006 TA-level yearly population estimate.

1.3 History of SAE projects in SNZ

Statistics NZ has conducted several research projects for SAE since 2001:

- expenditure at TA level using the Household Economic Survey
- unemployment at TA level using HLFS
- business indicators using GST data
- assessing disability at district health board level using the Disability Survey.

Recently, two reports about TA-level unemployment estimation were produced, which used HLFS and MSD data:

- **Report 1***: New approaches to small area estimation of unemployment (Haslett, Noble, & Zabala, 2008)*
- **Report 2***:* 'Small area estimation of unemployment for territorial authorities using commonly applied estimation models in SAS and R' (unpublished report by Ralphs, Hansen, Song, & Smith, 2010).

Report 1 described models of structure preserving estimation (SPREE), Bayesian, and relative risk using quarterly HLFS data and auxiliary data from the MSD and the population census. Report 2 described models in EURAREA packages (described in section 1.4) about GREG, synthetic, and EBLUP models using artificial yearly HLFS data and auxiliary data from MSD and the population census.

Report 2 recommended an experimental series for producing unemployment rates for the quarterly HLFS. This recommendation instigated this current report.

1.4 EURAREA and its application

Statistical agencies and academic researchers have developed different small area estimation methods to produce detailed statistics using both individual sample data and aggregated auxiliary data.

Recently, we introduced EURAREA, which was developed by a research programme funded by Eurostat. The EURAREA development was carried out by a group of national statistics institutes, universities, and research consultancies from the European Union. The project was coordinated by the United Kingdom's Office for National Statistics (ONS) from January 2001 to June 2004, and was signed off by Eurostat in February 2005.

EURAREA was originally designed to implement a simulation study for small area estimation models containing GREG, synthetic, and EBLUP including direct estimate method. The program modules were developed using intensive SAS macros based on PROC IML. It is very hard for ordinary SAS users to understand the original source macro programs. However, ordinary SAS users can modify parameters in modules to implement once iteration to produce estimates rather than repeated iterations.

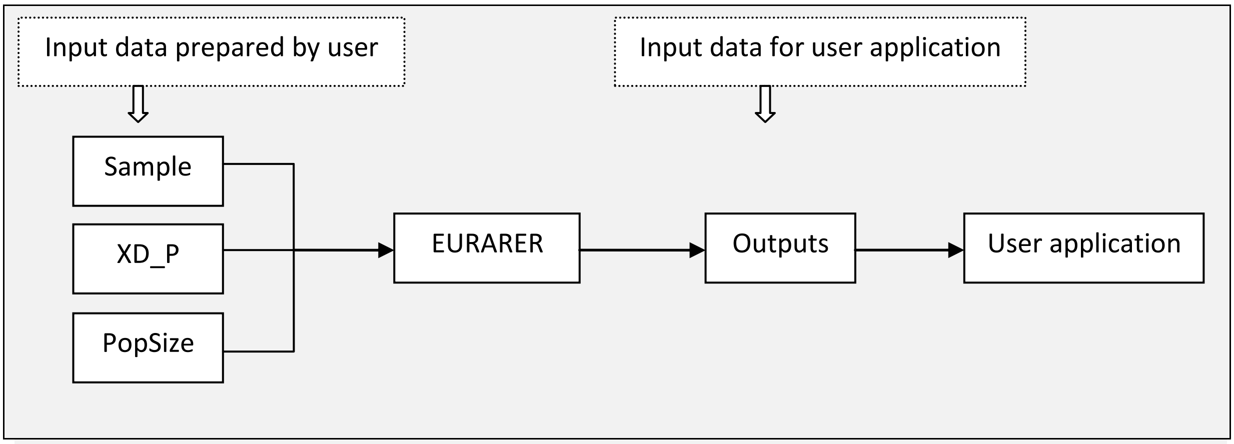
In the project, we need three macro modules in EURAREA such as DIRECT (direct survey estimate method), EBLUPA (unit level EBLUP method), and EBLUPB (area level EBLUP method). We organised a user-friendly macro module to implement three models (%EURArea).

To run EURAREA, we need to prepare three input datasets as shown by the processing diagram figure 1-1:

- Sample: individual sample dataset
- XD_P: aggregated dataset for population means of covariates
- PopSize: aggregated dataset for population size.

Note that formats for the three datasets are described in section 7.8.

Figure 1-1: Processing diagram for using EURAREA



Outputs from EURAREA are composed of four estimates:

- estimate (proportion of y variable)
- MSE (mean square error)
- 95 percent upper bound
- 95 percent low bound.

Major input datasets for three modules in EURAREA:

- DIRECT: sample, XD_P, and PopSize
- EBLUPA: sample and XD_P
- EBLUPB: sample, XD_P, and PopSize.

Three models need individual sample data including area index. If we provide weight in sample data, then population size is not a major contribution to the EURAREA implementation. If we do not provide weight in sample data, then population size plays a key role in working out weight-based population and sample sizes at TA level.

However, we needed reasonable area-level population size to produce the number of unemployed. This is because models in EURAREA produce a proportion estimate, which is different from unemployment rate. In order to run modules in EURAREA, we have to organise three datasets. The format of these datasets is described in detail in section 7.8.

1.5 Model limitation and outputs

1.5.1 Requirement of two models

Each model in EURAREA produces an estimate of y variable with a proportion. If we put unemployment as the y variable into the processing model, then we can have a proportion estimate of unemployment in the HLFS population. Strictly speaking, the proportion of unemployment is different from the unemployment rate.

The International Labour Organization defines unemployment rate as the unemployed proportion of the labour force population. This population is composed of the unemployed and employed. However, the HLFS population is composed of three types of persons: the employed, unemployed, and not in the labour force.

We need two proportion estimates, unemployment and employment, to produce the unemployment rate. After we produce two proportion estimates, we can derive the proportion of not in labour force, which is one minus the two proportions of unemployment and employment.

Therefore, we need to establish at least two models separately instead of three to produce the unemployment rate. In this report, we established two models to produce the proportion estimates of unemployment and employment. We processed two models independently rather than simultaneously because the EURAREA package did not have a multivariate analysis functionality to handle multi-dependent variables in built-in models.

1.5.2 Derived outputs

If we have the proper population size at TA level, then we can derive some useful variables based on the proposed estimates in the previous section and the calculation steps in section 7.4. Let us assume that we produce two proportion estimates of unemployment and employment. We can derive the:

- number of unemployed
- number of employed
- number of not in the labour force
- unemployment rate
- labour force participation rate.

In this project, we produced all outputs proposed above because we derived the method of the TA-level quarterly population shown in section 2. The final output format is summarised in table 1-2. We processed two models, unemployment and employment, but we only produced the unemployment rate model error in the final output.

Table 1-2: The output table format

Total People Employed, Unemployed and Not in Labour Force *By territorial authority area*						
	Labour force	Not in labour force	Working-age population	Labour force participation	Unemployment rate	Model error

	Employed	Unemployed	Total			rate		
	(Number)				(Number)	(%)		
Far North District								
Quarter								
2006 Mar								
Jun								

1.5.3 Different regional outputs

Statistics NZ publishes HLFS statistics using the direct estimate method for national and regional level outputs. We are not able to build up regional and national-level statistics using TA-level model-based estimates. Regional estimates which are built by summing the TA-level model based estimates are not the same as regional estimates produced by the direct estimate methods due to the different estimation methods used. The different area structures are not the major reason for the difference (see section 5.3).

Note that in this report, we built up regional-level estimates using TA-level model-based estimates. This is so that we could compare these with the regional-level direct estimates as part of our evaluation of the model performance (see section 9.3).

2. Territorial authority level quarterly population

The models in EURAREA produce the proportion estimates of target variables, which are unemployment and employment. In order to produce the number of unemployed and employed at TA, we need to adopt a proper TA-level quarterly population. We can use this to produce the TA-level unemployed and employed count estimates and organise the EURAREA input data of **PopSize** (population size). Also, we may use it to produce weights to focus on the TA-level estimates if it is appropriate.

Statistics NZ produces **national-level quarterly population estimates** to feed into the current quarterly HLFS weighting system. However, we do not produce **TA-level quarterly population estimates**. So, we considered using the following options to obtain TA-level population: population census, estimation using current HLFS sample, TA-level **yearly** population estimate, and estimation of TA-level **quarterly** population.

2.1 Population census

We can take the TA-level population from population census data. This is the best population source for the period immediately after the census. However, it does not reflect the population at the current time.

Furthermore, there is a difference in the definition of population coverage between the population census and the HLFS survey population. For example, HLFS excludes non-private dwellings from the survey population whereas the population census includes them.

Population census is not a suitable option for TA-level quarterly HLFS population in terms of timeliness and the coverage of survey population.

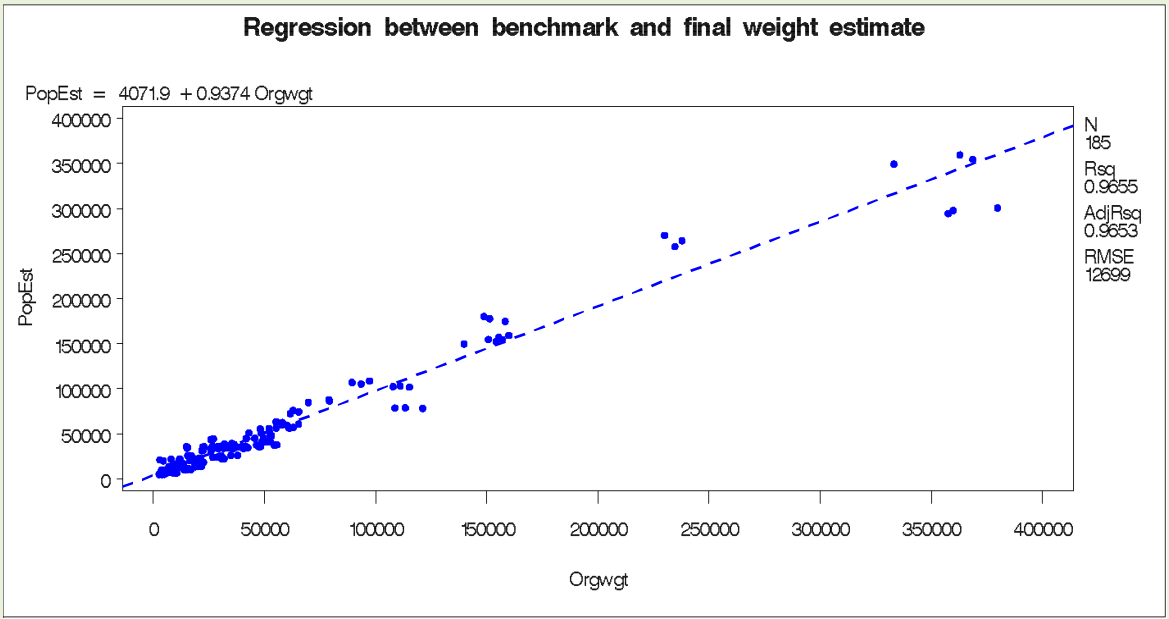
2.2 Estimation using current HLFS sample

We can estimate the TA-level quarterly population from the current period of the HLFS sample. This is a good option for producing consistent populations of national, regional, and TA levels.

However, one concern is that we are not able to estimate TA-level populations for all TAs, because we have three absent TAs in the current HLFS sample (HLFS sample does not require all TAs to be included). The other concern is that we have to tolerate large sampling errors for TA-level population estimates, because we have designed the current HLFS sample to focus on the national-level estimates.

We investigated the relationships between TA-level population estimates calculated from the HLFS September 2006 quarter sample and the TA-level yearly population estimates produced in October 2006. Although these two sources were not of the same time point for exact comparison, they had very close time points. We found very large deviations between two population estimates for big-sized TAs shown in figure 2-1.

Figure 2-1: Scatter plot and regression line between TA-level yearly population estimates and TA-level population estimates using the final weight in sample data



Note: X-axis is TA level direct estimate using final weight and y-axis is TA-level yearly population estimate. Dot is regression line between two TA-level population estimates.

2.3 Territorial authority level yearly population estimate

At around mid-October each year, Statistics NZ produces TA-level yearly population estimates based on mid-year vital data. We can use this data for four quarters, starting from the fourth quarter of the same year to the third quarter of the following year.

We have to use constant populations for four quarters until the TA-level yearly population estimate is available in the following year. This is an option under the assumption that population sizes do not vary hugely between years.

