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# Pandemic shock and regional economic resilience in Indonesia: A linear mixed model

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**Abstract**

**Background:** The COVID-19 pandemic has emerged as a major non-traditional security threat, generating substantial economic disruptions and destabilizing labor markets worldwide. In Indonesia, the surge in open unemployment during the pandemic has raised concerns regarding regional economic resilience and its broader implications for national economic security. As unemployment can exacerbate social vulnerability and weaken adaptive capacity, understanding regional labor market dynamics is critical for strengthening national resilience.
**Aims:** This study aims to examine the impact of pandemic-induced shocks on provincial open unemployment rates in Indonesia and assess regional heterogeneity in economic resilience.
**Method:** The study employs provincial level panel data and applies a Linear Mixed Model (LMM) to capture both temporal effects and regional heterogeneity. The model incorporates pandemic indicators alongside structural economic variables, including informal employment and commodity distribution dynamics, to evaluate their roles as vulnerability factors or resilience buffers during the crisis period.
**Results:** The findings show that the COVID-19 pandemic has significantly increased the open unemployment rate in all provinces in Indonesia. This study also shows that the percentage of trade and transportation margins (MTT) for shallots influences the open unemployment rate with a p-value of 0.017 and a variable coefficient of 0.021. In addition, it was also found that the proportion of informal workers in the total national workforce also has a significant effect on changes in the open unemployment rate (p-value: 0.001, coefficient: -0.077). Another finding from this study is that the level of high school education does not have a significant effect on the open unemployment rate.
**Conclusion:** This study on pandemic induced unemployment shocks contributes by integrating regional heterogeneity into economic resilience analysis using a multilevel modeling framework. Strengthening regional economic resilience through labor market flexibility, supply chain stability, and adaptive policy coordination is essential to safeguarding socioeconomic stability and reinforcing Indonesia's national resilience against large-scale non-traditional threats.

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## INTRODUCTION

Unemployment refers to a situation where individuals of working age actively seek employment at current wage rates but cannot find suitable jobs. This creates an imbalance in the labor market (Irawan & Suparmoko, 2002; Nizova & Sorokina, 2019; Aygun et al., 2022; Zieliński, 2022). In Indonesia, unemployment has remained one of the most persistent economic and social challenges, impacting both urban and rural communities. Despite ongoing efforts by government and private sectors to generate job opportunities, the issue remains complex due to factors like population growth, low job absorption rates, skill mismatches, and economic fluctuations (Ayeni & Shaib, 2020; Blustein et al., 2020; Adely et al., 2021; Mbatha, 2021; Oshora et al., 2021; Florez & Gomez, 2024). Finding effective and sustainable solutions to reduce unemployment is therefore crucial for ensuring economic stability, improving social welfare, and boosting national productivity (Hensher, 2020; Tesso, 2020; Sağlam, 2025).

The COVID-19 pandemic has generated unprecedented disruptions to global economic systems across the globe. Beyond its immediate health impacts, the pandemic has created severe economic disruptions that have tested national resilience and revealed structural weaknesses in labor markets (Rahman et al., 2025). In this context, unemployment represents more than just an economic measure but serves as a vital component of socioeconomic stability and national security. Sustained increases in unemployment can worsen inequality, increase social tensions, and reduce a country's ability to adapt during crises (World Health Organization [WHO], 2020).

Indonesia presents a particularly compelling case, given its geographically dispersed archipelagic structure and pronounced regional heterogeneity. Economic activities across Indonesian provinces vary significantly in terms of sectoral composition, infrastructure development, and labor market characteristics, which in turn influence the extent to which regions are exposed to and capable of responding to external shocks (Sjaf et al., 2025; Bildirici & Gokmenoglu, 2026). While national-level indicators provide an aggregate view of economic disruption, they often obscure regional heterogeneity in vulnerability and recovery capacity. Understanding how unemployment dynamics vary across provinces is therefore essential for assessing broader national economic security (Hausmann, 2020; Sani et al., 2022).

