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SOCIAL AND ECONOMIC IMPACTS OF THE DISASTER-RESILIENT VILLAGE PROGRAM WITH BAYESIAN DECISION-MAKING

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ABSTRACT

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This study evaluates the social and economic impacts of the Disaster-Resilient Village (DRV) Program using Bayesian Decision-Making. Conducted in Pekalongan City, a region frequently affected by tidal flooding and coastal erosion, this research employs a quantitative approach to assess the program’s effectiveness in enhancing disaster resilience. The study involves 563 respondents, including 18 government officials and 545 affected community members, selected through purposive and proportional sampling. Data were collected through structured surveys measuring disaster preparedness, economic losses, and financial accessibility. Bayesian probabilistic modeling was applied to analyze decision-making patterns in disaster risk reduction and to optimize resource allocation strategies. The results indicate that financial aid and credit accessibility significantly accelerate economic recovery, while disaster preparedness alone does not directly influence resilience. Infrastructure damage, however, prolongs recovery time, underscoring the need for resilient infrastructure investments. These findings highlight the importance of integrating financial mechanisms into the DRV framework to enhance economic stability post-disaster. Policymakers should prioritize expanding financial aid programs, improving credit accessibility, and strengthening infrastructure resilience to minimize long-term economic disruptions. Future research should incorporate longitudinal studies and explore the role of social factors in disaster recovery to provide a more comprehensive analysis.

INTRODUCTION

Disaster resilience is a key concern in global development, particularly for coastal cities facing increasing climate risks. The Disaster-Resilient Village (DRV) Program has been implemented to enhance local capacity in mitigating disaster risks through community empowerment, early warning systems, and infrastructure development. This initiative is essential in areas where natural disasters, such as floods, earthquakes, and typhoons, frequently occur, disrupting economic activities and endangering human lives (Muhamme et al., 2024). Meanwhile, Bayesian Decision-Making has emerged as a probabilistic approach to optimize disaster response and resource allocation under uncertainty. By incorporating prior knowledge and real-time data, this approach enables continuous learning and adaptation,

which is crucial for improving disaster preparedness and mitigation strategies (Gourisetti et al., 2020; Şengöz, 2024; Sun et al., 2020).

The DRV Program aims to empower communities by strengthening disaster preparedness and response mechanisms. It incorporates leadership development, improved early warning systems, and fostering social cohesion to minimize disaster disruptions. The program is designed to enhance local resilience by equipping communities with the knowledge and tools necessary to respond effectively to disasters and recover swiftly afterward. Previous studies have highlighted the program's success in enhancing social resilience and economic stability, particularly in disaster-prone areas (Kolopaking et al., 2022). However, its effectiveness largely depends on adaptive decision-making frameworks that address uncertainty and dynamic risk variables. Without a well-structured decision-making approach, the implementation of disaster resilience programs may face inefficiencies in resource distribution and emergency response coordination (Haris et al., 2023).

Bayesian Decision-Making provides a structured probabilistic framework for evaluating disaster risks and optimizing emergency response strategies. This method integrates prior knowledge and real-time data, enabling dynamic risk assessments and efficient resource allocation. The ability to update predictions based on new information allows policymakers to respond more effectively to changing disaster conditions, making Bayesian modeling a valuable tool in disaster risk reduction (Ferreira et al., 2023). Studies have demonstrated its effectiveness in disaster recovery planning, economic resilience forecasting, and optimizing emergency resource deployment. By leveraging Bayesian techniques, disaster management agencies can enhance decision-making efficiency, reducing losses and improving recovery rates (Nguyen et al., 2024).

The city of Pekalongan faces significant disaster challenges, particularly tidal flooding (rob) and coastal abrasion, which have resulted in property damage and loss of livelihoods. Tidal flooding has become a persistent issue, submerging residential areas (Bosserelle et al., 2022; Silveira et al., 2021; Suryani & Sekarjati, 2023), schools (Lassa et al., 2023; Riyansyah & Masturi, 2023) and commercial centers (Dube et al., 2022; Fant et al., 2021) forcing residents to adapt to recurring water intrusions. Many batik artisans, a key economic sector in the city, suffer from production halts due to flooding, leading to economic instability. Furthermore, environmental degradation affects agricultural and fisheries sectors, compounding the social and economic vulnerabilities of the city's residents. The local government has implemented mitigation policies, including improved drainage systems and coastal embankments, but gaps remain in coordination, resource sustainability, and long-term disaster adaptation. The complexity of disaster management in Pekalongan necessitates a robust and adaptive decision-making framework to ensure efficient resource utilization and sustainable recovery efforts (Bakti et al., 2023; Madusari et al., 2024).

Despite growing recognition of Bayesian Decision-Making and the DRV Program, few studies have explored their integration in disaster risk reduction. The DRV Program focuses on strengthening community-driven resilience, while Bayesian analysis provides data-driven decision support to refine strategies. Research suggests that probabilistic modeling enhances the efficiency of aid distribution and disaster response mechanisms by allowing policymakers to make informed decisions in real time (Erbeyoğlu & Bilge, 2020; Sadeghi et al., 2021; Supari & Anton, 2022; Yazdani & Haghani, 2024). However, empirical validation is required to assess their combined effectiveness in enhancing disaster resilience in Pekalongan. Understanding how

Bayesian Decision-Making can support DRV initiatives will provide valuable insights into improving disaster mitigation policies at both local and national levels.

