The impact of natural disasters in Indonesia: How does welfare accentuate and attenuate the loss of people?

A P S Prasojo*, G A K Surtiari and P Prasetyoputra

Research Center for Population, Indonesian Institute of Sciences, Jl. Jend. Gatot Subroto Kav. 10, Jakarta 12710, Indonesia

*arip002@lipi.go.id

Abstract. The increasing number of disasters in Indonesia exerts significant economic loss and human casualties, whereas Indonesia has focused on disaster risk reduction. Recent studies are lacking to explore how economic growth influences the impact of disasters. This paper aims to seek a deeper understanding of how welfare that represented by the human development index influences the impact of disaster on the people. We implement the concept of welfare and risk reduction as an approach to analyze disaster and welfare data with a focus on flood events in 2008-2018. We obtained the data from BNPB and Statistics Indonesia. We fitted a multivariable negative binomial regression with ‘human losses from deaths’ as the outcome and provincial Human Development Index (HDI) and provincial gross domestic product (GDP). The results suggest that Provincial HDI is negatively significant associated with human losses from deaths. However, GDP was also found to be positively significant associated, albeit less strongly, with human losses from deaths. These associations bring about potentially significant policy implications.

1. Introduction

Indonesia, one of the largest archipelagic countries in the world, is facing a high risk of both natural and climate-related disasters [1]. In the last ten years, the number of extreme events followed by the number of loss and death toll has increased significantly [2]. There are at least 117 earthquakes in 2018-2019, including the most extreme one earthquake in Lombok, Nusa Tenggara Barat (NTB), followed by an earthquake to trigger a tsunami in Central Sulawesi. Drought and extreme floods and flash floods have also continuously occurred across Indonesia [2]. The Indonesian National Board for Disaster Management (BNPB) officially recorded that more than 26 million people have been evacuated, and more than 7000 people have died during the last ten years instead of significant economic loss. In 2019, for instance, a series of disasters had caused 80 trillion of economic loss [3].

Scholars and risk practitioners have questioned why the devastating impact is significantly high even though the Government of Indonesia (GoI) has focused on disaster risk management [4-6]. On a global scale, there are intensive studies on seeking relation between the impact of disaster and preparedness of exposed areas. For instance, the catastrophe caused by Earthquake and Haiti and Tsunami in Japan can be an example of how impact can emerge within the extreme events. Haiti experienced a significant human and economic loss compared with Japan, even though the magnitude of extreme events is higher in Japan. The level of welfare was found to influence the economic loss and death toll [7,8]. In contrast, the economic growth of developed areas also triggers fatalities regarding the disaster. Cities are at high...
risk because most of the accumulation of built environments such as construction and vital infrastructure [9,10]. The number of vital infrastructures that have tremendous economic values will cause significant economic loss in addition to its cascading impact on the people. For example, termination of electricity during a disaster will impact all activities both at the household level up to the regional scale. It furthermore led to the problem in the health care provision and to secure food supply.

The recent studies on the impact of disasters tend to focus on the vulnerability assessment by proposing economic growth as one of the instruments to reduce risk. However, based on evidence of disasters in Indonesia, we argue that understanding the contribution of economic growth to more frequent disasters is also essential. Also, social capital has been revealed to overcome the severe impact instead of economic condition [11-14]. In the context of Indonesia, social capital has proved to save lives through implementing local knowledge and optimize mutual assistance (gotong royong) to support each other to respond to disaster [6,15].

The question is on how welfare and economic growth will influence the number of human casualties. The number of the loss of people is selected as an outcome to represent the robustness of disaster preparedness. Against the background above, it is crucial to examine whether welfare will accentuate or attenuate the impact of disaster; thus, we could manage risk appropriately. Therefore, this paper is aiming at finding the correlation between welfare and the impact of a disaster. We utilize two types of secondary data, namely the Human Development Index of Indonesia and the number of disasters that are taken from online data of Statistics Indonesia and the National Disaster Management Authority. The count data regression is the main approach in the data analysis.

The remainder of the paper is as follows. Section 2 outlines the method used in this paper. Section 3 presents the main empirical findings and discusses them. Section 4 then concludes the paper. The result of the analysis is important to complement current disaster management in Indonesia, specifically to enhance the effort to increase disaster preparedness such as to develop contingency plans.