In contemporary security studies, economic resilience has become an integral component of comprehensive security frameworks. Non-traditional threats, including pandemics, financial crises, and supply chain disruptions, can undermine national stability without involving conventional military confrontation (Marta et al., 2025; Ramdhani & Evito, 2025). Economic insecurity manifested through rising unemployment, labor market contraction, and regional disparities may weaken social cohesion and constrain state capacity to respond effectively to crises. Consequently, analyzing labor market resilience during the COVID-19 pandemic contributes not only to economic scholarship but also to the broader discourse on national resilience and security (Martin & Sunley, 2015).

Several factors shape this resilience capacity across regions. Differences in economic structure such as dependence on specific industries, the presence of diversified sectors, and the strength of local enterprises significantly influence how regions respond to shocks. Additionally, the prevalence of informal employment can either buffer or weaken resilience; while informal sectors may provide short-term flexibility, they often lack the stability and protection needed for long-term recovery. Based on Nguyen et al. (2020) research, Education level was recognized as one of the top 5 most significant criteria, as a more educated workforce tends to adapt more readily to new economic conditions and technological shifts. As emphasized by Briguglio et al. (2014) and Eraydin (2016), these structural and social dimensions collectively determine how resilient a region is in facing crises, highlighting the need for policies that enhance diversification, formal employment opportunities, and human capital development to strengthen economic resilience.

One of the phenomena that was rife during the pandemic was the termination of employment (PHK) of employees, causing the unemployment rate to increase (Krisnandika et al., 2021; Dakhilullah, 2023). There are many factors that affect the unemployment rate, including margin of trade and transportation (MTT) of shallots. The higher the MTT, the higher the price, making it difficult for consumers to buy. This resulted in a decrease in sales and onion entrepreneurs would lay off their employees. The proportion of employment also affects the unemployment rate. At the time COVID-19 was implemented, the PPKM program or activity restrictions and WFH (Work From

Home) had made fewer jobs and found it more difficult to find work and increased the unemployment rate. Completion of high school education also influences the unemployment rate. However, humans are creatures that are designed to be able to adapt and have a high instinct for survival.

Existing studies have documented the macroeconomic consequences of the COVID-19 pandemic, including output contraction, reduced labor mobility, and increased unemployment rates. However, despite extensive research on the economic impacts of COVID-19, limited studies incorporate regional heterogeneity within a multilevel modeling framework to assess economic resilience (Odasseril & Shanmugam, 2025; Umoh & Aluko, 2025). The role of supply chain dynamics and informal labor structures in shaping unemployment resilience remains underexplored. Much of the literature focuses on aggregate national indicators or sector-specific impacts. Moreover, empirical investigations often employ conventional regression approaches that may not adequately capture hierarchical and spatial variations across subnational units (Sadhu et al., 2025).

How did the COVID-19 pandemic affect unemployment across regions? How does regional heterogeneity influence economic resilience? What roles do informal employment and supply chain factors play? This study addresses this gap by specifically examining the influence of the COVID-19 pandemic on open unemployment rates across Indonesian provinces and evaluating regional economic resilience through a panel-data framework. Using a linear mixed model approach, the analysis accounts for both temporal shocks and regional heterogeneity, enabling a more nuanced understanding of labor market responses during crisis conditions. In addition to pandemic effects, the study considers structural factors such as informal employment and commodity distribution dynamics that may function as either vulnerability drivers or resilience buffers.

## METHOD

### Dataset

In this section, we describe the data sources and structures employed in the empirical analysis. The study utilizes secondary historical data obtained from the official database of Indonesia's Central Statistics Agency (Badan Pusat Statistik, BPS) covering the period 2018–2021. The selection of this time frame enables a comparative assessment between the pre-pandemic (2018-2019) and pandemic periods (2020-2021), thereby facilitating an evaluation of labor market dynamics before and after the COVID-19 shock.