We investigated changes of population sizes between years shown in table 2-1. About 87 percent of total TAs was changed by less than 2 percent. The TA in the greatest change was Queenstown-Lakes District by 5.2 percent.

Table 2-1: Estimated TA population change between years

Change between years	Number of TAs	Proportion (%)
0.0%–0.4%	65	22.3
0.5%–0.9%	83	28.4
1.0% - 1.9%	108	35.9
2.0% +	36	13.4
Total	292[(1)]	100.0

1. 73 TAs multiplied by 4 years (2006, 2007, 2008, and 2009).

Another assumption made is a stability of population structure between years. We had a look at the changes of age groups. The average change of age-group structure between 2006 estimates and 2009 estimates is shown in table 2-2.

Surprisingly, compared with other age groups, the young age group (15–24) was very stable and the older age group (50 and over) was relatively unstable. However, three age groups were changed by less than an average of 2 percent every year.

Table 2-2: Average changes of age proportions between 2006 estimates and 2009 estimates

Percent change	Age 15-24 (%)	Age 25-49 (%)	Age 50 and over (%)
0.0%–0.4%	95.9	12.3	15.0
0.5%–0.9%	4.1	60.3	83.6
1.0%–2.0%	.	27.4	1.4
	100.0	100.0	100.0

The TA-level yearly population does not exactly reflect the current TA-level quarterly populations. However, this is a reasonable option if there are no other options available.

2.4 Estimation of territorial authority level quarterly population

As we investigated the change of age group population structure between years in the previous section, we found the age group structure of TA to be very stable.

We can apply the idea of the stable distribution of age group to estimate the TA-level quarterly population estimate. We can estimate it by using two sources: the previous year's TA-level yearly population estimate, and the current quarter's national-level population estimate, which currently uses the HLFS benchmark data for the HLFS weighting process.

Firstly, we calculate the TA-level proportions for sex by age group based on the previous year's TA-level population, that is, ${}_{PreviousYear\ TA}\,p_{ijk} = \frac{{}_{PreviousYear\ TA}N_{ijk}}{{}_{PreviousYear\ Nation}N_{jk}}$, where *i*=TA, *j*=sex, *k*=age group and *N*=population. Secondly, we multiply TA-level proportions by the current quarter's national-level population, by sex and age groups, that is: ${}_{CurrentQuarterTA}\hat{N}_{ijk} = {}_{PreviousYear\ TA}P_{ijk} * {}_{CurrentQuarterNation}N_{jk}$.

This method is suitable when we have stable sex by age group structure between years.

2.5 Conclusion of territorial authority level quarterly population

The estimation of TA-level quarterly population using two population sources, described in section 2.4, would be the best option for reflecting current TA-level populations. In this case, we have to assume that the population structure is stable between years.

The TA-level quarterly population estimate can be used to calculation of the population means in the XD_P data and the population sizes of PopSize data. Also, we can use it as the population benchmark for producing TA-level weight adjustment factor. TA-level weighting issue will be discussed in the weighting issue (see section 6.2).

3. Covariates for model input

We need to put significant covariates into the model to estimate plausible unemployed and employed proportion estimates. The two proportions must be strongly correlated to demographic variables. We investigated covariate sources for sex, age, ethnicity, and benefit recipients based on the recommendation of previous research.

3.1 Covariate sources

3.1.1 Sex and age group

3.1.1.1 Estimate of territorial authority populations at 30 June

Statistics NZ produces subnational population estimates annually. The variables in the output are:

- sex: male and female.
- age: five-year age groups (0–4. 5–9, ... , 80–84, 85 years and over) and broad age groups (0–14, 15–39, 40–64, 65 years and over)
- available year: estimates from 2006 onwards, based on the latest territorial authority area boundaries, are available from Statistics NZ's website. Estimates from 1996 onwards are available on request.

Subnational estimates are produced annually, 'at 30 June', for regional council areas, territorial authority areas, urban areas, and area units. Estimates of the total population of territorial authority areas are available in October each year, and territorial authority area estimates broken down by five-year age group and sex are available in December each year.

3.1.1.2 Estimate of territorial authority level quarterly population

This source is not official statistics adopted by Statistics NZ. For the purpose of the model development, we derived the method of TA-level quarterly population estimation as we have introduced in the previous section.

The variables we can use:

- sex : male and female
- age: 15–24, 25–49 and 50 and over.

3.1.2 Ethnicity

3.1.2.1 Estimate of subnational ethnic populations

Statistics NZ produces subnational population estimates for broad ethnic groups after each Census of Population and Dwellings. The variables are:

- sex: male and female
- age: five-year age groups (0–4. 5–9, ... , 80–84, 85 years and over) and broad age groups (0–14, 15–39, 40–64, 65 years and over)
- ethnicity: ‘European or other’ ethnicity (including New Zealander), Māori, Pacific peoples, Asian, Middle Eastern/Latin American/ African

- available year: 1996, 2001, 2006

The next release of subnational population estimates for broad ethnic groups will occur after the 2013 Census.

3.1.2.2 Population census

We can use ethnicity population from Statistics NZ's population census every five years. We investigated ethnicity distribution change between the 2001 and 2006 Censuses. The ethnicity composition of the combined Māori and Pacific peoples is stable between two censuses.

Table 3-1: Change of combined Māori and Pacific peoples between 2001 and 2006 Censuses

Percent change	Number of TAs	Proportion (%)
0–1	63	86.3
2–3	8	11.0
3+	2	2.7
Total	73	100.0

3.1.3 Working-age unemployment benefit recipients (aged 18–64)

The Ministry of Social Development produces statistics of unemployment benefit recipients every quarter. The variables are:

- sex: male and female
- age: individual age from 18 to 64
- ethnicity: European/Pakeha, New Zealand Māori, Chinese/Indian, Pacific peoples and other
- number of benefit recipients
- available period: quarter.

3.2 Discussion of covariates

In the preliminary HLFS small area estimation research, we investigated models using covariates of sex, age group (15–24, 25–49, 50 and over) and MSD benefit recipients. When the model test was implemented based on artificial HLFS yearly data, we discovered tested covariates were good for predicting variables for the unemployment rate estimate.

In this project, we are going to estimate quarterly HLFS unemployment-related statistics, so we may revisit these three variables for unemployment-related statistics prediction. Also, we can add the ethnicity variable into the covariates to investigate its contribution to accurate model estimates.

Sex and age group: We can use TA-level yearly population estimates for sex and age covariates if we do not have any other option. Also, we can use sex and age covariates estimated by the proposed method of TA-level quarterly population. We can use the same age group for the quarterly HLFS data as we tested in the previous project. Broad age category may make sense due to the small sample size of TAs. The wide range of age category could reduce errors of TA-level population estimates compared with five-year age groups. We will stick to a broad age category, which ONS is currently implementing in similar unemployment model practice.

Ethnicity: In this project, we are going to add the ethnicity covariate into the models based on the recommendation of the previous project. Ethnicity can be categorised very similarly to the way we categorise age. We can categorise two ethnic groups (combined one group of Māori and Pacific peoples and the rest of ethnicities). We will not attempt to test models using various age and ethnicity groups, as many TA-level population sizes are too small and there is limited time for testing detailed models.

MSD data: We can use age and ethnicity variables for MSD benefit recipients, but we do not have enough time to investigate their quality. We will use the number of benefit recipients, which is aggregated at TA level. We need to investigate age and ethnicity variables in MSD data to feed into the models.

3.3 Conclusion of covariates for input model

Four covariates will be tested for their significance in the model for predicting unemployment and employment proportions:

- sex and three age groups (15–24, 25–49, 50 and over) will be organised using TA-level quarterly population estimates produced by part of the HLFS small area estimation processing system

- ethnicity (Māori plus Pacific peoples and others) will be organised using 2006 Population Census ethnicity

- MSD data will be used for the number of unemployment benefit recipients at TA level.

4. Test data preparation

4.1 HLFS data

Table 4-1 shows data mapping between quarter number and period. The HLFS sample has been redesigned twice since March 1999 based on the result of the 1996 and 2001 population censuses. When we redesigned HLFS sample, we had several overlapping quarters to replace old sample units with new sample units based on the sample rotation strategy. There are eight rotation groups, each in the sample for eight quarters before they are rotated out.

Table 4-1: HLFS dataset map between quarter number and period

Quarter number	Matched quarter	Number of quarters	Note
54–57	From Mar-99 to Dec-99	4	1996 Census rebase (overlapping quarters)
58–73	From Mar-00 to Dec-03	16	
74–81	From Mar-04 to Dec-05	8	2001 Census rebase (overlapping quarters)
82–93	From Mar-06 to Dec-08	12	
94–101	From Mar-09 to Dec-10	8	

4.2 Ministry of Social Development benefit recipient data

We received two datasets from MSD. We checked these based on the Territorial Local Authority Benefit Factsheets from the MSD website and discovered different contents between two datasets from MSD.

4.2.1 Data received in June 2006

- The data scope is working-age 'main benefit recipients', which is all benefit recipients.
- The content consists of six variables shown in table 4-2.

Table 4-2: Variables from received dataset in June 2006

Variable	Contents
Age	2-year age groups (from 18 to 64 years)
Ethnicity	European/Pakeha, NZ Māori, Chinese/Indian, Pacific peoples and other
Gender	Male and female
TA	Territorial authority
Month	Time period covered from 1996Q3 to 2006Q2
Count	Number of benefit recipients

4.2.2 Data received in February 2010

- The data scope is working-age 'unemployment benefit recipients' which is a subset of all benefit recipients.
- The content consists of five variables shown in table 4-3.

Table 4-3: Variables from received dataset in February 2010

Variable	Contents
Sex	Male and female
Age	Individual age from 18 to 64
TA	Territorial authority
Quarter	Time period covered from 1998Q4 to 2008Q3
Count	Number of benefit recipients

4.2.3 Absent territorial authorities

When MSD extracted the benefit recipient data from MSD database, they might have missed 11 TAs shown in table 4-4. We looked at MSD's factsheets and found that data were available for the absent TAs.

Table 4-4: TAs with absent benefit recipients based on the dataset in February 2010

TA_code	TA name
049	Carterton
067	Chatham Islands Territory
058	Hurunui
054	Kaikoura
065	Mackenzie
018	Otorohanga
062	Selwyn
050	South Wairarapa
073	Southland
066	Waimate
057	Westland

4.3 Conclusion of test dataset preparation

In order to make the process of organising model test dataset simpler, we excluded time periods of overlapping quarters after sample redesign. Otherwise, we have to be careful with applying the proper meshblock concordance code in each sampled meshblock to identify the right TA codes. Since we want MSD data to feed into the model test with other covariates (sex, age, and ethnicity from Statistics NZ), we have to use the HLFS data before the December 2008 quarter to align with MSD data available.

We have used the MSD dataset received in February 2010 and HLFS datasets from March 2006 to December 2008 for testing models. Also, to test models, we have to ignore 11 TAs shown in table 4-4. Therefore, the final test dataset was 62 TAs out of the total 73.

5. HLFS sample

In this section, we discuss an overall HLFS sample structure. If we understand current HLFS sample structure well, it will be helpful in organising a better model. We had a look at basic sample features based on data from the March 2006 quarter (quarter number 82 in table 4-1).

5.1 Sample

The sample was designed based on targeting national-level outputs.

> We selected about 1800 PSUs, 15,000 households and approximately 30,000 individuals in the civilian non-institutionalised usually resident population aged 15 years and over. The groups that are excluded from the survey sample are: those living in non-private dwellings, long-term residents of old people's homes, hospitals and psychiatric institutions; inmates of penal institutions; members of the permanent armed forces; members of the non-New Zealand armed forces; overseas diplomats; overseas visitors who expect to be resident in New Zealand for less than 12 months; those aged under 15 years of age; and people living on offshore islands (except for Waiheke Island).
>
> (From 'HLFS summary profile' in SIM database, Statistics New Zealand internal document.)

5.2 Key outputs

Statistics NZ produces statistics related to the variable of labour force status (unemployment, employment, and not in labour force) defined by ILO for the working-age population aged 15 years and over. Statistics of the number of employed, unemployed, not in the labour force and labour force participation rate are produced within 6 weeks of the end of each quarter.

The unemployment rate is one of the major indicators in labour market activity. We produce it with sex and age group breakdown at the national level and for the 12 regions, which is calculated based on the direct estimation method.

5.3 Territorial authorities that cross regional boundaries

We have two TAs (Franklin District and Rotorua District) that crossed the regional boundary as shown in table 5-2. This is a potential problem for building regional statistics based on TA-level model-based estimates. Currently, we publish unemployment rates at regional level with the direct estimate using final weights rather than model-based estimates.