2. Methods

2.1. Data source
This paper examines the link between welfare and loss caused by natural disasters at the provincial level in Indonesia. We obtained the data from two sources. First is the Indonesian Disaster Data and Information Database (Data dan Informasi Bencana Indonesia - DIBI) of the Indonesian National Board for Disaster Management (Badan Nasional Penanggulangan Bencana - BNPB; retrieved from <http://dibi.bnpb.go.id/>). For this article, we focused on flood events that occurred from 2008 to 2018. Flood events have served as our case analysis because flood is the most frequent disaster and occurred across Indonesia. We obtained data on the number of deaths attributable to floods. Another source of the data is Statistics Indonesia (Badan Pusat Statistik - BPS; retrieved from <https://www.bps.go.id/>) from which we obtained provincial-level gross domestic product and human development index.

2.2. Variables
The main outcome variable is ‘human losses from deaths,’ particularly annual average of human losses (DL), which calculated using total deaths divide by number of years that flood occurrence with human deaths (rounded to integer). While the independent variables comprise provincial-level gross domestic product (GDP) and human development index (HDI) in 2018 as proxy of economic and welfare condition, respectively.

2.3. Regression analysis
As the outcome variable is count data, there are several choices of regression models, such as poisson, zero-inflated, and negative binomial regression models [16]. However, we opt to employ negative binomial regression due to overdispersion when using the poisson regression model. Overdispersion in poisson model was diagnostic using dispersion statistics based on pearson residual [17]. The model fitted based on probability density which formulated in (1) with conditional mean and conditional
variance in (2). Where $\alpha$ is dispersion parameter, and $\beta_0, \beta_1, \beta_2$ are regression parameter, while province indices were represented by $i(i = 1, 2, ..., 34)$.

$$f(DL_i|HDI_i, \text{Ln}_GDP_i) = \frac{\Gamma(DL_i + \alpha^{-1})}{DL_i!\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}}^{\alpha^{-1}}^{\mu_i}, DL_i = 0, 1, 2, ..., (1)$$

$$E(DL_i|HDI_i, \text{Ln}_GDP_i) = \mu_i = \exp(\beta_0 + \beta_1HD_i + \beta_2 \text{Ln}_GDP)$$

$$\text{Var}(DL_i|HDI_i, \text{Ln}_GDP_i) = \mu_i (1 + \alpha \mu_i)$$

The regression parameter was estimated using maximum likelihood method. We used 5% significance level for statistical inference. All of the data analyses were processed using R statistical software, mainly using ‘MASS’, ‘msme’, ‘lmtest’ library [18-20]. R programming code to aid with regression analysis available at: https://github.com/aripurwantosp/humlossesdeaths.

3. Results and discussion

3.1. Regression results

Table 1 presents the negative binomial regression results for the relationship between provincial-level GDP, Provincial HDI, and human losses from deaths. Two independent variables were both found to be significantly associated with human losses from deaths, albeit with different strengths. Both HDI and GDP were significant at the 5% level.

| Coefficients | Likelihood ratio test | Dispersion |
|--------------|-----------------------|------------|
| Intercept    | HDI                   | Ln_GDP     | Prob(>Chisq) |
| Estimate     | 8.3435                | -0.1530    | 0.3653       | 0.0032 | \textsuperscript{a}1.6279 |
| Standard error | 2.7480               | 0.0436     | 0.1460       |        | \textsuperscript{b}14.7414 |
| Wald statistic (z) | 3.0360          | -3.5090    | 2.5020       |        |
| Prob (>|z|)   | 0.0024                | 0.0004     | 0.0123       |        |

Notes: \textsuperscript{a}dispersion parameter for binomial negative regression model; \textsuperscript{b}dispersion statistics when data fitted to poisson regression model.

3.2. Discussion

The objective of this paper is to examine how welfare and economic growth influence the impact of disasters, with a focus on the number of people losses. This paper explores whether welfare will accentuate or attenuate the number of victims.

The regression model suggests that both provincial GDP and HDI are significantly associated with human losses from deaths. The higher provincial income corresponds to higher human losses from deaths. However, increases in HDI corresponds with lower human losses from deaths. This result shows an interesting finding. In general, the capacity to respond to disasters in Indonesia is dominated by economic factors. Well-developed regions potentially as the most affected while human development such better education and health levels could reduce the number of people losses.

Our finding shows a new insight in comparison with recent studies that highlight the loss of people will dominate in lower economic growth regions. However, our analysis reveals that fatalities are found...
in the areas with better economic growth or in the welfare society. This result shows that economic growth is a contributor to the high risk of disaster [21,22]. Well-developed regions, for instance, could be the most susceptible to the natural hazard due to the concentration of population and high-density assets together with functioning as the center of socio-economic activities [23,24]. Those regions are severely affected due to the sizeable economic exposure to hazards. The infrastructure that has been built can cause multiple impacts, for instance, the leak of dyke, dams, and buildings [22]. Therefore, better socio-economic conditions could fail to avoid economic loss and also the death of people without adaptive risk management [25].