The dataset included the percentage of the unemployment rate, margin of trade and transportation (MTT) of shallots, the proportion of informal employment, and the completion rate of high school education. Shallots are a key staple commodity in Indonesia, and their distribution margins serve as a proxy for supply chain efficiency and market distortion during crisis periods. We grouped the observation data into 6 regions consisting of Java, Sumatra, Sulawesi, Kalimantan, Papua, and Lesser Sundas as well as 34 provincial segments. This hierarchical structure supports the application of multilevel modeling to capture regional heterogeneity.

### Variables

The study includes one dependent variable (open unemployment rate) and three key independent variables predictors as following.

Response variable:

$Y$ = Unemployment rate

Predictor variables:

$X_1$ = Percentage of MTT commodities

$X_2$ = Percentage of informal employment

$X_3$ = Percentage of completion rate of high school education

All statistical analyses are conducted using RStudio, employing appropriate packages for multilevel modeling. Model estimation is performed using maximum likelihood methods, and statistical significance is evaluated at the 5% significance level ($\alpha = 0.05$). (Prasani et al., 2015; Zannah, et al., 2022).

### Linear Mixed Model

A linear mixed model (LMM) is an extension of the classical linear regression model that simultaneously incorporates fixed effects and random effects influencing the response variable. Fixed effects represent the primary explanatory variables of interest, whereas random effects

account for additional sources of variability arising from hierarchical or clustered data structures. In this study, two model specifications were considered: (1) a model including only fixed effects (without random effects), and (2) a model incorporating both fixed and random effects to capture potential unobserved heterogeneity.

Model without random effects,

$$Y_{ij} = \beta_0 + \beta_1 t_j + \epsilon_{ij} \quad (1)$$

Model with random effect

$$Y_{ij} = \beta_0 + \beta_1 t_j + \alpha_i + \epsilon_{ij} \quad (2)$$

with, $k \in \{0,1\}$ is the time before and after the COVID-19 corona virus, $j$ is the provincial representation and $i$ is the regional representation.

## RESULTS AND DISCUSSION

Data processing is carried out by analyzing data collected before and after the COVID-19 pandemic. Various models were created and processed using RStudio. Below, we explain the results of longitudinal data analysis using various model combinations.

### No Random Effects

The first model we constructed was a simple linear mixed model (LMM) which only looked at the impact of the Covid-19 pandemic on the open unemployment rate in all Indonesian provinces, without considering random effects and other certain variables. The model construction used is as follows:

$$\begin{gathered} Y_{ijk} = \beta_0 + \beta_1 t_k + \varepsilon_{ijk} \\ \varepsilon_{ijk} \sim N(0, \sigma^2_{residu}) \end{gathered} \quad (3)$$

The response variable is expressed by the variable $Y_{ijk}$ which is a representation of the percentage of open unemployment in the $i$-th region, $j$-th province, and $k$-th measurement. Index $i$ is a member of the set $\mathbb{Z}_7 - \{0\}$ to represent six regions based on major islands in Indonesia. Index $j$ is a member of the set $\mathbb{Z}_{35} - \{0\}$ to represent 34 provinces in Indonesia. Meanwhile index $k$ is a member of the set $\mathbb{Z}_2$ with k=0 for variable data before the pandemic and k=1 otherwise. The data is processed using a significance of $\alpha = 5\%$.

**Table 1**. Model (3) parameter test results with no random effects

| | Estimation | Std. Error | p-value |
|---|---|---|---|
| Intercept ($\beta_0$) | 4,614 | 0.293 | 0.0000*** |
| Time ($\beta_1$) | 0.884 | 0.414 | 0.0365** |

Table 1 shows the p values for the coefficients $\beta_1$ is 0.0365. Therefore, the time variable is considered to have a significant effect on changes in the open unemployment rate variable in Indonesia (Y). The positive coefficient (Coefficient $\beta_1$) indicates that the pandemic systematically increased unemployment, reflecting widespread labor market contraction across provinces.in Indonesia. This is in line with Svabova et al. (2020) statement, there was a greater increase in unemployment figures after the COVID-19 cases, even higher than the number of deaths (Su et al., 2022).

