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Urban and Rural Slums: An Exploratory Analysis of Slums Formation in Indonesia

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ABSTRACT

Slums are growing. New slums are forming. Characterized by low service provision, poor shelter and lacking in security of tenure, they located in urban and rural areas alike. This article follows a quantitative methodology to explore factors contribute to the formation of slums in urban and rural areas in Indonesia. Data published by BPS-Statistics Indonesia used for this exploration. The proportion of slum households by province in 2019 is used as the dependent variable. The explanatory variables include poverty gap index, poverty severity index, Gini ratio, gross domestic regional product at current price, head count index and percentage of urban population. Since the dependent variable assumes values in proportions and beta-distributed, beta regression is used using betareg function from betareg package implemented in open source R-program. Analysis of the data has found that all proposed explanatory variables are not statistically significant. Discussion provided relating strategies in doing quantitative research in Indonesia.

Keywords: slums; beta regression; urban; rural.

1. INTRODUCTION:

Slums represent disadvantaged communities where people living under substandard housing and living conditions. Such conditions that exist in slums affect their residents such as frequent physical threat from natural disasters and violent (Napier, 2007). The residents usually have neither adequate education nor skills make them prone to unemployment and low economic conditions. Consequently their capacity to recover from disasters/threats/violent is low (Ajibade & McBean, 2014; Ebert, Kerle, & Stein, 2009).

The lack of basic services among slum households make them consumed polluted water and air. Moreover, they also contaminate water and soil. Thus, slums have depressing effects on both humans and the environment. This perpetuates a declining cycle of quality for both slum dwellers and the environment. Therefore, the expansion of slums could present danger to sustainable development at local, national and regional scales (Patel, Crooks, & Koizumi, 2012).

This paper presents statistical models to explore on factors contribute to slums formation using publicly available data. This paper also reports the results of the statistical analysis and the challenge of doing quantitative approach in understanding the existence and growth of slum households in Indonesia.

2. FACTORS CONTRIBUTE TO SLUMS FORMATION

Slums grow rapidly in many different places for several reasons. Various economic factors are associated with the slums' growth. These factors include economic condition, high unemployment rates, the depth and severity of poverty, urbanization exacerbated with weak urban planning, political interest, natural disasters (Goussous & Tayoun, 2020) and social conflict (Patton, 1998). Mahabir, Crooks, Croitoru, & Agouris (2016) contended that location factors, urbanization, poor urban governance and ill-designed policies contribute to slums formation.

2.1 Location factors

Due to the low of economic condition of slum households, several locations become the typical location of slum dwellers including as river banks, steep slopes or dumping grounds (Ajibade & McBean, 2014; Praharaj, 2013; Sietchiping, 2004). In Indonesia such as Jakarta or Surabaya slums are also notoriously known for building on marginal areas such as riverbanks, underbridges, or steep slopes.

2.4 Poverty and a lack of economic growth

As far as African countries being concerned, the growth and persistence of slums are common (Fox, 2012). With the growth of their population, the demand for housing increases as well. However, the non-affordability of housing contributes to formation of slum formation. Moreover, slums is associated with the persistence of global poverty (U.N. Habitat, 2016).

2.5 Population growth

Majority of urban growth happens in emerging economies. This is due to their average annual population growth rate four times higher than those of more developed countries. Slums emerge and continue to spread rapidly for these emerging economies are unable to adequately meet the needs of their growing populations, (Mahabir et al., 2016).

2.6 Urbanization

Many scholars such as (Malecki & Ewers, 2007; Srivastava & Singh, 1996; Turok, 2015) contend that factors contribute to the growth of slums around urban areas are rural-to-urban migration, high birth rate compare with the unavailability of social structures to absorb the pace of such rapid population growth.

The world population is urbanizing very quickly. With the current rate of urbanization in emerging countries, it is estimated that one third of the urban population are poor with many living in informal settlements (U.N. Habitat, 2016).