This study aims to evaluate the social and economic impacts of the DRV Program by integrating Bayesian Decision-Making as a strategic tool for disaster preparedness. By conducting systematic literature reviews and empirical case studies, this research seeks to provide evidence-based recommendations for strengthening disaster resilience strategies in vulnerable communities. The study will examine how Bayesian models can enhance DRV effectiveness by optimizing disaster risk management, improving early warning systems, and facilitating better coordination among stakeholders. The findings will contribute to the ongoing discourse on disaster mitigation strategies and inform policymakers on the best approaches for implementing resilient and adaptive disaster management frameworks (Park et al., 2023).

## **METHOD**

This study employs a quantitative research design to evaluate the social and economic impacts of the Disaster-Resilient Village (DRV) Program using Bayesian Decision-Making. The research focuses on statistical analysis to assess disaster resilience strategies objectively. The study was conducted in Pekalongan City, a region frequently affected by tidal flooding and coastal erosion, which significantly disrupts local economies and community well-being (Muhammed et al., 2024). The research sample consists of 563 respondents, including 18 government officials and 545 affected community members, selected through purposive and proportional sampling to ensure representation of key stakeholders.

Data were collected through structured surveys distributed to both government officials and community members to measure their perceptions of disaster preparedness, economic losses, and social resilience. The questionnaire consisted of closed-ended questions designed to assess respondents' experiences with disaster mitigation and the perceived effectiveness of the DRV Program. Bayesian modeling techniques were applied to analyze decision-making patterns in disaster risk reduction (Nguyen et al., 2024).

The collected data were analyzed using descriptive statistics and Bayesian probabilistic modeling. Descriptive statistics were applied to measure the frequency and distribution of key variables, providing insights into disaster preparedness and economic recovery trends. Bayesian Decision-Making models were developed to assess risk probabilities and optimize resource allocation strategies in disaster mitigation (Supari & Anton, 2022). This probabilistic approach helped identify high-risk areas and recommend targeted interventions. By relying solely on quantitative analysis, this study provides an objective assessment of the DRV Program's effectiveness in enhancing disaster resilience.

Bayesian regression was chosen as the primary analytical method due to its ability to incorporate prior information and update estimates based on observed data. Unlike traditional frequentist regression, Bayesian regression produces probability distributions for each parameter, allowing for a more nuanced interpretation of results, particularly in uncertain environments. The Bayesian framework is particularly useful for disaster risk assessment (Wu et al., 2020), as it enables decision-makers to continuously refine predictions as new data become available, making it an effective tool for evaluating financial aid effectiveness, credit accessibility, and infrastructure resilience in post-disaster recovery efforts. A key component of Bayesian analysis is the density plot, which illustrates the posterior distribution of model parameters by providing a smooth representation of the probability density function (Broemeling, 2017; de Schoot et al., 2021). This helps identify the range and concentration of

estimated values, offering a clearer interpretation of parameter uncertainty and effect sizes. Unlike standard point estimates, which provide a single value, density plots show the full distribution of possible values, making them ideal for assessing the reliability and stability of regression estimates. In this study, density plots were used to visualize the effects of financial aid, credit accessibility, infrastructure damage, and preparedness score on economic recovery time. The sharper and more concentrated distributions for financial aid and credit accessibility indicate greater certainty in their impact on accelerating recovery, whereas the broader distribution for preparedness score suggests more uncertainty in estimating its effect. These visualizations enhance understanding of the reliability of model estimates, aiding policymakers in identifying the most influential factors in disaster recovery planning.

## RESULTS AND DISCUSSION

The results of this study provide insights into the key determinants of economic recovery following a disaster. Using Bayesian regression analysis, the effects of disaster preparedness, financial aid, infrastructure damage, and credit accessibility on recovery time were examined. The table 1 bellow presents the estimated coefficients, standard errors, 95% confidence intervals, and interpretations of the regression results.

**Table 1. Bayesian Regression Results for Economic Recovery Days**

| Variable               | Estimate (Mean) | Std. Error | 95% CI (Lower - Upper) | Interpretation                                                                          |
|------------------------|-----------------|------------|------------------------|-----------------------------------------------------------------------------------------|
| Intercept              | 129.14          | 8.50       | 111.93 – 145.69        | The average recovery time, assuming all other variables are zero, is 129.14 days.       |
| Preparedness_Score     | 0.04            | 0.04       | -0.03 – 0.12           | Not significant; preparedness does not strongly influence economic recovery time.       |
| Financial_Aid_Received | -12.68          | 1.79       | -16.04 – -9.13         | More financial aid leads to faster economic recovery (12.68 days shorter).              |
| Infrastructure_Damage  | 9.36            | 2.68       | 4.11 – 14.55           | Greater infrastructure damage increases recovery time (by 9.36 days).                   |
| Credit_Accessibility   | -33.28          | 1.09       | -35.39 – -31.16        | Easier access to credit significantly speeds up economic recovery (33.28 days shorter). |

Based on table 1 above, the Bayesian regression results indicate that disaster preparedness, measured by the Preparedness Score, does not have a significant effect on the speed of economic recovery. The estimated coefficient of 0.04, with a 95% confidence interval ranging from -0.03 to 0.12, suggests that an increase in preparedness does not necessarily lead to faster economic recovery. This finding contrasts with previous studies that emphasize preparedness as a crucial factor in post-disaster resilience. The results suggest that while preparedness strengthens community resilience in non-economic aspects, economic recovery may depend more on external support mechanisms such as financial aid and credit access.