### Regional Random Effects

The next model that we construct in this study is the LMM model which considers regional random effects on the impact of the COVID-19 pandemic on the open unemployment rate in all Indonesian provinces. The regional random effects included in the model are intended to accommodate the different regional influences, culture, habits, and community mobility in each major island region in Indonesia. This difference is considered capable of influencing the open

unemployment rate in Indonesia when dealing with a pandemic. The model construction used is as follows:

$$Y_{ijk} = \beta_0 + \beta_1 t_k + a_i + \varepsilon_{ijk}$$
$$a_i \sim N\left(0, \sigma^2_{regional}\right), \varepsilon_{ijk} \sim N(0, \sigma^2_{residu}) \quad (4)$$

This second model is similar to the previous one but adds the variable $a_i$ as a regional random effect representation. In this model $a_i$ and $\varepsilon_{ijk}$ are independent. The results of data processing are listed in Table 2.

**Table 2**. Model (4) parameter test results with regional random effects

| | Estimation | Std. Error | p-value |
|---|---|---|---|
| Intercept ($\beta_0$) | 4,614 | 0.297 | 0.0000*** |
| Time ($\beta_1$) | 0.884 | 0.413 | 0.0365** |

Table 2 shows the p-value for the coefficient $\beta_1$ is 0.0365. Therefore, the time variable is considered to have a significant effect on changes in the open unemployment rate variable in Indonesia (Y). A positive coefficient $\beta_1$ indicates that the COVID-19 pandemic has increased the open unemployment rate in Indonesia statistically significantly. This shows that this second model can be considered as a better model than the previous one because it is able to explain the open unemployment rate more broadly.

**Provincial Random Effects**

The next model we construct is the LMM which considers the random effect of the province on the impact of the COVID-19 pandemic on the open unemployment rate in all Indonesian provinces. The provincial random effect is intended to accommodate regional influences, culture, habits, and community mobility at the provincial level in Indonesia which can be different. This difference is considered capable of influencing the open unemployment rate in Indonesia when dealing with a pandemic. For example, the economic and social life of the community in Jakarta is of course different from that in North Kalimantan. This random effect is expected to explain how the model should be built. The model construction used is as follows:

$$Y_{ijk} = \beta_0 + \beta_1 t_k + b_{j(i)} + \varepsilon_{ijk}$$
$$b_{j(i)} \sim N\left(0, \sigma^2_{provinsi}\right), \varepsilon_{ijk} \sim N(0, \sigma^2_{residu}) \quad (5)$$

This third model is similar to the previous one but adds variables $b_{j(i)}$ as a provincial random effect representative. On this model $b_{j(i)}$ and $\varepsilon_{ijk}$ are mutually independent. The results of data processing are listed in Table 3.

**Table 3**. Model (5) parameter test results with provincial random effects

| | Estimation | Std. Error | p-value |
|---|---|---|---|
| Intercept ($\beta_0$) | 4,614 | 0.293 | 0.000*** |
| Time ($\beta_1$) | 0.884 | 0.162 | 0.000*** |

Table 3 shows the p-value for the coefficients $\beta_1$ is 0.000. Therefore, the time variable is considered to have a significant effect on changes in the open unemployment rate variable in Indonesia (Y). This shows that COVID-19 has brought significant changes to changes in the unemployment rate in Indonesia. The coefficient $\beta_1$ a positive value indicates that the COVID-19 pandemic has increased the open unemployment rate in Indonesia statistically significantly. This fact can be used by policy makers to make the best decisions in reducing unemployment in Indonesia.