Table 5-1: TAs that cross regional boundaries

Region	TA code	TA name
Auckland region	010	Franklin
Waikato region	010	Franklin
Waikato region	024	Rotorua
Bay of Plenty region	024	Rotorua

5.4 Distribution of selected sample primary sampling units, households, and persons

The distribution of the number of selected sample PSUs is summarised in table 5-3. About 40 percent of a total of 70 TAs consist of less than or equal to10 PSUs.

Table 5-2: Selected sampled PSUs distribution

Number of selected PSUs	Number of TAs	Proportion (%)
2–10 PSUs	27	38.6
11–19 PSUs	18	25.7
20–50 PSUs	15	21.4
50 and over PSUs	10	14.3
Total(1)	70	100.0

1. Chatham Islands, Carterton, and Kaikoura district are not in the HLFS sample.

The distribution of the number of selected sample households is summarised in table 5-4. About 11 percent of a total of 70 TAs consists of less than 50 households.

Table 5-3: Distribution of the number of sampled households

Number of households	Based on selected households		Based on responding households	
	Number of TAs	Proportion (%)	Number of TAs	Proportion (%)
00–49	8	11.4	14	20.0
50–69	4	5.7	10	14.3
70–99	10	14.3	6	8.6
100–149	9	12.9	14	20.0
150 +	39	55.7	26	37.1
Total	70	100.0	70	100.0

The distribution of the number of selected sample persons is summarised in table 5-5. About 31 percent of a total of 70 TAs consists of less than 200 selected persons.

Table 5-4: Distribution of the number of sampled persons

Number of persons	Based on selected persons		Based on responding persons	
	Number of TAs	Proportion (%)	Number of TAs	Proportion (%)
0 –99	5	7.1	14	20.0
100–199	17	24.3	20	28.6
200+	48	68.6	36	51.4
Total	70	100.0	70	100.0

6. Weight issues

We have tested three models (direct, EBLUPA, and EBLUPB) built in the EURAREA package. Although previous research favoured the EBLUP model, in this project we have also tested the EBLUPA model to confirm whether the EBLUPB model is better in quarterly HLFS data. Since the model of direct estimate and EBLUPB requires weight parameter in module specification in EURAREA, we considered a suitable weight for meeting TA-level estimates rather than using the final weight produced by current estimation system.

6.1 EBLUP model components

There is a common component in the EBLUPA and EBLUPB models, which is using population means of covariates and parameter ($\overline{X}_D^T \hat{\beta}$).

The EBLUPA model is composed of two sets of estimate components for adjustment (bracket part) shown in table 6-1. One set is the direct estimate component ($\bar{y}_d$) using the sample mean of y variable of interest, and the other is the model estimate component ($\bar{x}_D^T \hat{\beta}$) using model parameters and sample means of covariates. Small y bar and small x bars can be calculated using purely the sample without applying weight. EBLUPA is totally independent on weight.

The EBLUPB model is also composed of two sets of estimate components for adjustment (ie bracket part) shown in table 6-1. One set is the direct estimate component ($\hat{Y}_D^{Direct}$) estimated using survey weight, and the other is the model estimate component ($\overline{X}_D^T \hat{\beta}$) using model parameters and population means of covariates. Where large X bars can be calculated using population sources (ie XD_P). EBLUPB is partially dependent on weight.

Note that model parameters of betas and sigmas for EBLUPA and EBLUPB can be estimated with/without weight. In this report we estimated without weight based on ONS practice.

Table 6-1: Model formulas[1]

EBLUPA model: $\hat{Y}_D^{EBLUPA} = \overline{X}_D^T \hat{\beta} + \gamma_D \left(\bar{y}_D - \bar{x}_D^T \hat{\beta} \right)$

EBLUPB model: $\hat{Y}_D^{EBLUPB} = \overline{X}_D^T \hat{\beta} + \gamma_D \left(\hat{Y}_D^{Direct} - \overline{X}_D^T \hat{\beta} \right)$

$$\gamma_d = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2 + \hat{\sigma}_e^2 / n_d}$$

$\hat{\sigma}_u^2$ = area level varinace $\hat{\sigma}_e^2$ = unit level varinace n_d = area level sample size

1. For detailed formula component descriptions see *Project Reference Volume: Volume Three: Software and documentation* (EURAREA Consortium, 2003).

6.1.1 Model parameters and variances

Model parameter of betas can be estimated with/without weights. The EURAREA package can handle modules to estimate parameters in two different ways. One is named 'standard module', which calculates betas and variances without weights. The other is called 'weighted module', which calculates betas and variances using weights. Therefore, we needed to consider whether we could use the final weight or produce another weight for small area estimation purposes.

6.2 Weighting options

We considered three possible weight options:

- original survey weight (finalwgt)
- direct post stratification (TAfinalwgt1)
- final weight adjustment (TAfinalwgt2).

6.2.1 Original survey weight

The original weight (final weight) is produced by the HLFS quarterly processing system. The process is in conjunction with selection probability, non-response adjustment, and post-stratification using the national-level quarterly population estimate benchmark. The final weight is focused on the national-level estimation using categories of sex and five-year age groups.

The final weight (finalwgt in HLFS variable) is not designed to target TA-level estimates. Therefore, we could expect large variations between TA true values and estimates due to the small sample size of TAs. Also, if we build up the national-level totals using estimated TA level totals, then the national-level totals will be overestimated because the three absent TAs in the sample will be added into the national-level totals. ..

6.2.2 Direct post-stratification

The idea of direct post-stratification is to independently produce the TA-level weight. This weight is based on the number of final respondents in each TA and TA-level quarterly population estimate using weighting class of sex by age group. This approach is a default option in EURAREA if we don't provide weight to the parameter in module description. The model procedure assumes the sample can be selected using a simple random sample method in each TA. This approach is very simple because it does not need account for the sample design information and non-response factor.

6.2.3 Final weight adjustment

The idea of this method is to use both the final weight produced by the current HLFS estimation processing system and the TA-level quarterly population estimate. Firstly, we can calculate the adjusted factor based on the TA-level quarterly population estimate and the summation of final weights in each TA. Secondly, we multiply the adjusted factor to the final weight in the individual record in sample. This step is to adjust the final weight to reflect only the population of selected TAs.

6.3 Decision of weight option

Both the final weight and weight of direct post-stratification are not plausible options because they do not reflect the population of total TAs and sample-design base information. However, we used all the proposed weights to produce direct estimates in model decision section to see the difference between estimates.

In the end we decided to use the adjusted weight (TAfinalwgt2) for the final estimates.

7. Overview of testing methods

This section describes the practical methods applied in model identification using EURAREA.

7.1 EBLUPA and EBLUPB

The previous research indicated that the best model might be the area-level EBLUP model (ie EBLUPB). That research project was conducted on artificial yearly HLFS data to compare with the 2001 Census unemployment rate. Since we used quarterly HLFS data in this project, we tested the unit-level EBLUP model (ie EBLUPA) because underlying quarterly data could have different characteristics compared with artificial yearly data.

7.2 Direct estimate

We produced direct estimates using weights proposed in the previous weight issue section in order to appropriately compare these to the model estimates and then check bias under the assumption of unbiased direct estimate. The direct estimate used as the relative measurement of efficiency of model-based estimates.

7.3 Significant covariates

Since the EURAREA package was not designed to identify significant covariates for fitting models, we needed to borrow other tools. In the previous research project, we compared model parameter estimates between SAS proc mixed and EURAREA. We identified significant covariates using SAS proc mixed for deciding on model input covariates. In order to simplify application of covariates into the models, we did not try to apply interaction terms of covariates for testing the proposed models.

7.4 Outputs and two models

Firstly, we produced two proportions (unemployment and employment) using model-based estimates and then we produced derived outputs.

Derived outputs using estimates are the:

- number of persons employed, unemployed, and not in the labour force
- number of persons in the labour force which is the sum of employed and unemployed
- number of persons not in the labour force, which is the working-age population minus the number of persons in the labour force
- unemployment rate and labour force participation rate.

We were not able to directly produce the unemployment rate with the proposed models using the EURAREA. The estimates produced by built-in models in the EURAREA package are the unemployed and employed proportions of the working-age population, which are composed of three categories (employed, unemployed, and not in the labour force). The unemployment rate is the proportion of those unemployed among the labour force population (unemployed plus employed).

EURAREA was not designed to handle multivariate models to estimate unemployment, employment, and not in labour force simultaneously. Therefore, we organised two independent models to separately produce unemployment and employment proportions of the working-age population. For two estimates, we converted to count variables and derived other count variables based on the TA-level population estimate:

- The number of unemployment : $Unemployed_{TA} = Population_{TA} * UnemployedEstimate_{TA}$
- The number of employment : $Employed_{TA} = Population_{TA} * EmployedEstimate_{TA}$
- The number of labour force : $LabourForce_{TA} = Unemployed_{TA} + Employed_{TA}$
- The number of not in the labour force : $NotInLabourForce_{TA} = Population_{TA} - LabourForce_{TA}$

Also, we calculated the unemployment rate and labour force participation rate using derived count variables.

- Unemployment rate : $UnemploymentRate_{TA} = 100 * \dfrac{Unemployed_{TA}}{LabourForce_{TA}}$
- Labour force paticipation rate : $LabourForcePaticipation_{TA} = 100 * \dfrac{LabourForce_{TA}}{Population_{TA}}$

7.5 Covariates in model estimate component

As we have seen the model formula in table 6-1, we have two parts of estimated components in the proposed models:

- EBLUPA: $\hat{Y}_D^{EBLUPA} = \bar{X}_D^T\hat{\beta} + \gamma_D\left(\bar{y}_D - \bar{x}_D^T\hat{\beta}\right)$
- EBLUPB: $\hat{Y}_D^{EBLUPB} = \bar{X}_D^T\hat{\beta} + \gamma_D\left(\hat{Y}_D^{Direct} - \bar{x}_D^T\hat{\beta}\right)$

One is the direct estimate component ($\bar{y}_D$ and $\hat{Y}_D^{Direct}$) and the other is model estimate component ($\bar{X}_D^T\hat{\beta}$ or $\bar{x}_D^T\hat{\beta}$).
Where,

- $\bar{X}_D^T$ is population means of covariates calculated from population and
- $\bar{x}_D^T$ is sample means of covariates calculated from sample.

We have to organise the input dataset (XD_P) of population means of covariates to feed into $\bar{X}_D^T$ matrix format process in the EURAREA program. We do not need to organise sample means of covariates to feed into $\bar{x}_D^T$ matrix format process because sample means of covariates is automatically calculated in the EURAREA processing steps.

In order to organise the input covariate dataset (XD_P), we created indicator variables for all categorical covariates after ignoring the first category of covariate of interest.

For example, if we want to create the indicator variables of age group composed of three categories like category of 1 (15–24), category of 2 (25–49) and category of 3 (50 and over), then we have to create two indicator variables for category of 2 (age2) and category of 3 (age3) and we ignore the first category of 1 (15–24) in the input covariate dataset. Following these rules, we created XD_P dataset for EURAREA.

The link function for the model estimate component is:

$\overline{X}_D^T \hat{\beta}$ = β_1MSD(proportion) + $\beta_2$sex2(female proportion) + $\beta_3$age2(age25-49 proportion) + $\beta_4$age3 (age 50 and over proportion) + $\beta_5$ethnicity(Maori plus Pacific proportion).

7.6 EBLUP time series model

The EURAREA package has a functionality of adapting a time-varying area effect which is named EBLUP_TS. It is based on a linear mixed model with area level covariates and a pooled sample estimate within area and time. This assumes that the survey errors are autocorrelated over time due to the rotating panel nature of the sample. The survey error autocorrelation structure can be estimated and a model for the survey error can be developed and combined with a model for the population values.

We tested the EBLUP time series model with the same covariates used for the EBLUPA and EBLUPB models to determine whether the estimates have been improved (see the results in section 9.2).

For the detailed EBLUP_TS concept, see *Project Reference Volume: Volume Three: Software and documentation* (EURAREA Consortium, 2003).

7.7 Standard version or weighted version for EURAREA

EURAREA has two different versions: the standard version, which does not use weight for producing coefficients and variances, and the weighted version, which uses weight for producing coefficients and variances. When ONS developed the EURAREA package, they discussed the issue of using weight for handling sample survey data.

We compared two model parameters. One was produced using weight option in SAS proc mixed and the other was produced without weight option in SAS proc mixed. We discovered different variances between the two outputs. We discussed the two versions with ONS and followed the ONS practice using the standard version of EURAREA for producing model-based estimates.

