

UNEMPLOYMENT RATE ESTIMATION IN BALI PROVINCE: A SMALL AREA ESTIMATION APPROACH

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Abstract. *Good development and economic growth increase the opportunities for people in the related areas to become more prosperous so that they can become a benchmark for the country's economy. One way that can be used to measure the level of development and economic growth is through microeconomic indicators such as the unemployment rate. Detailed information on the unemployment rate will certainly be a good consideration in the formation of economic policy. The development of estimation methods up to a very small area is very well used to estimate a parameter in a small area where there is not an adequate sample for use in direct estimation. This study discusses the unemployment rate at the sub-district level in Bali Province in 2020 with the result that estimating a small area using the empirical best linear unbiased prediction method gives a smaller mean square error value than the direct estimation method. The results obtained are that East Denpasar District has the largest unemployment rate of 8.49%.*

Keywords: *empirical best linear unbiased prediction, small area estimation, unemployment.*

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1. INTRODUCTION

Economic development and growth is one of the important parameters used as a measure of the success of a government in managing the economy. Basically, economic development can be seen from several economic indicators, both macroeconomics and microeconomics. Macroeconomic indicators that are commonly used as considerations, for example, are inflation and people's welfare which is described by the poverty level. One of the micro-economic indicators used is the unemployment rate. The higher the unemployment rate, the lower the economic development in a region [1] [2]. The more detailed the measurements made, the better the results obtained by an estimation [3] [4]. This study focuses on determining the unemployment rate at the sub-district level in Bali Province.

One method that can be used in various estimations is direct estimation. Direct estimation will give good results as more samples are used. The use of large samples in the case of estimation in a small area would be inefficient considering the large cost and time spent in collecting samples [5] [6]. Therefore, the use of alternative methods such as indirect estimation can be a middle ground for efficiency problems that arise [7] [8].

Reported by the National Research Council [9] [10], the use of estimation methods in small areas (small area estimation) can be used to solve problems in several sectors such as the economy and education so that estimating the unemployment rate at the sub-district level can be done using small area estimation.

Small area estimation is a statistical method or technique used to estimate a population parameter in a small area. Small area is referred to from the foreign term "Small Area" or "Minor Domain" which means an area with an insufficient number of samples for use in direct estimation [11] [12]. The accuracy of the estimation results is highly dependent on the selection of predictor variables that have a high correlation with the parameters to be measured [2] [13]. Small area estimation has three commonly used methods, namely empirical best linear unbiased prediction (EBLUP), empirical Bayes (EB), and hierarchical Bayes (HB) [14] [15] [7].

Bali Province is one of the provinces that is a destination for job seekers because Bali Province is a tourist destination with a fairly promising income. Referring to data from the Central Statistics Agency for Bali Province, in 2019 the percentage of open unemployment in Bali was 1.52%. Availability of information regarding the unemployment rate is found in the national labor force survey (Sakernas) which is carried out twice a year which produces estimates at the provincial and district/city levels but there is no unemployment rate data at the sub-district level [16] [17].

This study discusses the unemployment rate at the sub-district level in Bali Province using the empirical best linear unbiased prediction (EBLUP) method. The advantage of the EBLUP method compared to the other two methods is that this method uses a classical approach which gives fixed results because there are no simulations carried out such as using the Bayes approach [18] [7].

2. RESEARCH METHODS

1. Calculating the estimated unemployment rate in each sub-district in Bali Province and then determining the estimated mean square error (MSE) by direct estimation

$$\hat{\theta}_i = \frac{\sum_{i=1}^n y_i}{n_i} \text{ and } MSE(\hat{\theta}_i) = n\hat{\theta}_i(1 - \hat{\theta}_i) \quad (1)$$

$\hat{\theta}_i$: parameter of the i-th conjecture

y_i : i data value (1 if unemployed and 0 if not unemployed)

n : number of data

i : 1,2, ...