The analysis confirms that financial aid plays a crucial role in accelerating economic recovery. The coefficient for Financial Aid Received, at -12.68 with a confidence interval

between -16.04 and -9.13, suggests that for every additional unit of financial aid received, the economic recovery time is reduced by approximately 12.68 days. This finding underscores the importance of direct financial support in mitigating the economic shocks experienced by disaster-affected households. Communities that received timely financial aid exhibited a shorter recovery period, enabling them to restore their businesses and livelihoods more efficiently.

Infrastructure damage was found to have a significant and negative impact on economic recovery. The coefficient of 9.36, with a confidence interval between 4.11 and 14.55, indicates that greater infrastructure damage is associated with prolonged economic recovery times. This result aligns with existing research that highlights the detrimental effects of damaged roads, water supply systems, and public services on post-disaster economic activities. Households in areas with severe infrastructure damage required significantly more time to restore their economic stability, as access to markets, transportation, and utilities were severely affected.

The most significant factor influencing economic recovery time was credit accessibility. The coefficient for Credit Accessibility, at -33.28 with a confidence interval between -35.39 and -31.16, shows that households and businesses with better access to credit recovered 33.28 days faster than those with limited credit access. This suggests that having the ability to secure loans or financial assistance immediately after a disaster is critical for maintaining economic stability. The findings indicate that microfinance programs and disaster recovery loans should be prioritized as part of resilience-building strategies in disaster-prone communities.

The findings of this study challenge the conventional notion that disaster preparedness alone is sufficient to ensure rapid economic recovery. Instead, they highlight the importance of financial support mechanisms such as aid distribution and accessible credit. As shown in Figure 1, the density plots illustrate the distribution of estimated effects, reinforcing the significance of financial aid and credit accessibility in reducing recovery time, while also highlighting the substantial impact of infrastructure damage. To enhance the effectiveness of the DRV Program, policymakers should consider increasing access to financial aid for disaster-affected communities to shorten recovery time, prioritizing infrastructure resilience to minimize the long-term economic impact of disasters, expanding access to credit facilities to enable small businesses and households to recover faster, and integrating data-driven decision-making through Bayesian models to optimize resource allocation and disaster response efforts.

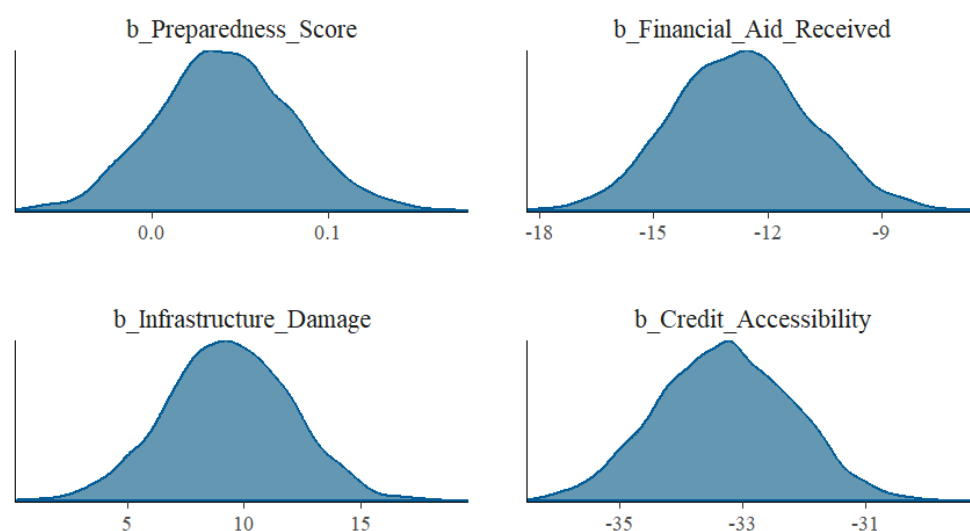


**Figure 1. Density Plots of Estimated Effects of Key Variables on Economic Recovery Time**

The posterior density plot above, illustrates the distribution of Bayesian regression parameters for each independent variable in the model. This distribution provides insights into the uncertainty of coefficient estimates and the magnitude of each variable's effect on economic recovery time. The variables financial aid received and credit accessibility have distributions concentrated around negative values, indicating that both factors consistently shorten recovery time. In contrast, the variable infrastructure damage has a positive distribution, signifying that greater damage leads to longer recovery periods. Meanwhile, the preparedness score variable has a distribution centered around zero, suggesting that its influence on economic recovery is not significant.