7.8 Preparation for input datasets

Three input datasets with the right format were required to run the EURAREA package properly (Sample, XD_P and PopSize).

7.8.1 Sample

This is the dataset of the HLFS sample. We can organise variables of sex, age, ethnicity, and MSD from HLFS sample data. However, MSD is not available in sample, so we have to impute it using population means (mean imputation) using XD_P. The sex, age, and ethnicity are categorical numeric variables. Dependent variables of unemployment and employment are numeric indicator values of 'o' or '1'. The area identifier of TA is numeric value. The order of covariates in sample should be followed in XD_P data order.

Table 7-1: Sample dataset format

	Variables							
Variable name	TA	MSD	Sex	Age	Ethnicity	Y1	Y2	W
Description (values)	Identifier	Imputed value using XD_P	(1,2)	(1,2,3)	(1,2)	Unemployment (0,1)	Employment (0,1)	weight

Note: In the system, we should name sample dataset with "sample1"

7.8.2 XD_P

This is the dataset of the population means of covariates, which is summary data at TA level. In the covariate for input model section, we identified four variables (sex, age, ethnicity, and MSD benefit recipients). Sex and age were organised using the TA-level quarterly population estimate proposed. Ethnicity was organised using data from the 2006 Census (note that ethnicity could be extracted from estimates of ethnic population). The MSD benefit recipient was organised using MSD data.

Due to the small sample size of TAs, we categorised three age groups (15–24, 25–49, and 50 and over) based on the recommendation of the previous research. Ethnicity was categorised into two groups (combined category of Māori and Pacific peoples and others). As a result, the population of covariates dataset (XD_P) was organised with six variables including an area index variable as shown in table 7-2. We need to have the values of all these variables for all TAs for model implementation even if three TAs are absent from the sample data.

Table 7-2: XD_P dataset format

	Variables					
Variable name	TA	MSD	Sex	Age2	Age3	Ethnicity
Description	Identifier	Proportion of benefit recipients	Proportion of female	Proportion of age 25–49	Proportion of age 50 and over	Proportion of Māori and Pacific peoples

Note: Should keep variable order, such as the numeric variable is first followed by categorical variables.

7.8.3 PopSize

This is the dataset of the TA-level population size. We organised the number of persons using the TA-level quarterly population estimates. We need to have the value for all TAs for model implementation even if three TAs are absent from the sample data.

Table7-3: PopSize dataset format

	Variables	
Variable name	TA	Popsize
Description	Identifier	The number of persons

8. Significant covariates

8.1 Testing significant covariates

We used HLFS 2008 Q4 data to identify significant covariates. We assumed that data from other periods would have the same pattern as the tested data. Based on the diagnosis output produced by SAS proc mixed without weight option, we found all covariates were significant.

8.1.1 Unemployment proportion estimate

We compared two parameters for the unemployment proportion estimate produced by EBLUPA in EURAREA and SAS proc mixed shown in table 8-1. They were very similar except for slightly different decimal points. We found all covariates were statistically significant at p-value of 0.05. For the unemployment proportion estimation, MSD and Maori/PI have positive effect whereas female and age group 2 and 3 have negative effect.

Table 8-1: Parameter estimates for SAS proc mixed and EURAREA for unemployment

Unemployment: Testing in unit model without weight

SAS proc mixed output:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z
UN(1,1)	TA	0.000036	0.000021	1.75	0.0404
Residual		0.02961	0.000249	118.74	<.0001

Solution for Fixed Effects

Effect	sex	ageband	eth	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept				0.07676	0.003640	270	21.09	<.0001
MeanMSD				0.5118	0.2092	93.6	2.45	0.0163
sex	1 Female(2)			-0.00490	0.002053	28E3	-2.39	0.0170
sex	2 Male(1)			0	.	.	.	.
ageband		1 age group(2)		-0.05487	0.002966	28E3	-18.50	<.0001
ageband		2 age group(3)		-0.07196	0.003056	28E3	-23.54	<.0001
ageband		3 age group(1)		0	.	.	.	.
eth			1 Maori/PI	0.01787	0.002431	7341	7.35	<.0001
eth			2 Others	0	.	.	.	.

EURAREA parameter output:

Method	Parameter	Estimate	sigma2_u	sigma2_e
EBLUPA	Beta0	0.07676	.000035846	0.029606
EBLUPA	Beta1	0.51334	.000035846	0.029606
EBLUPA	Beta2	-0.00490	.000035846	0.029606
EBLUPA	Beta3	-0.05487	.000035846	0.029606
EBLUPA	Beta4	-0.07195	.000035846	0.029606
EBLUPA	Beta5	0.01787	.000035846	0.029606

8.1.2 Employment proportion estimate

We compared two parameters for the employment proportion estimate produced by EBLUPA in EURAREA and SAS proc mixed shown in table 8-2. They were very similar other than slightly different decimal points. We found all covariates were statistically significant at p-value 0.05. For employment proportion estimation, MSD, female and Maori/PI have negative effect whereas age has mixed effect.

Table 8-2: Parameter estimates for SAS proc mixed and EURAREA for employment

Employment: Testing in unit model without weight

SAS proc mixed output:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z
UN(1,1)	TA	0.001121	0.000374	3.00	0.0013
Residual		0.2029	0.001709	118.70	<.0001

Solution for Fixed Effects

Effect	sex	ageband	eth	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept				0.6684	0.01139	148	58.70	<.0001
MeanMSD				-1.8486	0.7169	83.1	-2.58	0.0117
sex	1 Female(2)			-0.1241	0.005375	28E3	-23.09	<.0001
sex	2 Male(1)			0	.	.	.	.
ageband		1 age group(2)		0.2471	0.007768	28E3	31.82	<.0001
ageband		2 age group(3)		-0.06459	0.008010	28E3	-8.06	<.0001
ageband		3 age group(1)		0	.	.	.	.
eth			1 Maori/PI	-0.08273	0.006442	22E3	-12.84	<.0001
eth			2 Others	0	.	.	.	.

EURAREA parameter output:

Method	Parameter	Estimate	sigma2_u	sigma2_e
EBLUPA	Beta0	0.66835	.001120893	0.20286
EBLUPA	Beta1	-1.84856	.001120893	0.20286
EBLUPA	Beta2	-0.12409	.001120893	0.20286
EBLUPA	Beta3	0.24713	.001120893	0.20286
EBLUPA	Beta4	-0.06459	.001120893	0.20286
EBLUPA	Beta5	-0.08273	.001120893	0.20286

Based on testing the significant covariates for unemployment and employment proportion estimates, we used all covariates for identifying the best model.

8.2 Combination of covariates

We tested the target variables of unemployment and employment separately using several combinations of covariates to identify the best model. We found very similar results for checking indicators described in this section. Note that in this report, we only focus on the unemployment related outputs.

The combinations of covariates are:

- MSD variable only
- sex and age variables
- sex, age, and ethnicity variables
- sex, age, ethnicity, and MSD variables.

We tested all eight models (four combinations of covariates for EBLUPA and EBLUPB).

8.2.1 Mean square error-related indicator comparison

Firstly, we produced mean square error (MSE) for unemployment proportion estimate based on the proposed models using combinations of covariates. Secondly, we identified the best MSE, which is the smallest MSE out of the proposed models.

We did not test the interaction terms of covariates due to the complexity of the EURAREA input dataset preparation. We tested each combination of covariates for EBLUPA and EBLUPB separately. The results are shown in below table 8-3 with average root mean square error (RMSE) and the number of best MSE indicators.

Based on the number of best MSE and average RMSE, we can see that the best model is EBLUPA using covariates of sex, age, ethnicity, and MSD. This is followed by EBLUPA with sex, age, and ethnicity. We also found that EBLUPA might be a better model and adding variables reduced the MSE.

Table 8-3: Best indicator and average RMSE of unemployment proportion

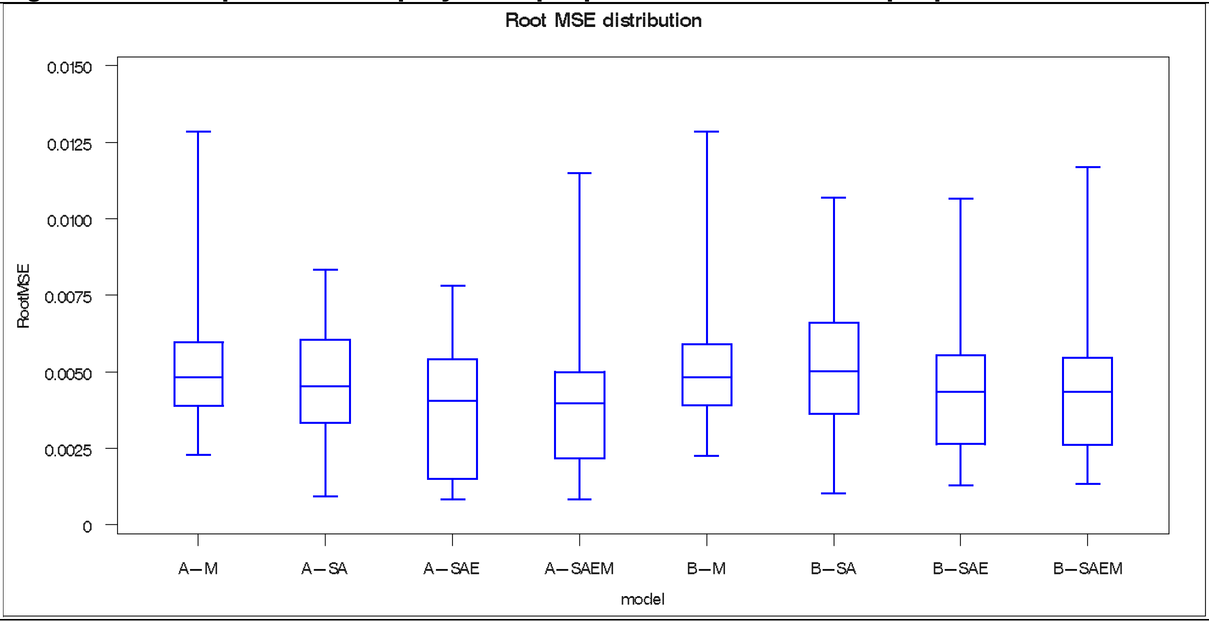
Model and used covariates	The number of best MSEs(1)	Average RMSE(2)
Total	742(3)	0.48
EBLUPA-MSD	2	0.52
EBLUPA-SexAge	99	0.50
EBLUPA-SexAgeEth	184	0.42
EBLUPA-SexAgeEthMSD	230	0.41
EBLUPB-MSD	46	0.52
EBLUPB-SexAge	.	0.54
EBLUPB-SexAgeEth	122	0.47
EBLUPB-SexAgeEthMSD	59	0.46

1. Firstly identified the smallest MSE out of eight methods in each TA and quarter and then added all best indicator.
2. Calculated using all TAs and quarters.
3. 742=62 testing TAs times 12 quarters minus 2 missing TA quarters due to no sample units.

8.2.2 MSE distribution

We also plotted the distributions of MSEs between the proposed models shown in figure 8-1. The EBLUPA model using sex, age, and ethnicity appears to have a stable MSE distribution. The EBLUPA model using sex, age, ethnicity, and MSD has the smallest average MSE shown in above table 8-4, but it also includes some outliers shown in figure 8-1. The EBLUPB models have slightly higher average MSEs than the EBLUPA model using sex, age, ethnicity, and MSD. Both EBLUPA and EBLUPB using MSD data only have very compact MSE distribution with some outliers.

Figure 8-1: Box plot of unemployment proportion MSE for each proposed model



Note: Y-axis is root MSE. In x-axis the first character (before hyphen) of label denotes A=EBLUPA and B=EBLUPB. And The character after hyphen is S=sex, A=age, E=etnicity and M=MSD data. For example A-SA means EBLUPA with sex and age variables and B-SAE means EBLUPB with sex, age and ethnicity.

8.2.3 Bias check for model-based estimates

The model-based estimates should be unbiased predictors of the direct estimates. To check for predictive bias in the model-based estimates, we can plot model-based estimates against direct estimates. We assume that the direct estimates are unbiased. Then we can test whether the regression line can be fitted to these points and is significantly different from the identity line.

