\[ \hat{M}_i = g_i(\hat{\beta}_i \hat{\alpha}_i) \frac{m-1}{m} \sum_{j=1}^{m-1} g_j(\hat{\beta}_j, \hat{\alpha}_j) - g_i(\hat{\beta}_i, \hat{\alpha}_i) \]

And \( g_i(\hat{\sigma}_i^2) \) is the variance estimator of posterior distribution which is used to measure the variability associated with \( \theta_i \). The use of \( g_i(\hat{\sigma}_i^2) \) leads to severe of underestimation of \( \text{MSE}(\hat{\theta}_i^{EB}) \) related with estimation in prior parameter. Therefore, the estimator \( \hat{M}_i \) correct the bias of \( g_i(\hat{\sigma}_i^2) \).

3. Calculate the jackknife estimator of \( \text{MSE}(\hat{\theta}_i^{EB}) \) as:
\[
\text{MSE}_j(\hat{\theta}_i^{EB}) = \hat{M}_{ii} + \hat{M}_{ij}
\]

\section*{METHODOLOGY}

\section*{Data}

This research assumed that the available auxiliary data is on area level, so this research used basic area level model. The data were simulated with 30 small areas and one covariate. Every batch generated different conditions of excess-zeros data, start from 0.1 until 0.9 probability of zero in small area. This research assumed structure of relation between respond and covariate was linear.

\section*{Methods}

The following steps in generating data using SAS 9.1 were used:
1. Fix the value of \( X_i \), for the \( i \)-th area
2. Define the expected probability of zero in each small area \( P(Y_i = 0) \), then calculate: \( \text{Lambda}_i = -\log(P(Y_i = 0)) \)
3. Generate : \( \theta_i \sim \text{Gamma}(1,1) \)
4. Calculate : \( \hat{\chi}_i = \log(\text{Lambda}_i, /\theta_i) \)
5. Fit linear regression between \( \hat{\chi}_i \) and \( X_i \) to obtain \( \hat{\beta}_i \) and \( \hat{\beta}_i \)
6. Calculate : \( \mu_i = \exp(X_i /\beta) \)
7. Calculate: \( \text{parmlambda} = \mu_i \times \theta_i \)
8. Generate : \( y_i \sim \text{Poisson}(\text{parmlambda}) \)

Moreover, in analyzing data the following steps were applied:
2. Estimate the prior parameter, which are \( \beta \) and \( \alpha \)
3. Estimate using EB method.
4. Calculate \( \text{MSE} \) for indirect estimation.
5. Calculate \( \text{RRMSE} \) (Root Relative Mean Square Error):
\[
\text{RRMSE}(\hat{\theta}_i) = \frac{\sqrt{\text{MSE}(\hat{\theta}_i)}}{\hat{\theta}_i}
\]

\section*{RESULT AND DISCUSSION}

\subsection*{Estimation of Prior Parameter is Based on EB Method with Negative Binomial Regression}

In case of non-excess-zero data, the estimator produced small and consistent MSE. Meanwhile, if the number of excess-zero is approximately 30% or more with expected probability of zero 0.6, the performance of estimates tends to be unreliable. As a result, EB estimation produced negative values.

\( \text{RRMSE} \) of the estimator increases simultaneously along with the increase of number of zero in the data. Furthermore, if the data contain excess zero at least 30%, the estimator is unreliable.

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|c|}
\hline
\text{Probability of zero} & \text{Mean of MSE} & \text{Median of MSE} & \text{Mean of RRMSE} & \text{Median of RRMSE} \\
\hline
0.1 & 0.33 & 0.16 & 0.18 & 0.13 \\
0.2 & 0.35 & 0.20 & 0.26 & 0.20 \\
0.3 & 0.40 & 0.23 & 0.36 & 0.30 \\
0.4 & 0.42 & 0.27 & 0.50 & 0.42 \\
0.5 & 0.45 & 0.31 & 0.72 & 0.59 \\
0.6 & -128.75 & 0.33 & -0.38 & 0.81 \\
0.7 & 2536.71 & 0.40 & -12.16 & 1.35 \\
0.8 & -584495 & 0.30 & 309.46 & 2.11 \\
0.9 & 39135606 & 0.16 & 1.16E+10 & 6.64 \\
\hline
\end{tabular}
\caption{MSE and RRMSE of EB Estimator with NBR}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|c|}
\hline
\text{Probability of zero} & \text{Mean of MSE} & \text{Median of MSE} & \text{Mean of RRMSE} & \text{Median of RRMSE} \\
\hline
0.1 & 0.33 & 0.16 & 0.18 & 0.13 \\
0.2 & 0.35 & 0.20 & 0.26 & 0.20 \\
0.3 & 0.40 & 0.23 & 0.36 & 0.30 \\
0.4 & 0.42 & 0.27 & 0.50 & 0.42 \\
0.5 & 0.46 & 0.31 & 0.71 & 0.58 \\
0.6 & 261.97 & 0.33 & -0.35 & 0.75 \\
0.7 & 2536.71 & 0.40 & -12.16 & 1.35 \\
0.8 & -584495 & 0.30 & 309.46 & 2.11 \\
0.9 & 39135606 & 0.16 & 1.16E+10 & 6.64 \\
\hline
\end{tabular}
\caption{MSE (II) and RRMSE (II) of EB Estimator with NBR}
\end{table}