In terms of welfare represented by HDI, our finding shows that the level of the economic condition of a region that represented by GDP could represent the capacity to prepare, respond and recover after a disaster [26-28]. Disaster preparedness is vital to avoid fatalities, including loss of people [29]. Capacity to prepare, for instance, installing an early warning system to tsunami and flood has proved to reduce the number of loss of people [30]. It can happen under better education and awareness. The level of education has to be at all levels, from the government officers until the communities. In the case of early warning, for instance, not only a formal early warning system provided by the government but community-based early warning also significantly to avoid fatalities [30].

Moreover, intensive studies show that level of vulnerability which is sketched by socio-economic condition, contributes to the impact of an extreme event. In general, welfare could contribute to a less vulnerable level of society [31,32]. Stronger economic condition before the disaster strike is found to reduce the region's economic losses [33]. They argue that the current socio-economic condition combined with social capital, will effectively build disaster resilience. By comparing developed and developing countries, it is said that the latter will be seven times more affected than the former [25]. A study on the economic impact of natural disasters shows that developing countries are stronger compared with developed countries [34]. Based on that evidence, many almost all vulnerable regions stimulate the developing risk financing mechanism, such as insurance [34].

3.3. Study limitations

There are several limitations in this paper—first, natural disaster which analyzed only floods. Second, analysis based on time periods is calculated in the aggregated. Suggestions for future research are to examine the impact of other types of natural disasters and examine them using panel data approach.

4. Conclusion

This paper addresses the correlation between welfare and the number of disasters followed by the impact on the loss of people in Indonesia. We used GDP and HDI as indicators of welfare. We fitted multivariable negative binomial regression model to the data obtained from several national agencies. Our study confirms that the level of welfare that is represented by HDI will lead to a lower impact of disasters. Moreover, higher socio-economic development could avoid fatalistic loss [35]. Their study on economic development and natural disasters shows that better income, better educational attainment, and also good governance in the financial system have proven to reduce losses. The HDI is one of the aspects to describe the level of welfare of a country or a province. It consists of education attainment, health quality that is represented by life expectancy, and a decent life that is expressed through expenditure. Based on those indicators, it assumes that susceptibility could be lower while the capacity to respond to risk is high; hence society is low vulnerable to disaster. However, we note that community initiatives must be considered to combine with our findings.

Acknowledgments

We would like to thank Statistics Indonesia and the Indonesian National Board for Disaster Management for providing access to the data required in this study.
References

[1] Djalante R, Garschagen M, Thomalla F and Shaw R 2017 *Disaster Risk Reduction in Indonesia: Progress, Challenges, and Issues*, ed R Djalante, et al. (Cham: Springer International Publishing) pp 1-17

[2] BNPB 2020 UPDATE: Rekapitulasi Data Bencana di Indonesia per 21 Januari 2020. BNPB Editorial (Jakarta: Badan Nasional Penanggulangan Bencana (BNPB))

[3] BNPB 2019 Data Informasi Bencana Indonesia (DIBI) (Jakarta: Badan Nasional Penanggulangan Bencana (BNPB))

[4] Djalante R and Garschagen M 2017 *Disaster Risk Reduction in Indonesia: Progress, Challenges, and Issues*, ed R Djalante, et al. (Cham: Springer International Publishing) pp 21-56

[5] Surtiari G A K, Hidayati D, Alihar F, Hidayati I, Dalimunthe S A, Putri I A P, Katherina L K, Abdurrahim A Y, Pradipta L, Kusumaningrum D, Hastuti P and Prasojo A P S 2019 *Laporan Kaji Cepat Penanganan Pasca Bencana Di Palu, Sigi dan Donggala: Pemulihan Tempat Tinggal dan Penghidupan* (Jakarta: Pusat Penelitian Kependudukan LIPI)

[6] Surtiari G A K, Djalante R, Setiadi N J and Garschagen M 2017 *Disaster Risk Reduction in Indonesia: Progress, Challenges, and Issues*, ed R Djalante, et al. (Cham: Springer International Publishing) pp 469-93

[7] Birkmann J ed 2013 *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies* (Bonn: United Nations University Press)

[8] Pelling M 2011 *Adaptation to Climate Change: From Resilience to Transformation* (London and New York: Routledge)