We tested EBLUPA and EBLUPB models with various combinations of covariates and applied different weights. We found that weight did not play a big role in changing estimates. So we used the adjusted final weight (TAfinalwgt2) for EBLUPA and EBLUPB models using various combinations of covariates. Also, while checking for their bias, we found that the estimates were not much different between EBLUPA and EBLUPB. So we presented plots and regression lines fitted for EBLUPA models against direct estimates.

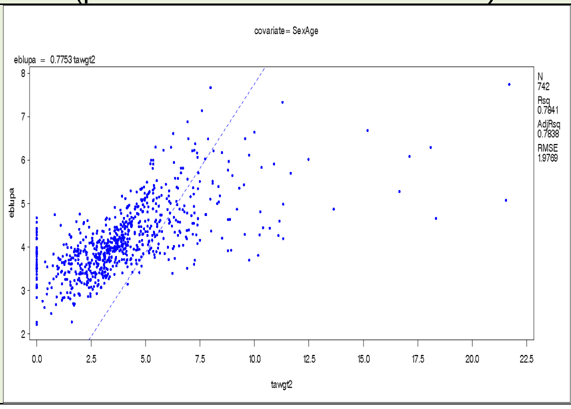
All models were fitted well with the OLS (ordinary least squares) regression line. As we can see from the fitted results shown in figure 8-2, the model using sex and age appeared to have a coefficient of 0.7753; adding ethnicity improved it to 0.7950. When we added the MSD covariate into the model, the coefficient was improved significantly to 0.8439.

Surprisingly, when we used the models with single MSD covariate, the coefficient and model error appeared to be closer to the direct estimate compared with other model estimates. Anyway, we found the slope of all model outputs were close to one.

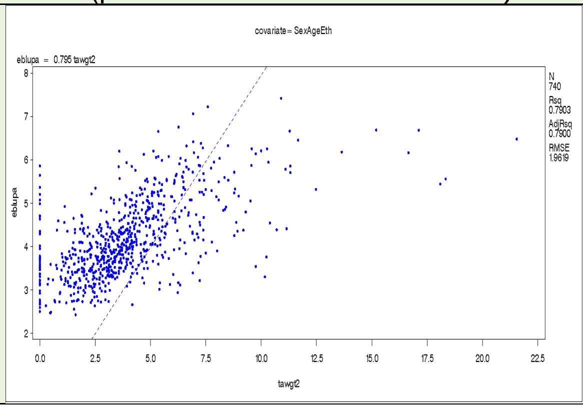
All model-based estimates would be unbiased estimates under assumption of unbiased direct estimate as they were only fitted slightly differently from the OLS regression line. So, here we assume that the model-based estimates are likely to be unbiased estimates.

Figure 8-2: Linearity of EBLUPA model estimate and direct estimate

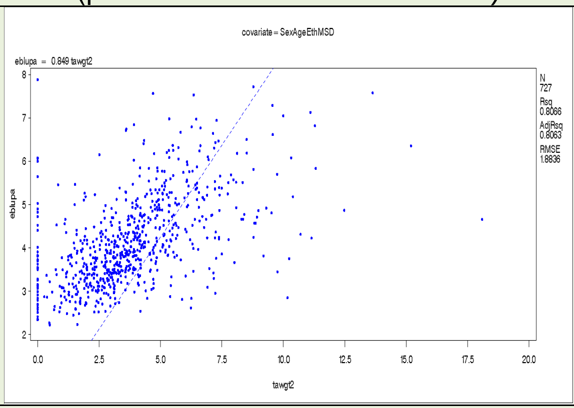
Using sex and age
(β=0.7753 R^2=0.78 RMSE=1.98)



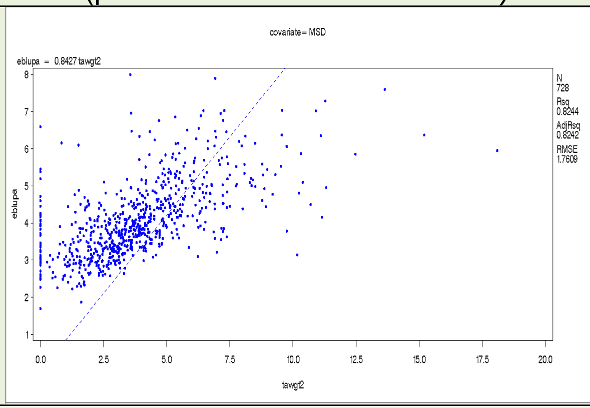
Using sex, age and ethnicity
(β=0.7950 R^2=0.79 RMSE=1.96)



Using sex, age, ethnicity and MSD
(β=0.8490 R^2=0.81 RMSE=1.88)



Using MSD
(β=0.8427 R^2=0.82 RMSE=1.76)



Note: Y-axis is unemployment rate(%) using EBLUPB and x-axis is unemployment rate(%) using direct estimate method.

8.3 Discussion of covariate decision

Based on the investigation of average RMSE and best indicator for the proposed eight models, EBLUPA using sex, age, ethnicity, and MSD covariates appeared to be the best model, followed by EBLUPA with sex, age, and ethnicity covariates.

Based on the investigation of MSE distribution for the proposed models, EBLUPA with sex, age, and ethnicity variables looked to be the best model, followed by EBLUPA with sex and age variables.

Based on MSE comparisons, it was hard for us to tell which model of the combination of covariates would be the best for the unemployment proportion estimate. EBLUPA using sex, age, and ethnicity seemed to be a good model. When we added the MSD variable into the covariates, then the estimate could be slightly improved in terms of the average MSE.

MSE is only one view of model diagnostics. Hence, we have to look into many different ways before making a decision on the best model. We decided to use all covariates for further testing models.

9. Output comparisons

We produced the model-based estimates of EBLUPA and EBLUPB using sex, age, ethnicity, and MSD variables. We also produced the direct estimates using the final weight (original survey weight) and the adjusted final weight. Note that the adjusted final weight has been discussed in the weighting issue section. The EBLUPB model needs weight parameter for producing estimates. In order to produce the model-based estimate for EBLUPB, we used the adjusted final weight (TAfinalwgt2).

We focused on comparing the model-based estimates with the direct estimates, which used the final weight to determine how much they were different over time. We expected less variability over time if the model-based estimates performed well. We also compared two model-based estimates of EBLUPA and EBLUPB to determine how much they were different over time.

Note that in this section, we will only discuss **unemployment rate estimates**.

9.1 Comparison of territorial authority level estimates

In order to compare estimates, we made four groups of TAs based on the number of selected sample PSUs for the 2006 Q1 HLFS (the groups of TAs can be found in the sample structure section). Both size A and size B are small sizes of sampled PSU TAs, size C is a medium size of sampled PSU TAs, and size D is a large size of sampled PSU TAs.

For visual illustration, we selected two sample TAs in each size group:

- size A (02-10 PSUs): Kawerau district and Wairoa district
- size B (11-19 PSUs): Waipa district and Tararua district
- size C (20-50 PSUs): Tauranga city and Porirua city
- size D (50 over PSUs): New Plymouth district and Auckland city.

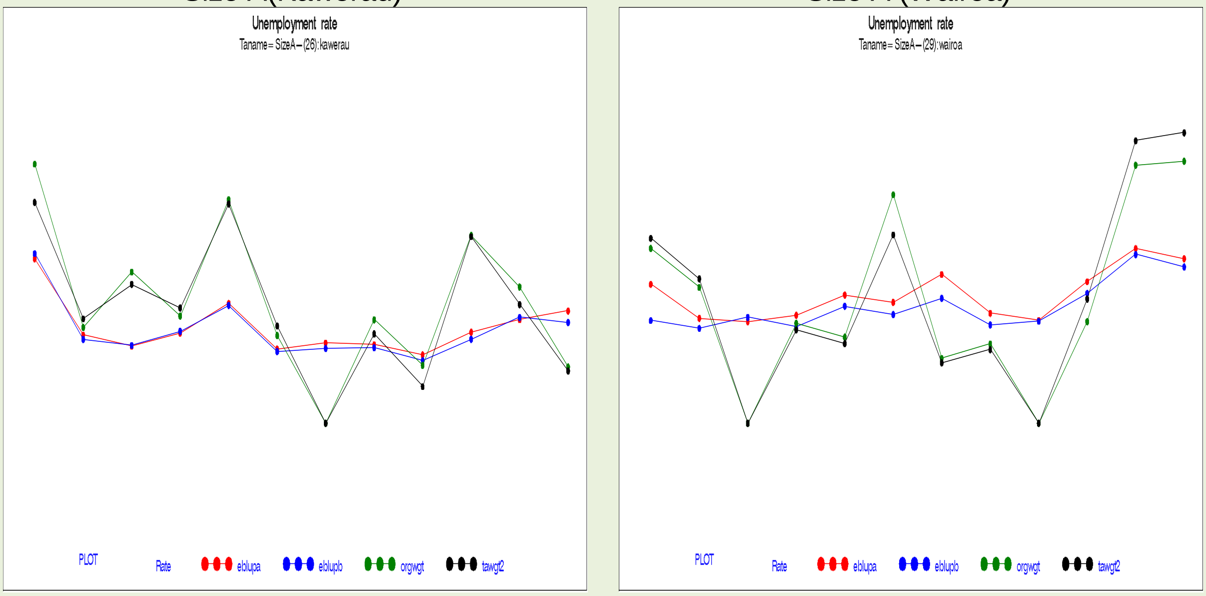
Note: Auckland city is not super city.

9.1.1 Size A and size B

We illustrated findings together for size A in figure 9-1 and size B in figure 9-2. All TAs in size A and size B appeared to have very similar pattern of direct estimates, which had large variation over time. This must have happened due to the small sample size. Estimates of EBLUPA were slightly higher than those of EBLUPB in most periods. As we expected it, we proved that the direct estimates showed greater variation over time than the model-based estimates. We could see little difference between direct estimate using the final weight and direct estimate using the adjusted final weight.

Figure 9-1
Comparison between EBLUP model estimates and direct estimates for size A

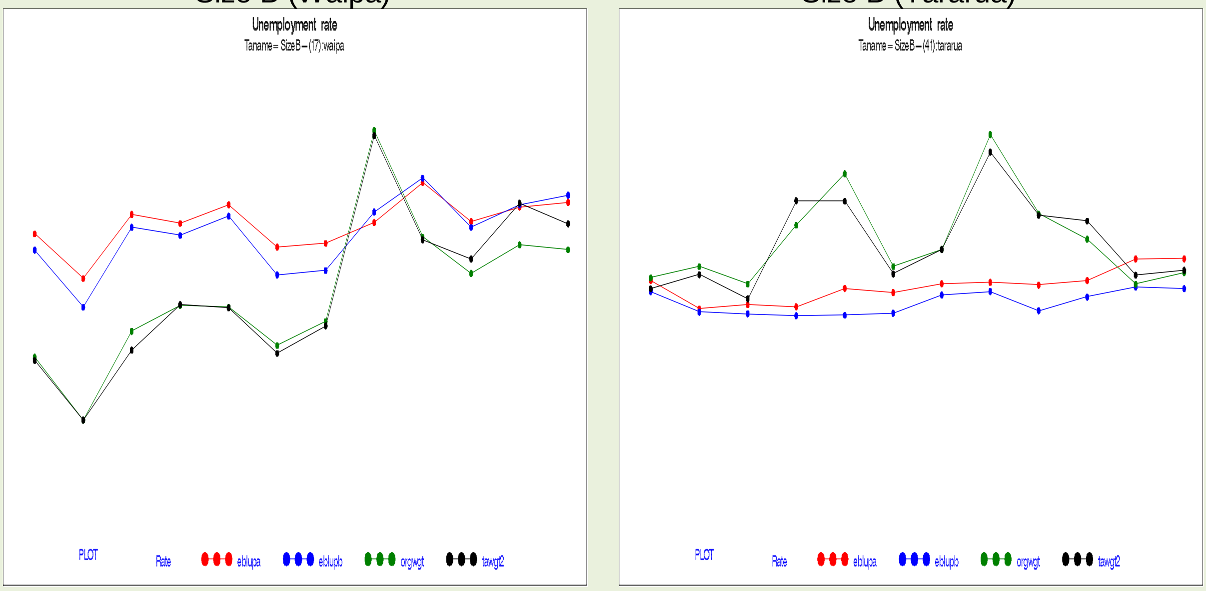
Size A(Kawerau) Size A (Wairoa)



Note: **Red line**=EBLUPA, **blue line**=EBLUPB, **green line**= direct estimate using the original final weight and **black line**=direct estimate using the adjusted final weight. Y-axis is unemployment rate(%) and x-axis is quarter

Figure 9-2
Comparison between EBLUP model estimates and direct estimates for size B