The sharper and narrower distribution for credit accessibility compared to other variables indicates that its effect on accelerating economic recovery is more certain and pronounced. Conversely, the wider distribution of preparedness score reflects greater uncertainty in estimating its effect, aligning with the regression results that showed it is not a significant factor. These findings reinforce the conclusion that access to credit and financial aid play crucial roles in expediting economic recovery after a disaster, while initial preparedness may not necessarily be a determining factor in the short term.

The summary statistics in Table 2 further support these conclusions. The Rhat values for all parameters are 1.00, indicating model convergence, while the effective sample sizes (Bulk\_ESS and Tail\_ESS) are sufficiently large for stable estimation. Notably, the estimation of financial aid and credit accessibility effects is backed by adequate sample sizes, ensuring reliable inferences about their impact on recovery time. These results strengthen the argument that financial support mechanisms should be a central focus in disaster response and recovery planning.

**Table 2. Convergence Diagnostics and Effective Sample Sizes for Model Parameters**

| Parameter              | Rhat | Bulk_ESS | Tail_ESS | Interpretation                       |
|------------------------|------|----------|----------|--------------------------------------|
| Intercept              | 1.00 | 4106     | 2688     | The model has converged well.        |
| Preparedness_Score     | 1.00 | 4415     | 2733     | No convergence issues.               |
| Financial_Aid_Received | 1.00 | 2955     | 2968     | Adequate sample size for estimation. |
| Infrastructure_Damage  | 1.00 | 4208     | 2803     | Sufficient sample size.              |
| Credit_Accessibility   | 1.00 | 3020     | 2814     | Sufficient sample size.              |

The convergence diagnostics presented in Table 2 confirm that the Bayesian regression model has achieved stable and reliable estimates. All parameters have an Rhat value of 1.00, indicating proper convergence across Markov Chain Monte Carlo (MCMC) simulations. The effective sample sizes (Bulk\_ESS and Tail\_ESS) for all variables are sufficiently large, ensuring that parameter estimates are not biased by autocorrelation or insufficient sampling. Notably, the estimates for financial aid received and credit accessibility, which were identified as key drivers of economic recovery, are supported by adequate sample sizes, reinforcing the robustness of their inferred effects. These results validate the reliability of the model in capturing the relationships between disaster preparedness, financial mechanisms, infrastructure damage, and economic recovery time.

To support the previous analysis, a posterior predictive check was conducted to assess the model's fit. Figure 2 below presents a comparison between the actual data (y) and the

replicated data generated by the model ( $y_{rep}$ ), providing insight into how well the model can reproduce the empirical data distribution.

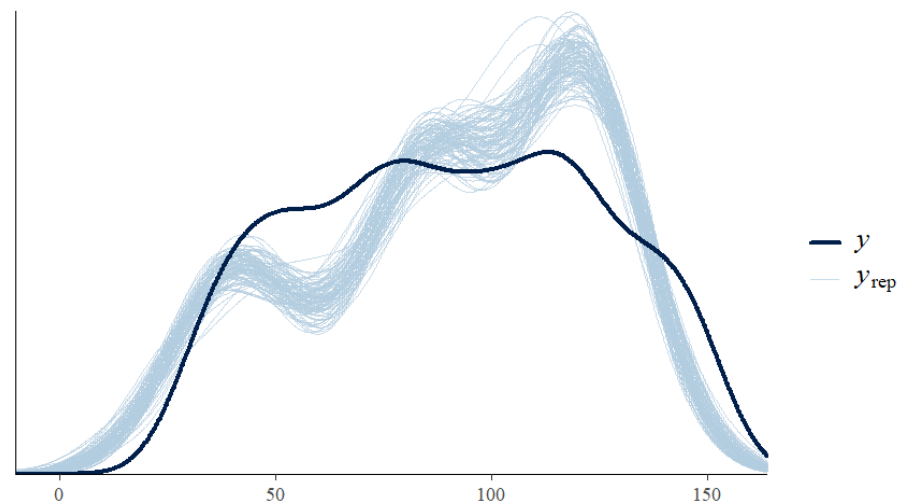


**Figure 2. Posterior Predictive Check Comparing Actual and Replicated Data**

From this visualization, it is evident that the model-generated data closely follows the actual data distribution, indicating that the model effectively captures the key patterns in the dataset. The variability in  $y_{rep}$  reflects uncertainty in the estimation, but overall, the model successfully replicates the observed trends. This suggests that the Bayesian approach used in the analysis provides a valid framework for evaluating the factors influencing post-disaster economic recovery.

This study provides insights into the key factors influencing economic recovery following a disaster, particularly in the context of the Disaster-Resilient Village (DRV) Program. Bayesian regression analysis reveals that access to financial aid and credit significantly accelerates economic recovery, whereas disaster preparedness, a key component of the DRV Program, does not have a significant impact on recovery speed. These findings align with Davlasheridze & Miao (2021) who found that financial aid in the form of grants is more effective in improving short-term financial stability, while disaster loans have a more sustainable long-term impact on economic recovery. These results suggest that while the DRV Program strengthens community resilience, it should incorporate stronger financial support mechanisms to ensure economic stability post-disaster.