2. Estimating parameters using the method and then determining the estimated mean square error using the jackknife method [19, 20]

3. $\hat{\mu}^H = 1^T \hat{\beta} + m^T v$ (2)

$$\text{with } y = x\hat{\beta} \quad (3)$$

$$\text{and } v = Var(y) \quad (4)$$

$\hat{\mu}^H$: estimated parameter of *empirical best linear unbiased prediction*

y : respond variable vector

m : coefficient of v

$$MSE_{jack}(\hat{\theta}_i^{EBLUP}) = M_{1i} + M_{2i} \tag{5}$$

$$\text{with } M_{1i} = g_{1i}(s_v^2) - \left(\frac{m-1}{m}\right) \sum_{m=1}^j [(g_{1i}(s_{v-1}^2)) - (g_{1i}(s_v^2))] \tag{6}$$

$$\text{and } M_{2i} = \left(\frac{m-1}{m}\right) \sum_{m=1}^j [(\hat{\theta}_{i-1}^{EB}) - (\hat{\theta}_i^{EB})]^2 \tag{7}$$

4. Comparing the estimated mean square error between direct estimation and empirical best linear unbiased prediction

3. RESULTS AND DISCUSSION

3.1. Direct Estimation

The results of the estimates made using the direct estimation method on 100 samples in each sub-district in Bali Province are the unemployment rate (in percent) and the mean square error:

Table 1. Estimation Results with Direct Estimation

Area	$\hat{\theta}_i$	$MSE(\hat{\theta}_i)$	Area	$\hat{\theta}_i$	$MSE(\hat{\theta}_i)$	Area	$\hat{\theta}_i$	$MSE(\hat{\theta}_i)$
NEGARA	5	0,05	KUTA SELATAN	7	0,01	MANGGIS	2	0,04
MENDOYO	5	0,05	KUTA UTARA	6	0,09	KARANGASEM	2	0,04
PEKUTATAN	5	0,05	SUKAWATI	6	0,15	ABANG	3	0,06
MELAYA	5	0,05	BLAHBATUH	7	0,05	BEBANDEM	4	0,16
JEMBRANA	4	0,05	GIANYAR	8	0,05	SELAT	3	0,06
SELEMADEG	4	0,02	TAMPAKSIRING	7	0,05	KUBU	2	0,04
SELEMADEG								
TIMUR	4	0,02	UBUD	7	0,05	GEROKGAK	5	0,02
SELEMADEG								
BARAT	4	0,02	TEGALALANG	7	0,05	SERIRIT	5	0,02
KERAMBITA								
N	4	0,02	PAYANGAN	7	0,05	BUSUNG BIU	5	0,02
TABANAN	4	0,02	NUSA PENIDA	6	0,06	BANJAR	5	0,02
			BANJARANGKA					
KEDIRI	4	0,02	N	5	0,04	SUKASADA	6	0,08
MARGA	3	0,12	KLUNGKUNG	5	0,04	BULELENG	6	0,08
PENEBEL	3	0,12	DAWAN	6	0,06	SAWAN	6	0,08
						KUBUTAMBAHA		
BATURITI	4	0,02	SUSUT	1	0,09	N	6	0,08
PUPUAN	5	0,08	BANGLI	2	0,01	TEJAKULA	6	0,08
						DENPASAR		
KUTA	8	0,11	TEMBUKU	2	0,01	SELATAN	7	0,01
						DENPASAR		
MENGWI	5	0,19	KINTAMANI	2	0,01	TIMUR	9	0,01
						DENPASAR		
ABIANSEMAL	6	0,09	RENDANG	2	0,04	BARAT	9	0,01
						DENPASAR		
PETANG	6	0,09	SIDEMEN	1	0,14	UTARA	8	0,01

In general, direct estimation with a sample of 100 households shows that East Denpasar and West Denpasar sub-districts have the largest unemployment rate at 9% while Mangosteen and Kubu sub-districts have the smallest 2%.