Size B (Waipa) Size B (Tararua)



Note: **Red line**=EBLUPA, **blue line**=EBLUPB, **green line**= direct estimate using the original final weight and **black line**=direct estimate using the adjusted final weight. Y-axis is unemployment rate(%) and x-axis is quarter

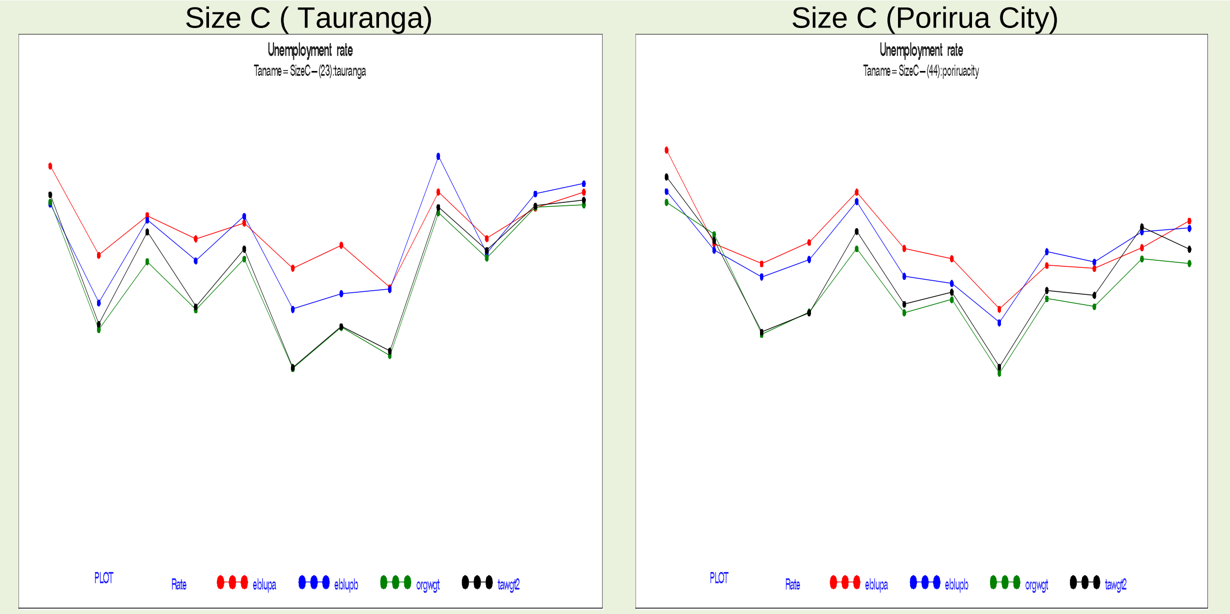
9.1.2 Size C

As with size A and size B, we also found that for size C, the trend over time for the model-based estimate and the direct estimate was different. However, the gap between the model estimate and the direct estimates for size C appeared much smaller than that for size A and size B.

The overall trend of EBLUP models and direct estimates were similar, with a minor gap in estimates. As we found in size A and size B, the estimates of EBLUPA were slightly higher than those of EBLUPB in most periods. For size C, we also could not see much difference between direct estimate using the final weight and direct estimate using the adjusted final weight.

Figure 9-3

Comparison between EBLUP model estimates and direct estimates for size C



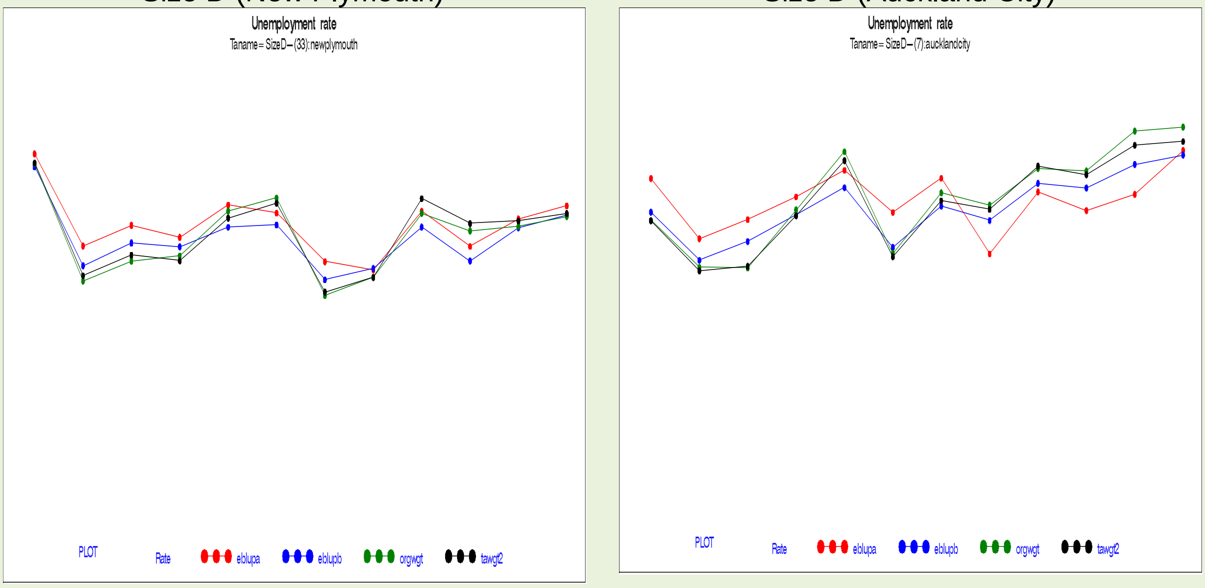
Note: **Red line**=EBLUPA, **blue line**=EBLUPB, **green line**= direct estimate using the original final weight and **black line**=direct estimate using the adjusted final weight. Y-axis is unemployment rate(%) and x-axis is quarter

9.1.3 Size D

We found that the gap between the model estimate and the direct estimates for size D was much closer than that for size C. Also, we found that there was not much difference between the direct estimates. We found that for most periods of TAs, the EBLUPA estimates were slightly higher than the EBLUPB estimates as seen in other size TA groups.

Figure 9-4
Comparison between EBLUP model estimates and direct estimates for size D

Size D (New Plymouth) Size D (Auckland City)



Note: **Red line**=EBLUPA, **blue line**=EBLUPB, **green line**= direct estimate using the original final weight and **black line**=direct estimate using the adjusted final weight. Y-axis is unemployment rate(%) and x-axis is quarter

We quantified the differences between average EBLUP model-based estimates and the average direct estimates. Note that the average EBLUP model-based estimate was calculated using EBLUPA and EBLUPB estimates and the average direct estimate was calculated using the direct estimate based on the final weight and the direct estimate based on the adjusted final weight. Table 9-1 shows the small size of size A was 2.3 percent and the large size of size D was 0.5 percent.

Table 9-1: Difference between average EBLUP model-based estimates and average direct estimates

TA size group	Average difference (%)
Size A (02–10 sample PSUs)	2.3
Size B (11–19 sample PSUs)	1.4
Size C (20–50 sample PSUs)	0.9
Size D (50 and over sample PSUs)	0.5

9.1.4 General findings between model-based estimates and direct estimates

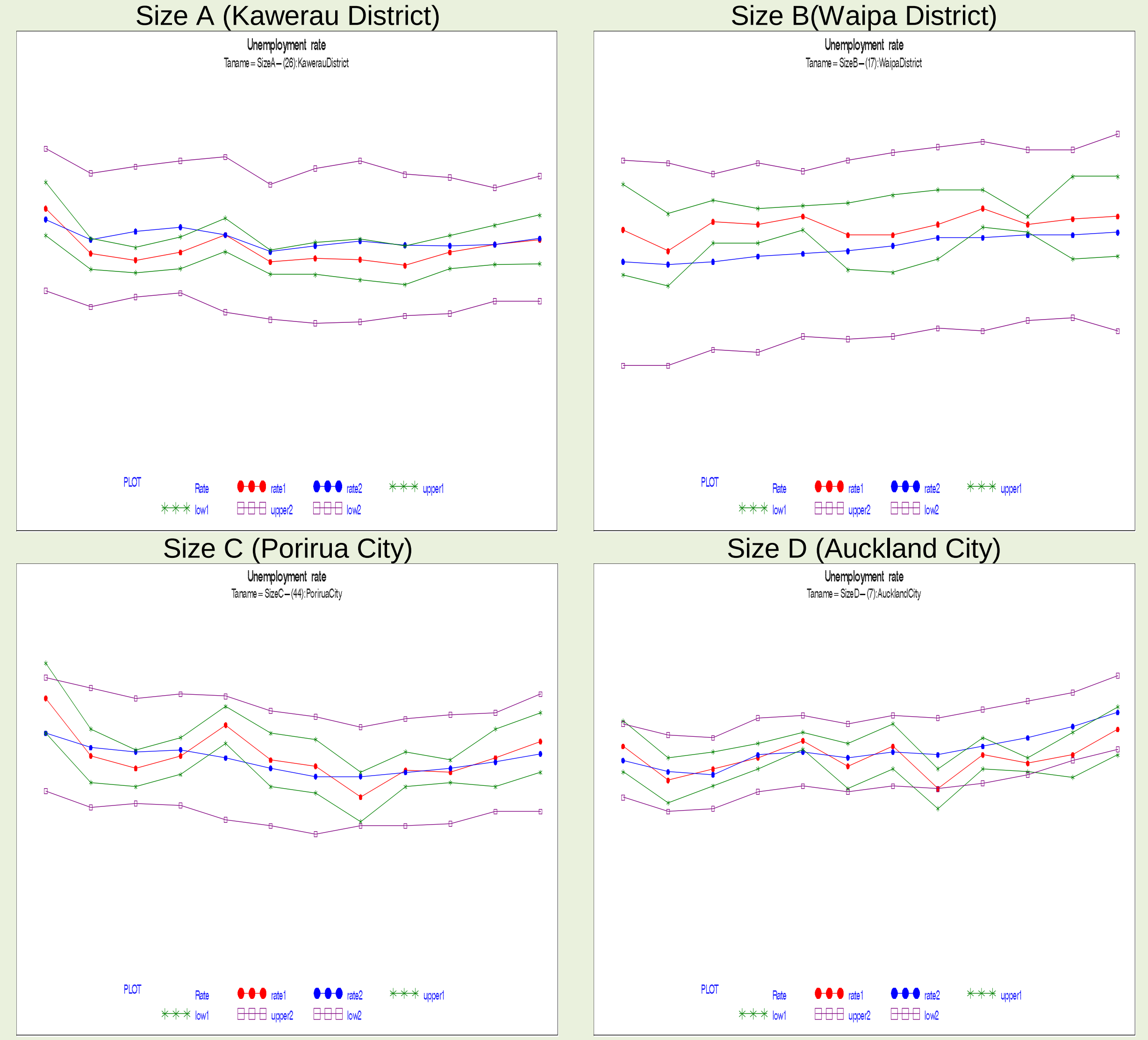
We have summarised major findings described in the above group analysis:

- The direct estimates from the small sizes of sampled PSU TAs showed a greater fluctuation over time than the model-based estimates.
- The estimates of EBLUPA model were slightly higher than those of EBLUPB model.
- Direct estimates using the final weight were not much different from those using the adjusted final weight.
- As sample size increased, the gap between the model-based estimates and the direct estimates was closer.

9.2 Comparison of EBLUP time series model estimates

We produced estimates of unemployment rate using EBLUP time series model to compare with EBLUPA and EBLUPB estimates and only presented four sampled TAs. Because 95 percent confidence intervals of EBLUPA and EBLUPB were not much different, we only showed the confidence interval of EBLUPA in the graphs shown in figure 9-5. The estimate of the EBLUP time series was much wider than that of EBLUPA and EBLUPB, which implied larger model errors for the EBLUP time series.

Figure 9-5: EBLUP time series estimates and EBLUP estimates



Note: **Red line** =EBLUPA, **green line**=95% upper and low bound for EBLUPA , **blue line**=EBLUP-TS, **purple line**=95% upper and low bound for EBLUP-TS. Y-axis is unemployment rate(%) and x-axis is quarter

Since twelve quarters of test data might be insufficient for a robust time-series analysis, larger model errors may have been produced. The EBLUP time series model was not further explored because we felt the EBLUP time series with the test data would not improve accuracy compared with EBLUPA and EBLUPB.