The Bayesian regression results presented in Table 1 show that the preparedness score (Preparedness\_Score) has an estimated coefficient of 0.04, with a 95% confidence interval ranging from -0.03 to 0.12. This indicates that preparedness does not have a significant impact on economic recovery time. This finding contradicts prior studies emphasizing the importance of preparedness in post-disaster resilience. However, recent research suggests that while preparedness measures enhance immediate disaster response, they do not necessarily lead to faster economic recovery unless supported by financial mechanisms (Crawford et al., 2024). Additionally, research on disaster recovery funding highlights that financial interventions such as grants and low-interest loans have a more immediate and measurable impact on economic stabilization (McCall et al., 2022). Since the DRV Program focuses heavily on preparedness measures, these findings suggest that while such efforts are valuable in mitigating disaster impacts, they must be complemented by direct financial interventions and improved access to economic resources for a more comprehensive recovery strategy. Furthermore, studies on post-

disaster recovery funding indicate that delayed financial aid distribution exacerbates economic instability, underscoring the importance of efficient financial response mechanisms (Reza, 2024). To enhance the DRV Program's effectiveness, policymakers should integrate financial mechanisms alongside preparedness initiatives, ensuring that affected communities have the necessary resources for rapid and sustainable recovery (Li et al., 2022).

The coefficient for financial aid received (*Financial\_Aid\_Received*) is -12.68, with a confidence interval between -16.04 and -9.13, indicating that increased financial aid leads to faster economic recovery. Specifically, each additional unit of financial aid received reduces recovery time by approximately 12.68 days. This finding is consistent with prior research showing that rapid and efficient distribution of financial aid can mitigate economic shocks and accelerate business sector recovery (McCall et al., 2022). Within the DRV framework, financial aid distribution should be structured more efficiently to support affected households and businesses. Studies indicate that delays in financial aid allocation can have severe economic consequences, leading to prolonged business closures and job losses (Attary et al., 2020). Moreover, targeted financial assistance has been found to enhance small business sustainability and improve local economic resilience, particularly in disaster-prone regions (Watson, 2021). Strengthening local financial institutions and incorporating cash-transfer programs into the DRV strategy could enhance the program's effectiveness in supporting economic recovery. Additionally, ensuring equitable distribution of financial aid is critical, as research highlights disparities in aid allocation that often leave vulnerable communities without adequate support (Ko et al., 2022). By addressing these challenges, policymakers can optimize financial recovery strategies and improve overall economic resilience in disaster-affected areas.

Infrastructure damage has a significant negative impact on economic recovery, with a coefficient of 9.36 and a confidence interval between 4.11 and 14.55. This suggests that greater infrastructure damage is associated with longer recovery times. This is consistent with prior studies showing that disasters affecting critical infrastructure prolong economic stagnation and disrupt key sectors such as trade, transportation, and public services (Santos et al., 2022). The long-term consequences of infrastructure failure include decreased business productivity, higher unemployment rates, and increased costs of reconstruction, further delaying economic stabilization (Li et al., 2022). Given that the DRV Program aims to build community resilience, infrastructure resilience should be integrated more comprehensively within the program's framework. Research has shown that investments in resilient infrastructure reduce economic losses and accelerate post-disaster recovery, particularly in urban areas where transportation and public services are crucial for economic stability (Kovarik et al., 2023). Moreover, strengthening infrastructure systems through adaptive urban planning has been identified as a key strategy in mitigating future disaster risks and ensuring long-term economic resilience (Ramada, 2024). By integrating these strategies into the DRV framework, policymakers can enhance disaster preparedness and minimize prolonged economic disruptions following catastrophic events.

Credit accessibility (*Credit\_Accessibility*) has the most significant impact on economic recovery acceleration, with a coefficient of -33.28 and a confidence interval between -35.39 and -31.16. This result suggests that communities and businesses with easier access to credit recover 33.28 days faster than those with limited credit access. Research has shown that credit availability is crucial for post-disaster recovery, as it enables affected households and businesses to stabilize their finances and resume economic activities more quickly (Meyer & Schweitzer, 2022). Osumba & Oboka (2022) also support this finding, stating that credit accessibility for

SMEs plays a crucial role in restoring working capital and operational stability post-disaster. Moreover, studies indicate that targeted credit programs, including government-backed low-interest loans and microfinance initiatives, significantly enhance economic resilience in disaster-prone areas (Bessonova et al., 2021).