3.2. Undirect Estimation with Empirical Best Linear Unbiased Prediction

The results of the conjecture carried out using the empirical best linear unbiased prediction method in each sub-district in the Province of Bali in the form of the unemployment rate (in percent) and the mean square error, namely:

Table 2. Estimation results with empirical best linear unbiased prediction

Area	$\hat{\theta}_t^{EBLUP}$	$MSE(\hat{\theta}_t^{EBLUP})$	Area	$\hat{\theta}_t^{EBLUP}$	$MSE(\hat{\theta}_t^{EBLUP})$
NEGARA	4,61	0,01	BANJARANGKAN	5,65	0,02
MENDOYO	4,83	0,03	KLUNGKUNG	4,78	0,03
PEKUTATAN	4,94	0,04	DAWAN	5,67	0,02
MELAYA	4,32	0,02	SUSUT	1,74	0,01
JEMBRANA	4,49	0,01	BANGLI	2,15	0,01
SELEMADEG	4,48	0,02	TEMBUKU	2,40	0,01
SELEMADEG					
TIMUR	4,51	0,02	KINTAMANI	2,13	0,01
SELEMADEG					
BARAT	4,29	0,01	RENDANG	2,44	0,01
KERAMBITAN	4,14	0,01	SIDEMEN	1,33	0,11
TABANAN	4,06	0,02	MANGGIS	1,95	0,03
KEDIRI	4,03	0,02	KARANGASEM	2,18	0,02
MARGA	3,46	0,07	ABANG	3,00	0,06
PENEBEL	3,46	0,07	BEBANDEM	3,68	0,13
BATURITI	3,70	0,01	SELAT	2,75	0,03
PUPUAN	4,72	0,05	KUBU	2,20	0,02
KUTA	7,60	0,07	GEROKGAK	5,41	0,01
MENGWI	5,37	0,16	SERIRIT	5,15	0,01
ABIANSEMAL	6,20	0,07	BUSUNG BIU	5,00	0,01
PETANG	6,48	0,04	BANJAR	5,27	0,01
KUTA					
SELATAN	7,17	0,01	SUKASADA	5,41	0,02
KUTA UTARA	6,28	0,06	BULELENG	5,84	0,07
SUKAWATI	6,43	0,11	SAWAN	6,19	0,07
BLAHBATUH	7,00	0,04	KUBUTAMBAHAN	5,64	0,05
GIANYAR	8,02	0,04	TEJAKULA	5,57	0,04
			DENPASAR		
TAMPAKSIRING	7,42	0,01	SELATAN	8,17	0,01
			DENPASAR		
UBUD	7,47	0,01	TIMUR	8,49	0,01
			DENPASAR		
TEGALALANG	7,24	0,03	BARAT	8,45	0,01
			DENPASAR		
PAYANGAN	7,20	0,03	UTARA	8,34	0,01
NUSA PENIDA	5,71	0,03			

Indirect estimation of small area estimation using empirical best linear and Jackknife methods shows that the unemployment rate in Bali Province varies from 1.33% to 8.49% with the largest value being in East Denpasar district, namely 8.49%.

Overall, indirect estimation in a small area (small area estimation) by giving the mean square error value (Mean Square Error) which is smaller than direct estimation. This estimate is better for very small area levels. Estimation using direct estimation will give a biased value because the number of samples is very small and cannot represent the entire population.

4. CONCLUSIONS

Small area estimation using empirical best linear unbiased prediction and Jackknife methods gives a mean square error value which is smaller than direct estimation because direct estimation gives bias values due to The number of samples is very small and is not able to represent the entire population. Using small area estimation, it is known that the unemployment rate at the sub-district level in Bali Province ranges from 1.74% to 8.49% or it can be interpreted that there are at most 8 unemployed at the sub-district level in Bali Province. The calculation error that occurs varies from 0.01 to 0.16 which is smaller than using the direct estimation method.

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