9.3 Comparison of regional-level estimates

We produced regional-level estimates with summation of the TA-level model-based estimates to compare with the regional level direct estimates. We had two TAs crossing two regional boundaries, which we discussed in the previous sample structure section. We allocated them to one region for practicality. See appendix 1 for concordance codes between region and TA.

Two TAs crossed boundaries allocated:

- Franklin district belonging to Auckland region and Waikato region, allocated to Auckland region.
- Rotorua district belonging to Waikato region and Bay of Plenty region, allocated to Bay of Plenty region.

In the current HLFS processing system, we produced the direct estimates of regional-level unemployment rates using the final weight. The regional-level direct estimates were used to a benchmark to compare with **building up EBLUP model estimates**.

The building up EBLUP model estimates are obtained by the following steps:

Firstly, we produced the number of unemployed and employed based on the TA-level model-based proportion estimates, which was shown in section 7.4. Secondly, we summed up the number of unemployed and employed by regional level and calculated unemployment rates. We followed the same processing steps for EBLUPA and EBLUPB estimates, respectively.

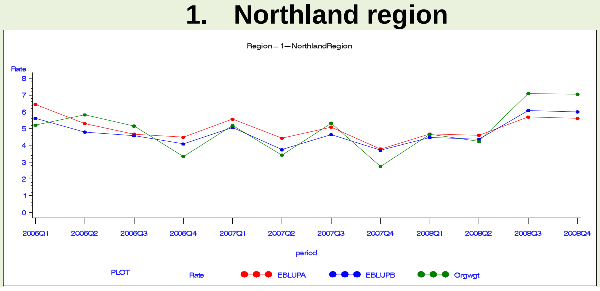
9.3.1 Investigation of individual regions

As we investigated in the previous TA-level comparison, we found very similar patterns between EBLUP estimates. For building up EBLUP model estimates, we found EBLUPA had slightly higher estimates over time than EBLUPB. Also, we found that the trend of regional-level direct estimates appeared to have mixed patterns compared with the building up of EBLUP model estimates.

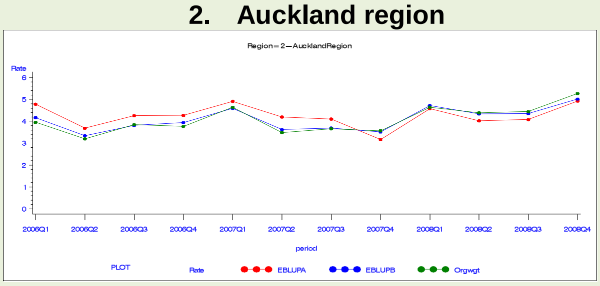
For some time periods, the regional-level direct estimates were higher or lower than the building up of EBLUP model estimates. However, the direct estimate of Southland region was constantly lower than the building up of EBLUP model estimates over all the time periods.

Figure 9-6: Comparison between direct estimate and EBLUPA and EBLUPB estimate by region

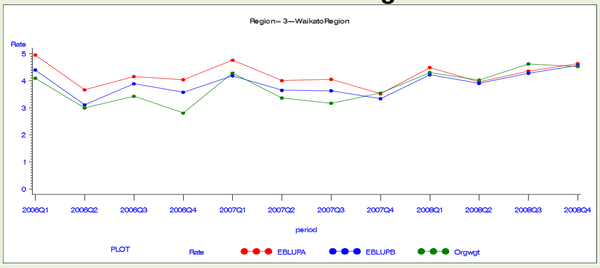
1. Northland region



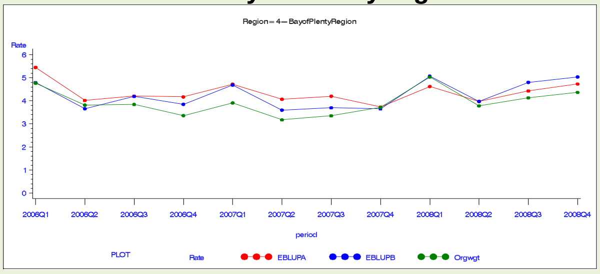
2. Auckland region



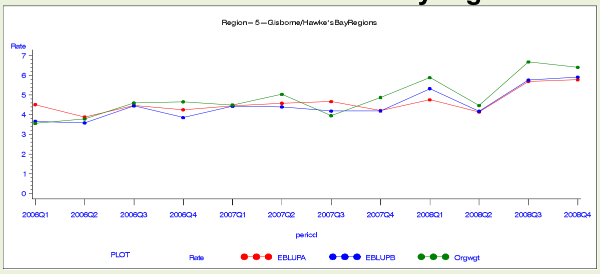
3. Waikato region



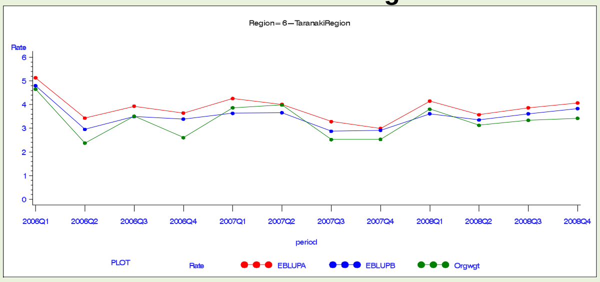
4. Bay of Plenty region



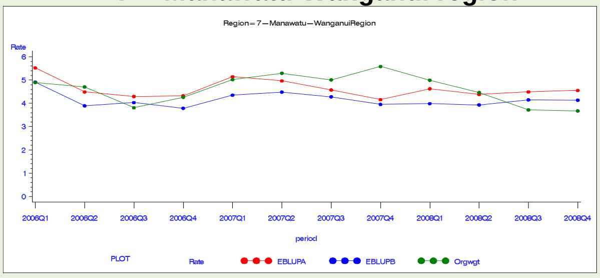
5. Gisborne/Hawke's Bay regions



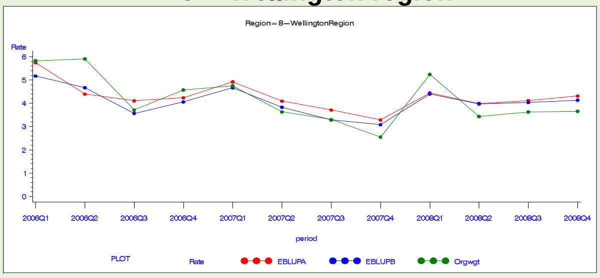
6. Taranaki region



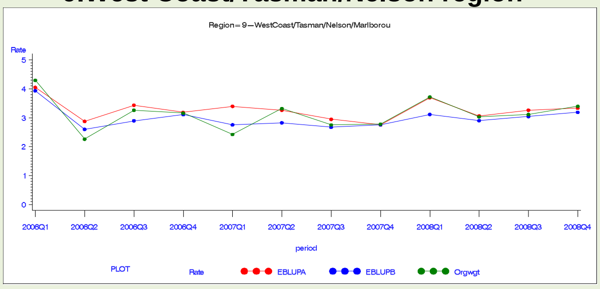
7. Manawatu-Wanganui region



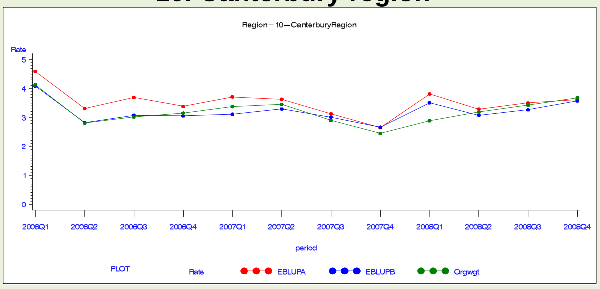
8. Wellington region



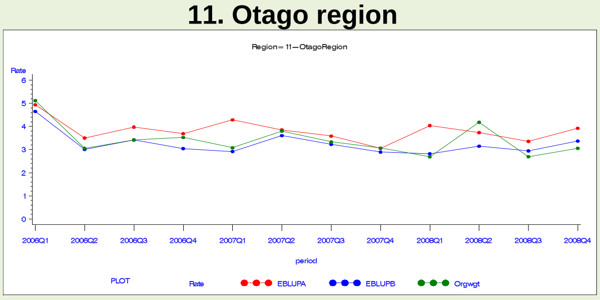
9.West Coast/Tasman/Nelson region



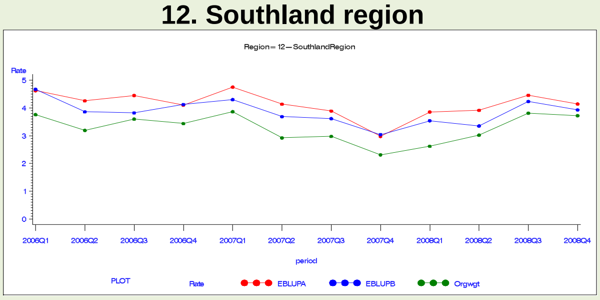
10. Canterbury region



11. Otago region



12. Southland region



Note: **Red line**=EBLUPA estimate, **blue line**=EBLUPB and green line= estimate using the original final weight. Y-axis is unemployment rate(%) and x-axis is quarter

9.3.2 Bias check for the building up of model estimates

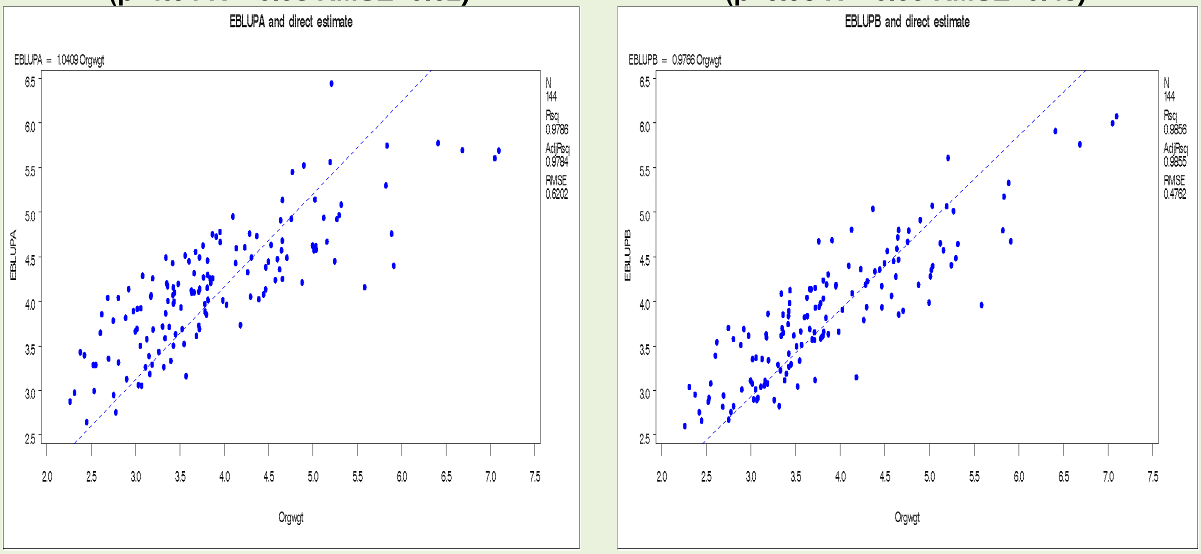
We checked whether building up the model estimates were unbiased or not, based on plotting two estimates. This comparison was conducted under the assumption that the regional-level direct estimates are unbiased. We compared the regional-level direct estimates with the building up of EBLUPA and EBLUPB model estimates separately.

Regression parameter of beta is 1.04 for EBLUPA and 0.98 for EBLUPB as shown in figure 9-7. The building up of EBLUPB model estimates were more fitted to linear relationship than the building up of EBLUPA model estimates for unemployment rates. In other words, EBLUPB appeared to have less biased estimates than EBLUPA.

Figure 9-7: Regression of the direct estimates and building up model-based estimates for regions

EBLUPA vs direct estimate (β=1.04 R^2 =0.98 RMSE=0.62)

EBLUPB vs direct estimate (β=0.98 R^2 =0.99 RMSE=0.48)



Note: Y-axis is unemployment rate (%) using EBLUP model and x-axis is unemployment rate(%) using final weight.

Also, we compared the average estimate differences between the building up EBLUP model estimates and the regional level direct estimates shown in table 9-2. Overall, the difference of unemployed number is 10.5 percent for EBLUPB and 11.9 percent for EBLUPA. The difference of unemployment rate is 0.37 percent for EBLUPB and 0.52 percent for EBLUPA. We found that EBLUPB had a much closer estimate for most regions than EBLUPA in terms of estimates of unemployment rates and numbers. In other words, EBLUPB appeared to have less biased estimates than EBLUPA.