To improve the DRV Program's economic impact, initiatives that facilitate easier credit access should be incorporated. Establishing community-based microfinance programs or government-supported credit schemes could empower disaster-affected individuals and businesses to recover more quickly (Silber & Sovern, 2020). Additionally, research has found that disparities in credit allocation can slow down recovery in marginalized communities, highlighting the need for inclusive financial policies (Yuan et al., 2021). Strengthening financial infrastructure and reducing bureaucratic barriers to credit access are essential steps in ensuring equitable and effective economic recovery (Li et al., 2022). By integrating these strategies into the DRV framework, policymakers can significantly enhance financial resilience and disaster recovery efforts

Table 2 indicates that the Rhat values for all parameters are 1.00, confirming that the Bayesian regression model has achieved proper convergence. Additionally, effective sample sizes (Bulk\_ESS and Tail\_ESS) are sufficiently large, particularly for financial aid and credit access variables, ensuring reliable parameter estimation. The stability and efficiency of Bayesian models in financial and economic applications have been well-documented, particularly in optimizing resource allocation in uncertain environments (Chen & Hu, 2024). Mhlungu (2021) also found that liquidity availability and flexible financing schemes are primary determinants of small business sustainability post-COVID-19. The ability of businesses to access sufficient liquidity during recovery periods is a fundamental factor in their long-term resilience, reinforcing the importance of incorporating financial stability into disaster recovery programs (Ahiakpor et al., 2023).

Bayesian modeling techniques have also been instrumental in financial risk assessment, particularly in predicting credit defaults and optimizing lending policies in uncertain economic conditions (Tham et al., 2023). The integration of Bayesian analysis into economic recovery planning allows for more accurate predictions of financial aid effectiveness and credit accessibility impacts, ensuring that resources are allocated efficiently (Provost, 2021). To align with these findings, the DRV Program should incorporate financial education and credit accessibility strategies to enhance the financial resilience of its beneficiaries, ensuring that disaster recovery efforts are both data-driven and sustainable (Li et al., 2022).

These findings suggest several policy recommendations to enhance the DRV Program's economic recovery contributions. Improving access to financial aid for disaster-affected communities should be a priority, ensuring that aid is both timely and equitably distributed. Infrastructure resilience must also be prioritized to minimize long-term economic impacts, particularly by investing in disaster-resistant construction and adaptive urban planning. Expanding credit facilities for small businesses and households will further support economic recovery by enabling businesses to rebuild and households to stabilize their finances. Additionally, integrating data-driven decision-making frameworks, such as Bayesian regression, will optimize resource allocation and disaster response efforts, ensuring that financial aid and recovery strategies are evidence-based and efficient. By implementing these strategies, the DRV Program can evolve into a more comprehensive disaster resilience initiative, effectively addressing both social and economic challenges post-disaster

## CONCLUSION

This study highlights the key determinants of economic recovery following a disaster, particularly within the framework of the Disaster-Resilient Village (DRV) Program. The findings indicate that financial aid and credit accessibility significantly accelerate recovery, whereas disaster preparedness alone does not directly influence economic resilience. Additionally, infrastructure damage prolongs recovery time, emphasizing the need for resilient infrastructure investments. These results suggest that economic recovery efforts should focus on financial mechanisms and infrastructure development rather than relying solely on preparedness strategies. To maximize the effectiveness of the DRV Program, financial support should be integrated alongside preparedness measures to ensure communities can rebuild efficiently post-disaster.

Policymakers should strengthen financial aid programs and expand credit access to support affected communities, while also prioritizing resilient infrastructure to minimize economic disruptions. The DRV Program should incorporate financial mechanisms to enhance recovery, ensuring that communities have access to necessary resources. Additionally, leveraging data-driven decision-making, such as Bayesian analysis, can optimize resource allocation and disaster response efforts. By implementing these strategies, governments and organizations can improve disaster recovery outcomes, strengthen the DRV Program, and enhance economic resilience in disaster-prone areas.

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## REFERENCES

- Ahiakpor, F., Nordjo, R., & Alnaa, S. (2023). Financial development and growth: Evidence from Bayesian Modelling. *Cogent Economics & Finance*, 11.  
<https://doi.org/10.1080/23322039.2023.2261798>
- Attary, N., Cutler, H., Shields, M., & van de Lindt, J. W. (2020). The economic effects of financial relief delays following a natural disaster. *Economic Systems Research*, 32, 351–377. <https://doi.org/10.1080/09535314.2020.1713729>
- Bakti, I., Zubair, F., & Budiana, H. R. (2023). Participatory communication as the key to successful disaster management in Pangandaran district. *Jurnal Kajian Komunikasi*, 11(2), 195–214.
- Bessonova, E., Popova, S., Turdyeva, N., & Tsvetkova, A. (2021). Productivity and lending during the pandemic. *Voprosy Ekonomiki*. <https://doi.org/10.32609/0042-8736-2021-7-123-141>