Interestingly, in developing countries the rapid movement of the rural population to urban spaces has intensified. The drivers of this movement include those related to the "incentive" for rural people to move to cities and those pertaining to poor rural conditions that push population away from rural areas.

Whichever is the factor, the impacts are overwhelming to the urban areas not ready to support the incoming population. With no alternatives, people chose slums for their basic housing needs (Vasudevan, 2015).

3. METHOD

3.1 Data

In this paper, slum household data for 34 provinces in 2019 taken from Statistics Indonesia (BPS). The dependent variable is the proportion of slum households per province. This paper only includes economic variables which are published by BPS as explanatory variables:

1. Poverty gap index (pgi): An index to measure the expenditure discrepancy of poor people towards the poverty line.
2. Proverty severity index (psi): An index to describe the distribution of expenditure among poor people.
3. Gross domestic regional bruto (gdpr_grwth) per province at current price.
4. Head count index (hci): An index to calculate the proportion of people living below the poverty line.
5. Percentage of urban population by province (pct_pop)

3.2 Model Specification and Statistical Analysis

Slumps data published by BPS is binary proportion noted in terms of a single category (proportion of slums households), with the complementary category (non-slump households) implied (e.g. non-cover).

Statistical analysis of proportions data can introduce some difficulties. By definition, the observations range between 0 and 1. Consequently, the variability in the observed proportions varies systematically with the mean of the response.

With these properties, the data will likely violate two important assumptions of standard statistical techniques: the normality of error term and the constancy of variance. Therefore, the standard techniques of statistical analysis are usually not appropriate for proportions data.

To assess factors that contribute to slumps formation, we modelled the dependent variable—the proportion of slump households—using beta regression with a logit link function, an extension of generalized linear modeling (Ferrari & Cribari-Neto, 2004), implemented in R (R Core Team, 2021) in the 'betareg' package (Cribari-Neto F. & Zeileis A., 2010). This analysis method is robust to heteroscedasticity and according to (Douma & Weedon, 2019), for proportional observation derived from continuous numbers with two categories, the most commonly used packages is betareg.

We used a beta regression model with a logit link for the mean as below. The interest lies in modelling how the proportion of slums household explained by five explanatory variables. Data and R codes can be found in the supplementary section of this paper.

```
slums_rur <- betareg (slums_rur ~ pgi_rur + psi_rur + gdpr_grwth + hci_rur, data = slums)   (1)

slums_urb <- betareg (slums_urb ~ pgi_urb + psi_urb + gdpr_grwth + hci_urb, data = slums)   (2)
```

Note: rur= rural, urb=urban

4. RESULTS

4.1. Descriptive Statistics

Descriptive statistics of the variables used in our model are given in Table 1.

Table 1. Descriptive statistics of the variables used in model

stat	slums_urb	slums_rur	pgi_urb	pgi_rur	psi_urb	psi_rur	gdpr	gini_ur	gini_ru	hci_urb	hci_rur
Min	0.01690	0.0378	0.3700	0.555	0.0600	0.1050	2.660	0.2760	0.2265	2.915	4.870
Med	0.06520	0.1252	0.8500	1.655	0.1900	0.4100	5.465	0.3533	0.2965	5.758	11.440
Mean	0.07253	0.1521	1.0531	2.403	0.2378	0.6508	5.588	0.3564	0.3075	6.769	13.265
Max	0.23590	0.5548	2.3350	9.065	0.5550	3.1950	15.720	0.4440	0.4180	15.295	36.100
Obs	34	33	34	33	34	33	34	34	33	34	33

The parameter estimates for rural and urban areas are given in Table 2 and 3 respectively. An inspection of values in Table 1 and 2 reveals that none of covariates for both rural and urban model are statistically significant at the 5% levels except the intercept where in this case it has no meaningful interpretation.