**Regional and Provincial Random Effects**

The next model we construct is the Linear Mixed Model (LMM) which considers regional and provincial random effects as well as the impact of the COVID-19 pandemic on the open unemployment rate in Indonesia. The random effects included in the model are intended to

accommodate regional influences, culture, habits, so that people's mobility in each province and region in Indonesia can be different. For example, Bengkulu Province and Riau Archipelago. The Riau Archipelago has Batam City, which is an international trade route, which Bengkulu does not have. This of course has a different effect on the open unemployment rate even though these two provinces are in the same region. The model construction used is as follows:

$$Y_{ijk} = \beta_0 + \beta_1 t_k + a_i + b_{j(i)} + \varepsilon_{ijk}$$
$$a_i \sim N\left(0, \sigma^2_{regional}\right), b_{j(i)} \sim N\left(0, \sigma^2_{provinsi}\right), \varepsilon_{ijk} \sim N(0, \sigma^2_{residu}) \quad (6)$$

This third model is similar to the previous one but adds the variable $a_i$and $b_{j(i)}$ as a representation of regional and provincial random effects respectively. on these models $a_i, b_{j(i)}$ and $\varepsilon_{ijk}$ mutually independent. The results of data processing are listed in Table 4.

**Table 4**. Model (6) parameter test results with provincial random effects

| | Estimation | Std. Error | p-value |
|---|---|---|---|
| Intercept ($\beta_0$) | 4,543 | 0.393 | 0.000*** |
| Time ($\beta_1$) | 0.884 | 0.162 | 0.000*** |

Table 4 shows the p-value for the coefficient $\beta_1$ is 0.0000. Therefore, the time variable is considered to have a significant effect on changes in the open unemployment rate variable in Indonesia (Y). The coefficient $\beta_1$ is positive indicating that the COVID-19 pandemic has increased the open unemployment rate in Indonesia with statistical significance.

After carrying out the model variations described above, the next model comparison will be attached with consideration of the standard error and total variance as feasibility indicators. Comparison of the feasibility of the models is attached in table 5.

**Table 5**. Comparison of model's feasibility

| | Model (3) | Model (4) | Model (5) | Model (6) |
|---|---|---|---|---|
| | | **Permanent effect** | | |
| Intercept ($\beta_0$) | 4.614 (0.293) | 4.611 (0.296) | 4.614 (0.293) | 4.614 (0.293) |
| Time ($\beta_1$) | 0.883 (0.415) | 0.883 (0.413) | 0.883 (0.162) | 0.883 (0.162) |
| | | **Variance** | | |
| $\sigma^2_{regional}$ | - | 0.0112 | - | 6,431 e-9 |
| $\sigma^2_{provinsi}$ | - | - | 2.4696 | 2.4696 |
| $\sigma^2_{residu}$ | 2.91483 | 2.90592 | 0.44526 | 0.44526 |
| **Total** | 2.91483 | 2.91712 | 2.91486 | 2.91486 |

Based on the comparison in Table 5, it can be seen that the random effect has little effect on the fixed effect but has a large effect on the Standard Error. The four models show that there has been a significant increase in the open unemployment rate from before the pandemic to after the COVID-19 pandemic. This can be seen from the positive value of the coefficient$\beta_1$ formed for all models.

The models also contain a specific correlation structure. As an example, the correlation structure will be described in Model (6). Observations from different regions, $i$ and $i^*$, $i \neq i^*$, are not correlated or $\widehat{Corr}\left(Y_{ijk}, Y_{i^*j^*k^*}\right) = 0$. Meanwhile observations in the same region but in different provinces, $j$ and $j^*$, $j \neq j^*$, correlated with,

$$\widehat{Corr}\left(Y_{ijk}, Y_{ij*k*}\right) = \frac{\hat{\sigma}^2_{regional}}{\hat{\sigma}^2_{regional} + \hat{\sigma}^2_{provinsi} + \hat{\sigma}^2_{residu}} = \frac{0.0112}{2.91486} = 0.03842 \quad (7)$$

Furthermore, in the same provincial observations at different times, $k$ and $k^*$, $k \neq k^*$, correlated with (8)

$$\widehat{Corr}(Y_{ijk}, Y_{ijk*}) = \frac{\hat{\sigma}^2_{regional} + \hat{\sigma}^2_{provinsi}}{\hat{\sigma}^2_{regional} + \hat{\sigma}^2_{provinsi} + \hat{\sigma}^2_{residu}} = \frac{0.0112 + 2.4696}{2.91486} = 0{,}8511$$

Additional covariates can also be discussed in research to explain the diversity in different models. This was also carried out to study the characteristics of each Indonesian province and region which are related to trends in data changes before and after the COVID-19 pandemic. Next, this study includes additional covariates in Model 3.4 to take a deeper look at the feasibility of the model.