- Bosserelle, A. L., Morgan, L. K., & Hughes, M. W. (2022). Groundwater rise and associated flooding in coastal settlements due to sea-level rise: a review of processes and methods. *Earth's Future*, 10(7), e2021EF002580.
- Broemeling, L. D. (2017). *Bayesian analysis of linear models*. CRC Press.
- Chen, Y.-C., & Hu, G. (2024). Convergence to Bayesian Stable States without Assuming Observability. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4720596>
- Crawford, F., Davison, O., Taylor, M., Muir, L., Maguire, R., Lewis, B., & Bull, M. (2024). *Sharing Responsibility for Disaster Justice: An analysis of submissions to the 2023 Senate Select Committee on Australia's Disaster Resilience*. Queensland University of Technology. <https://doi.org/10.5204/book.eprints.248998>
- Davlasheridze, M., & Miao, Q. (2021). Does post-disaster aid promote community resilience? Evidence from federal disaster programs. *Natural Hazards*, 109(1), 63–88. <https://doi.org/10.1007/s11069-021-04826-2>
- de Schoot, R., Depaoli, S., King, R., Kramer, B., Märtens, K., Tadesse, M. G., Vannucci, M., Gelman, A., Veen, D., Willemsen, J., & others. (2021). Bayesian statistics and modelling. *Nature Reviews Methods Primers*, 1(1), 1.
- Dube, K., Nhamo, G., & Chikodzi, D. (2022). Flooding trends and their impacts on coastal communities of Western Cape Province, South Africa. *GeoJournal*, 87(Suppl 4), 453–468.
- Erbeyoğlu, G., & Bilge, Ü. (2020). A robust disaster preparedness model for effective and fair disaster response. *European Journal of Operational Research*, 280(2), 479–494. <https://doi.org/https://doi.org/10.1016/j.ejor.2019.07.029>
- Fant, C., Jacobs, J. M., Chinowsky, P., Sweet, W., Weiss, N., Sias, J. E., Martinich, J., & Neumann, J. E. (2021). Mere nuisance or growing threat? The physical and economic impact of high tide flooding on US road networks. *Journal of Infrastructure Systems*, 27(4), 4021044.
- Ferreira, R., Cannon, C. E. B., Buttell, F., & Davidson, T. (2023). Explaining Disaster and Pandemic Preparedness at the Nexus of Personal Resilience and Social Vulnerability: An Exploratory Study. *Disaster Medicine and Public Health Preparedness*, 17. <https://doi.org/10.1017/dmp.2023.78>
- Gourisetti, S. N. G., Mylrea, M., & Patangia, H. (2020). Cybersecurity vulnerability mitigation framework through empirical paradigm: Enhanced prioritized gap analysis. *Future Generation Computer Systems*, 105, 410–431. <https://doi.org/https://doi.org/10.1016/j.future.2019.12.018>
- Haris, N., Furqan, A. C., Kahar, A., & Karim, F. (2023). Disaster risk index on disaster management budgeting: Indonesia's national data set. *Jàmbá : Journal of Disaster Risk Studies*, 15. <https://doi.org/10.4102/jamba.v15i1.1365>
- Ko, J., Kim, J., & Han, J. J. (2022). The Inequitable Distribution of Government Funds: The Case of COVID-19 Economic Injury Disaster Loans. *Journal of Student Research*. <https://doi.org/10.47611/jsrhs.v11i2.3654>

- Kolopaking, L., Wahyono, E., Irmayani, N. R., Habibullah, H., & Erwinsyah, R. G. (2022). Re-Adaptation of COVID-19 Impact for Sustainable Improvement of Indonesian Villages' Social Resilience in the Digital Era. *International Journal of Sustainable Development and Planning*. <https://doi.org/10.18280/ijstdp.170713>
- Kovarik, J., Evans, C., Godart, B., Fernando, J., Mendoza, Palhol, F., & Starnes, M. (2023). *Evaluating Resilient Infrastructure Systems : Task Force 3 Infrastructure Investment and Financing*.
- Lassa, J., Petal, M., & Surjan, A. (2023). Understanding the impacts of floods on learning quality, school facilities, and educational recovery in Indonesia. *Disasters*, 47(2), 412–436.
- Li, H., Xu, E., Zhang, H., & Zhong, S. (2022). A dynamic disastrous CGE model to optimize resource allocation in post-disaster economic recovery: post-typhoon in an urban agglomeration area, China. *Environmental Research Letters*, 17. <https://doi.org/10.1088/1748-9326/ac7733>
- Madusari, B. D., Fitri, A., Gunawan, M. A., & Mardiana, T. Y. (2024). Tidal Flood Mitigation Model Using the Life Cycle Approach (LCA) in Coastal Areas of Pekalongan City. *KnE Social Sciences*.
- McCall, J. R., Weston, B., Onorevole, J., Roberson, J., & Andrews, J. (2022). *Extraordinary Times Call for Extraordinary Measures: Use of Loans and Grants for Small Business Assistance During the COVID-20 Pandemic*. <https://doi.org/10.46712/extraordinary.times>
- Meyer, B. H., & Schweitzer, M. (2022). Access to Credit for Minority-owned Businesses. *Economic Commentary (Federal Reserve Bank of Cleveland)*. <https://doi.org/10.26509/frbc-ec-202204>
- Mhlungu, M. B. (2021). *Key success factors for developing and managing small and medium-sized enterprises post Covid-19 pandemic*.
- Muhame, C., Ncube, A., & Bahta, Y. (2024). Dissemination and participation in early warnings and disaster risk reduction in South Africa. *Jàmbá : Journal of Disaster Risk Studies*, 16. <https://doi.org/10.4102/jamba.v16i1.1566>
- Nguyen, T. G., Tran, B. T., Nguyen, M. T., & Le, D. (2024). Validation of the Disaster Adaptation and Resilience Scale for Vulnerable Communities in Vietnam's Coastal Regions. *Journal of Preventive Medicine and Public Health*, 57, 279–287. <https://doi.org/10.3961/jpmph.24.110>
- Osumba, J. L., & Oboka, W. (2022). The The Role and Effectiveness of the Cooperative Business Model in Economic Recovery Strategy and Resilience Building Post-Covid-19: A Co-operative solution to disasters. *African Journal of Co-Operative Development and Technology*, 7(1), 1–19.
- Park, H., Shin, Y., & Lee, S.-B. (2023). Relationship Between Community Resilience and Quality of Life of Disaster-Affected People: Reinforcement Effects of the Perception of Government Relief Services in South Korea. *Disaster Medicine and Public Health Preparedness*, 17. <https://doi.org/10.1017/dmp.2023.186>