[9] Vigué V, Hallegatte S and Rozenberg J 2014 Downscaling long term socio-economic scenarios at city scale: A case study on Paris *Technological Forecasting and Social Change* 87 305-24

[10] Garschagen M and Sandholz S 2017 Linking critical infrastructure resilience to social vulnerability through minimum supply concepts: review of gaps and development of an integrative framework *Natural Hazards and Earth System Sciences Discussions* 1 20

[11] Al-Nammari F and Alzaghal M 2015 Towards local disaster risk reduction in developing countries: Challenges from Jordan *International Journal of Disaster Risk Reduction* 12 34-41

[12] Parsons M, Glavac S, Hastings P, Marshall G, McNeight J, McNeill J, Morley P, Reeve I and Stayner R 2016 Top-down assessment of disaster resilience: A conceptual framework using coping and adaptive capacities *International Journal of Disaster Risk Reduction* 19 1-11

[13] Bott L-M and Braun B 2019 How do households respond to coastal hazards? A framework for accommodating strategies using the example of Semarang Bay, Indonesia *International Journal of Disaster Risk Reduction* 37 101177

[14] James H 2012 Social capital, resilience and transformation among vulnerable groups in the Burmese Delta after Cyclone Nargis. Paper presented at the Demographic Consequences of Asian Disasters: Family Dynamics, Social Capital and Migration Patterns, Canberra, Australia.

[15] Kusumasari B and Alam Q 2012 Local wisdom-based disaster recovery model in Indonesia *Disaster Prevention and Management: An International Journal* 21 351-69

[16] Long J S and Freese J 2014 *Regression Models for Categorical Dependent Variables using Stata* (College Station Stata Press)

[17] Hilbe J M 2014 *Modeling Count Data* (New York: Cambridge University Press)

[18] Venables W N and Ripley B D 2002 *Modern Applied Statistics with S* (New York: Springer)

[19] Zeileis A and Hothorn T 2002 Diagnostic Checking in Regression Relationships *R News* 2 7-10

[20] Hilbe J M and Robinson A 2018 *msme: Functions and Datasets for "Methods of Statistical Model Estimation"*. R package version 0.5.3.

[21] Pelling M 2003 *The Vulnerability of Cities: Natural Disasters and Sociai Resilience* (UK and USA: Earthscan Publications Ltd)
[22] Sawada Y and Oum S 2012 *Economic and Welfare Impacts of Disasters in East Asia and Policy Responses* (Jakarta, Indonesia: Economic Research Institute for ASEAN and East Asia (ERIA))

[23] Gencer E A 2013 *The Interplay between Urban Development, Vulnerability, and Risk Management* (New York: Springer)

[24] Botzen W J W, Deschenes O and Sanders M 2019 The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies *Review of Environmental Economics and Policy* 13 167-88

[25] Gu D 2019 Exposure and vulnerability to natural disasters for world's cities 1–43

[26] Cazabat C 2017 Human security and natural disasters

[27] Guha-Sapir D and Santos I eds 2013 *The Economic Impacts of Natural Disasters* (New York, NY: Oxford University Press)

[28] Hayat E and Amaratunga D 2014 The Impact of the Local Political and Socio-Economic Condition to the Capacity of the Local Governments in the Maintenance of Post-Disaster Road Infrastructure Reconstruction Assets *Procedia Economics and Finance* 18 718-26

[29] Hallegatte S 2015 The Indirect Cost of Natural Disasters and an Economic Definition of Macroeconomic Resilience. Policy Research Working Paper; No. 7357 (Washington, DC: World Bank)

[30] Collins Matthew L and Kapucu N 2008 Early warning systems and disaster preparedness and response in local government *Disaster Prevention and Management: An International Journal* 17 587-600

[31] Padli J, Shah Habibullah M and Baharom A H 2010 Economic impact of natural disasters' fatalities *International Journal of Social Economics* 37 429-41

[32] UNISDR 2009 UNISDR Terminology on Disaster Risk Reduction *International Strategy for Disaster Reduction (ISDR)* 1–30.

[33] Kim H and Marcouiller D W 2016 Natural Disaster Response, Community Resilience, and Economic Capacity: A Case Study of Coastal Florida *Society & Natural Resources* 29 981-97

[34] Panwar V and Sen S 2018 Economic Impact of Natural Disasters: An Empirical Re-examination *Margin: The Journal of Applied Economic Research* 13 109-39

[35] Toya H and Skidmore M 2007 Economic development and the impacts of natural disasters *Economics Letters* 94 20-5