Table 2. Parameter estimates for rural areas

```
## Coefficients (mean model with logit link):
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.67075    0.35665  -7.488 6.97e-14 ***
## pgi_rur     -0.89310    1.19951  -0.745    0.457
## psi_rur      1.65658    2.11779   0.782    0.434
## gdpr_grwth   0.07698    0.04754   1.619    0.105
## hci_rur      0.11705    0.13432   0.871    0.384
##
## Phi coefficients (precision model with identity link):
##       Estimate Std. Error z value Pr(>|z|)
## (phi)   23.653      5.814   4.068 4.74e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Type of estimator: ML (maximum likelihood)
## Log-likelihood: 42.57 on 6 Df
## Pseudo R-squared: 0.2575
## Number of iterations: 40 (BFGS) + 5 (Fisher scoring)
```

Table 3. Parameter estimates for urban areas

```
## Coefficients (mean model with logit link):
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.50946    0.35692  -7.031 2.05e-12 ***
## pgi_urb      2.33954    2.82584   0.828    0.408
## psi_urb     -5.72602    6.78847  -0.843    0.399
## gdpr_grwth   0.01583    0.04288   0.369    0.712
## hci_urb     -0.18167    0.23563  -0.771    0.441
##
## Phi coefficients (precision model with identity link):
##       Estimate Std. Error z value Pr(>|z|)
## (phi)    47.01      11.55   4.069 4.72e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Type of estimator: ML (maximum likelihood)
## Log-likelihood: 66.35 on 6 Df
## Pseudo R-squared: 0.02417
## Number of iterations: 53 (BFGS) + 5 (Fisher scoring)
```

5. DISCUSSION

The present of slums is enduring issues. Ironically, with such enduring presence, yet, there is no agreed-upon definition for what a slum is (Gilbert, 2011; Richter et al., 2011). Likewise, there is no consensus on what scale to study slums.

There are varied official and unofficial descriptions of slums depending on what issues or the location covered. In some places in Africa (Nairobi) and Latin America (Mexico City) for example, slums are defined subjectivity.

In this study slums are defined by on Indonesian Statistics as households that do not have access to adequate drinking water sources, do not have access to proper sanitation, do not have access to floor area> = 7, 2 m^2 per capita, do not have access to adequate roof, floor and wall conditions. The data were collected at province level.

BPS definition is in accordance with (U.N. Habitat, 2016) definition. In this case a slum household is categorized from one of the following criteria: (i) Limited access to a healthy water source, (ii) Limited access to good sanitation facilities, (iii) Inadequate living area, (iv) Lack of housing durability, and (v) An absent of security of tenure.

While the definition used by BPS is quite comprehensive, BPS uses traditional methods in collecting data on slums households. To detect the present of slums, traditional methods uses census data. Such methods collect information through surveys to infer deprivation or map poverty. While these the methods are readily available for most countries when compared with other forms of data. However, census data is problematic when used to detect slums

The source of BPS data is aggregated from census. This census data is available to at coarse spatial scales, dismissing the heterogeneity and uniqueness of each territory, which may hide the presence of slums.

It is thus difficult to link survey data collected on small populations with regional level data such as province. With these issues in hand, relying only on census data supply only limited spatial and temporally disaggregated information needed to inform more comprehensive slum assessments (Mahabir et al., 2016).

This problem is exacerbated with weak quality control during data collection in some developing countries, resulting in low confidence in datasets collected (Henderson, Storeygard, & Weil, 2012). Furthermore, the inadequacy of information infrastructure necessary for managing slum information hinder the use of data collected optimally.

6. LIMITATIONS

Some factors which is crucial in the formation of slums households are not included in this paper due to lack of data such as forced eviction. For those who are interested in using quantitative approach may try to use panel data covering 34 provinces for several years. BPS regularly publishes data the proportions of slum household at province level. However, currently betareg function does not accommodate panel data. Thus, researchers must rely on customized codes. Moreover, slums should be viewed from multidisciplinary approaches, to ensure a more holistic and systematic assessment of its presence, development and growth (Mahabir et al., 2016).

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