Table 9-2: Average absolute differences between building up EBLUP model-based and direct estimates

	Unemployment rate		Unemployment number	
Region	*EBLUPA and direct estimate (%)	*EBLUPB and direct estimate (%)	*EBLUPA and direct estimate (%)	*EBLUPB and direct estimate (%)
Whole country	**0.52**	**0.37**	**11.9**	**10.5**
1 Northland region	0.77	0.60	16.3	12.6
2 Auckland region	0.43	0.11	8.3	4.2
3 Waikato region	0.51	0.27	14.8	10.0
4 Bay of Plenty region	0.49	0.35	19.1	17.9
5 Gisborne/Hawke's Bay regions	0.55	0.43	15.7	14.3
6 Taranaki region	0.55	0.33	8.9	8.6
7 Manawatu-Wanganui region	0.48	0.65	10.6	16.6
8 Wellington region	0.55	0.47	15.2	17.4

9	West Coast/Tasman/Nelson/Marlborou	0.21	0.25	9.3	14.6
10	Canterbury region	0.33	0.16	7.6	13.9
11	Otago region	0.52	0.28	20.1	9.2
12	Southland region	0.86	0.58	11.9	7.1

Note: EBLUPA and EBLUPB estimates using sex, age, ethnicity, and MSD covariates.

9.4 Investigation of coverage diagnostics

This diagnostic evaluates the validity of the confidence intervals generated by the model-based estimates. The diagnostic is the measure of overlap between the 95 percent confidence intervals for the direct estimates and those for the model-based estimates.

We checked whether the 95 percent confidence intervals of the direct estimates contained EBLUPA and EBLUPB model estimates. As shown in table 9-3, 9.2 percent of EBLUPA and 6.6 percent of EBLUPB estimates were not included into the confidence intervals of the direct estimates. Conversely, we also checked whether the 95 percent confidence intervals of the EBLUP estimates contained in the direct estimates. A proportion of 43.9 percent of EBLUPA and 35.8 percent of EBLUPB were not included into the confidence intervals of EBLUP model estimates. EBLUPB is likely to be more inclusive than EBLUPA.

Table 9-3: Outside proportions of 95 percent confidence intervals for direct and EBLUP estimates

Total cases	**EBLUPA estimates beyond 95% confidence interval of direct estimate**	**EBLUPB estimates beyond 95% confidence interval of direct estimate**
742	68 (9.2%)	49 (6.6%)
	Direct estimates beyond 95% confidence interval of EBLUPA estimate	Direct estimates beyond 95% confidence interval of EBLUPB estimate
742	326 (43.9%)	266 (35.8%)

10. Model decision

We summarise the major findings from the output comparison section and EBLUP model components:

- EBLUPA model is totally free of survey weight, whereas EBLUPB model is partially dependent on weight. If we choose EBLUPA as our model, then we will lose weight contribution. HLFS is a sample survey data, so weight should be an important role for estimation.
- Also, as seen in regional level comparison and coverage diagnostic sections about unemployment rate estimates, EBLUPB was closer to the direct estimates than EBLUPA.
- As seen in the MSE comparison section, EBLUPA had slightly smaller model errors than EBLUPB.
- For most periods of TAs, the EBLUPA estimates were slightly higher than the EBLUPB estimates. We are not able to prove which one is closer to the true values.
- EBLUP time series model was out of our ideal range, because we did not carry out in-depth investigations and it produced large model errors compared with EBLUP models.

It was difficult to decide on one conclusive model due to the varied outcomes of all the comparisons made. In the end, we decided to use an average of EBLUPA and EBLUPB estimates as our final model using the covariates of sex, age, ethnicity, and MSD benefit recipient.

11. User validation

In the previous sections, we discussed the test dataset composed of 62 TAs, which were the common TAs between HLFS and MSD data from Q1 2006 to Q4 2008. However, we produced the final experimental estimates from Q1 2006 to Q4 2009 for 73 TAs without using MSD covariate.

The HLFS team will carry out a user validation exercise for the estimates produced by our average of the EBLUP models. They will check the estimates against their subject knowledge and 2006 Census results. We may adjust the final model based on their comments.

12. Discussions

12.1 MSD data

There is no argument that MSD data increases the model accuracy. However, we have to be aware of the following before organising MSD data:

- If we request further data from MSD in the future to incorporate into the model input variable for the regular HLFS processing system of small area estimation, we have to discuss the scope of the benefit recipient data and HLFS data corresponding TAs. We need only 'working-age unemployment benefit recipients'.
- We can use age and ethnicity variables for MSD benefit recipients to feed into the models. We need to investigate usability of age and ethnicity variables in MSD data.
- The age coverage of MSD data is 18 to 64 years, whereas that of HLFS population is 15 and over. We should be aware of the possibility of the estimate's impact due to the difference of age coverage between two sources.
- If we have any missing TAs for certain periods, then we have to impute the missing TAs to work out EURAREA. Otherwise, EURAERA cannot be implemented to produce estimates.

12.2 HLFS sample

We designed the current HLFS sample, which is of a relatively big sample size, to meet the target of the national-level estimate accuracy. Implementing a small area estimate model into the HLFS producing system may require some changes to the HLFS sample design. We would need to consider the followings to improve handling of small area estimation processing:

- Currently, we have absent TAs in the current HLFS sample but we would need all TAs in the HLFS sample.
- We have relatively a small size of sample TAs in the current HLFS sample, whereas we have relatively a large size of sample TAs. We can adjust the size of sample TAs while we maintain an overall size of sample units. We need to consider the issue of sample size adjustment between TAs in the future HLFS sample.
- We would need to organise an automatic output processing system to generate TA codes based on a rotated sample. Particularly, when we replace an old sample with a new sample, we have to be careful of using the right concordance codes between meshblock and TA codes.

12.3 Territorial authority level quarterly population estimate

We proposed the method of the TA-level quarterly population estimation based on the assumption of stable sex and age group structure at TA-level between years. We combined two estimated sources, the TA-level yearly population estimate and the national-level quarterly population estimate.

We used this TA-level quarterly population estimate with a population benchmark to revise the final weight and create the population means of XD_P, which was the model input data. Therefore, it plays a very important role in the model-based estimates. We would need a reliable population estimate at TA level to produce accurate estimates for variables of interest.

12.4 Model improvement and EURAREA

We processed two models of unemployment and employment independently rather than simultaneously because EURAREA is not capable of multivariate analysis functionality. Therefore, we cannot measure the interaction impact of unemployment and employment variables in the model. We did not use the change of labour force status over time for individual units, which are longitudinal data characteristics. We need to continue investigating these two areas to improve HLFS small area estimation in the future.

Also, we used three categorical variables of sex, three age groups, and two ethnicity groups without interaction terms between variables due to the complexity of organising the model input variables for EURAREA. We may need to investigate adding more related variables, more detailed age and ethnicity groups and their interaction terms into the model to improve estimates.

We used the standard version of EURAREA, which did not incorporate survey weight into the calculation steps for all the model parameters in EBLUP models. We may revisit the issue of using survey weight for producing all model parameters.

References

Australian Bureau of Statistics (2006). *A guide to small area estimation – version 1.1*, Available from www.nss.gov.au/nss/home.NSF/NSS/3A60738D0ABDF98CCA2571AB00242664?opendocument .

BIAS project team (2009). Software for ecological inference. Available from www.bias-project.org.uk/software, visited November 2009.

EURAREA Consortium, 2003, Project Reference Volume: Volume three: Software and documentation. Available from http://www.statistics.gov.uk/eurarea/ .

Haslett, S, Noble, A, & Zabala, F (2007, June). New approaches to small area estimation of unemployment. Available from http://www.stats.govt.nz/sitecore/content/statisphere/Home/official-statistics-research/series/volume-3-2008.aspx#5

Haslett S., Jones G., & Enright J. , Small-Domain Estimation of Māori Expenditure Patterns. Available from http://www.stats.govt.nz/sitecore/content/statisphere/Home/official-statistics-research/series/volume-3-2008.aspx#6

Ministry of Social Development (2010). Regional benefit factsheets. Available from www.msd.govt.nz/about-msd-and-our-work/publications-resources/statistics/benefit/index.html.

Pinheiro, J, Bates, D, DebRoy, S, Sarkar, D, and the R Core team (2009). *nlme: Linear and nonlinear mixed effects models*. R package version 3.1-93.

Rao, J.N.K (2003). *Small area estimation*. New Jersey: Wiley.

Ralphs, M, Hansen, C, Song, S, & Smith, H (2010 June). Small area estimation of unemployment for territorial authorities using commonly applied estimation models in SAS and R. (Unpublished report.)

Statistics New Zealand (2010). Household Labour Force Survey resource, http://www.stats.govt.nz/methods_and_services/guide-and-tutorials/hlfs-resource.aspx , visited January 2010.

Statistics New Zealand (2010), User manual for %EURArea. (Statistics NZ internal document).

Appendix

1. Concordance codes between region and TA*

LGR	Region name	TA	TA name
1	Northland Region	001	far north
1	Northland Region	002	whangarei
1	Northland Region	003	kaipara
2	Auckland Region	004	rodney
2	Auckland Region	005	north shore city
2	Auckland Region	006	waitakere city
2	Auckland Region	007	auckland city
2	Auckland Region	008	manukau city
2	Auckland Region	009	papakura
2	Auckland Region	010	franklin
3	Waikato Region	010	franklin
3	Waikato Region	011	thames-coromandel
3	Waikato Region	012	hauraki
3	Waikato Region	013	waikato
3	Waikato Region	015	matamata-piako
3	Waikato Region	016	hamilton city
3	Waikato Region	017	waipa
3	Waikato Region	018	otorohanga
3	Waikato Region	019	south waikato
3	Waikato Region	020	waitomo
3	Waikato Region	021	taupo
3	Waikato Region	024	rotorua
4	Bay of Plenty Region	022	western bay of plenty
4	Bay of Plenty Region	023	tauranga
4	Bay of Plenty Region	024	rotorua
4	Bay of Plenty Region	025	whakatane
4	Bay of Plenty Region	026	kawerau
4	Bay of Plenty Region	027	opotiki
5	Gisborne/Hawke's Bay Regions	028	gisborne
5	Gisborne/Hawke's Bay Regions	029	wairoa
5	Gisborne/Hawke's Bay Regions	030	hastings
5	Gisborne/Hawke's Bay Regions	031	napier city
5	Gisborne/Hawke's Bay Regions	032	central hawke's bay
6	Taranaki Region	033	new plymouth
6	Taranaki Region	034	stratford
6	Taranaki Region	035	south taranaki
7	Manawatu-Wanganui Region	036	ruapehu
7	Manawatu-Wanganui Region	037	wanganui
7	Manawatu-Wanganui Region	038	rangitikei
7	Manawatu-Wanganui Region	039	manawatu
7	Manawatu-Wanganui Region	040	palmerston north city
7	Manawatu-Wanganui Region	041	tararua
7	Manawatu-Wanganui Region	042	horowhenua
8	Wellington Region	043	kapiti coast
8	Wellington Region	044	porirua city
8	Wellington Region	045	upper hutt city
8	Wellington Region	046	lower hutt city

8	Wellington Region	047	wellington city
8	Wellington Region	048	masterton
8	Wellington Region	050	south wairarapa
9	West Coast/Tasman/Nelson/Marlborough Regions	051	tasman
9	West Coast/Tasman/Nelson/Marlborough Regions	052	nelson city
9	West Coast/Tasman/Nelson/Marlborough Regions	053	marlborough
9	West Coast/Tasman/Nelson/Marlborough Regions	055	buller
9	West Coast/Tasman/Nelson/Marlborough Regions	056	grey
9	West Coast/Tasman/Nelson/Marlborough Regions	057	westland
10	Canterbury Region	058	hurunui
10	Canterbury Region	059	waimakariri
10	Canterbury Region	060	christchurch city
10	Canterbury Region	062	selwyn
10	Canterbury Region	063	ashburton
10	Canterbury Region	064	timaru
10	Canterbury Region	065	mackenzie
10	Canterbury Region	066	waimate
11	Otago Region	068	waitaki
11	Otago Region	069	central otago
11	Otago Region	070	queenstown-lakes
11	Otago Region	071	dunedin city
11	Otago Region	072	clutha
12	Southland Region	073	southland
12	Southland Region	074	gore
12	Southland Region	075	invercargill city

Note: * Excluding TAs are 049 Carterton, 054 Kaikoura and 067 Chatham Islands.