- Provost, N. (2021). *Modelling Net Loan Loss with Bayesian and Frequentist Regression Analysis*.
- Ramada, A. (2024). Tanggap darurat, rehabilitasi, dan rekonstruksi: Studi kasus gempa Cianjur. *Information, Communications, and Disaster*. <https://doi.org/10.61511/icd.v1i1.2024.447>
- Reza, K. M. A. (2024). Impacts of Funding Gap Son Disaster Management: A Case Study of Bangladesh. *International Journal of Innovative Science and Research Technology (IJISRT)*. <https://doi.org/10.38124/ijisrt/ijisrt24sep181>
- Riyansyah, R., & Masturi, M. (2023). The Education of Tidal Flood Disaster Mitigation and Environmental Awareness Through Simulation Video Assisted-Problem Based Learning Model. *Jurnal Penelitian Pendidikan IPA*, 9(4), 1720–1726.
- Sadeghi, M. ebrahim, Khodabakhsh, M., Ganjipoor, M. R., kazemipoor, H., & Nozari, H. (2021). A New Multi Objective Mathematical Model for Relief Distribution Location at Natural Disaster Response Phase. *International Journal of Innovation in Engineering*, 1(1), 22–47. <https://doi.org/10.52547/ijie.1.1.22>
- Santos, J., Roquel, K. I. Z., Lamberte, A., Tan, R., Aviso, K., Tapia, J. F., Solis, C. A., & Yu, K. (2022). Assessing the economic ripple effects of critical infrastructure failures using the dynamic inoperability input-output model: a case study of the Taal Volcano eruption. *Sustainable and Resilient Infrastructure*, 8, 68–84. <https://doi.org/10.1080/23789689.2022.2127999>
- Şengöz, M. (2024). Harnessing Artificial Intelligence and Big Data for Proactive Disaster Management: Strategies, Challenges, and Future Directions. *Haliç Üniversitesi Fen Bilimleri Dergisi*, 7(2), 57–91. <https://doi.org/10.46373/hafebid.1534925>
- Silber, N. I., & Sovern, J. (2020). Placing Consumers at the Front of the Relief Effort: Redirecting Credit Card Interest Charges. *Poverty*. <https://doi.org/10.2139/ssrn.3569002>
- Silveira, F., Lopes, C. L., Pinheiro, J. P., Pereira, H., & Dias, J. M. (2021). Coastal floods induced by mean sea level rise—Ecological and socioeconomic impacts on a mesotidal lagoon. *Journal of Marine Science and Engineering*, 9(12), 1430.
- Sun, W., Bocchini, P., & Davison, B. D. (2020). Applications of artificial intelligence for disaster management. *Natural Hazards*, 103(3), 2631–2689. <https://doi.org/10.1007/s11069-020-04124-3>
- Supari, S., & Anton, H. (2022). The Impact of the National Economic Recovery Program and Digitalization on MSME Resilience during the COVID-19 Pandemic: A Case Study of Bank Rakyat Indonesia. *Economies*. <https://doi.org/10.3390/economies10070160>
- Suryani, R., & Sekarjati, D. (2023). Study Tide Dynamics and Impact of Coastal Floods on the Settlement Areas of Batam City. *Jurnal Miyang: Ronggolawe Fisheries and Marine Science Journal*, 3(2), 80–87.
- Tham, A. W., Kakamu, K., & Liu, S. (2023). Bayesian Statistics for Loan Default. *Journal of Risk and Financial Management*. <https://doi.org/10.3390/jrfm16030203>
- Watson, M. (2021). Disaster Assistance Winners and Losers. *Journal of the American Planning Association*, 88, 305–318. <https://doi.org/10.1080/01944363.2021.1980086>

- Wu, Z., Shen, Y., Wang, H., & Wu, M. (2020). Urban flood disaster risk evaluation based on ontology and Bayesian Network. *Journal of Hydrology*, 583, 124596.
- Yazdani, M., & Haghani, M. (2024). A conceptual framework for integrating volunteers in emergency response planning and optimization assisted by decision support systems. *Progress in Disaster Science*, 24, 100361.  
<https://doi.org/https://doi.org/10.1016/j.pdisas.2024.100361>
- Yuan, F., Esmalian, A., Oztekin, B., & Mostafavi, A. (2021). Unveiling Spatial Patterns of Disaster Impacts and Recovery Using Credit Card Transaction Variances. *ArXiv*, *abs/2101.10090*.