Covariate variables are variables that are useful for reducing noise in data analysis caused by variables other than the variable being studied. This causes the effects of the variables studied to be seen more clearly (Trochim, 2006). The covariate variables that were added were the Margin of Trade and Transportation (MTT) of Shallot Commodities, the Proportion of Informal Employment, and the Community High School Education Completion Rate. These data were compiled from the Central Bureau of Statistics for the period before and after the COVID-19 pandemic.

**Model (6) Modification with the Covariate Variable MTT for the Shallot Commodity**

Margin of trade and transportation (MTT) is the compensation of traders as distributors of goods, which is the difference between the sales value and the purchase value. This margin is a measure of the amount of output from trading activities. This study investigates the effect of Shallot MTT on open unemployment in Indonesia. Data processing was carried out with R Studio with the results attached in Table 6.

**Table 6**. Parameter test results with shallot's MTT covariate

| | Estimation | Std. Error | p-value |
|---|---|---|---|
| Intercept | 3.444 | 0.602 | 0.000*** |
| MTT KBM | 0.021 | 0.008 | 0.017*** |
| Time | 2.187 | 0.547 | 0.003*** |
| MTT KBM Time | 2.91483 | 2.91712 | 0.019*** |

Table 6 shows the p-value for the covariate variable margin of trade and transportation margin of shallot commodity less than significance α, indicating that this variable has a statistically significant effect on the open unemployment rate in the provincial segmentation in Indonesia. The coefficient for the MTT for the shallot commodity variable is also positive which indicates that the increase in the MTT for the shallot commodity rate is responsible for the increase in the open unemployment rate in the provincial segmentation in Indonesia. This statistical fact reinforces the allegation that the MTT for the shallot commodity does affect the open unemployment rate in Indonesia. This happens because the higher the percentage of MTT for the shallot commodity, the higher the price at the consumer level. As a result, people have difficulty buying shallots and sellers experience a decline in sales figures. Furthermore, sellers will reduce workers in their industries so that the unemployment rate will increase.

The result also shows that the p-value for the time variable is less than the significance of α, indicating that this variable has a statistically significant effect on the open unemployment rate in Indonesia's provincial segmentation. The coefficient for this variable is also positive, indicating that the change in time (before and after the pandemic) was also followed by an increase in the open unemployment rate in Indonesia's provincial segmentation.

Furthermore, this model also shows the p value for the variable MTT for the shallot commodity: Time is less than the significance of α, indicating that this variable has a statistically significant effect on the open unemployment rate in the provincial segmentation in Indonesia. This shows that the pandemic has affected the MTT for shallots and has resulted in a change in the open unemployment rate in Indonesia.

**Model (6) Modification with the Covariate Variable Proportion of Informal Employment**

Informal workers are residents who work as self-employed, try to be assisted by temporary workers/unpaid workers, casual workers, and family workers/unpaid. The Proportion of Informal Employment (PIL) describes labor market conditions in a more comprehensive manner, as a complement to the open unemployment rate indicator, so that it can provide an overview

(assessment) of the quality of available employment in a country. Informal employment conditions provide an illustration for establishing worker protection policies, namely improving working conditions, wages, and social protection. In addition, this condition can become the basis for making policies to increase the productivity of informal economic activities, planning skills development and training, and setting regulatory frameworks, institutional reforms, and regional development policies. This decrease in proportion shows that the economy, which is supported by the growth and development of micro, small and medium enterprises, has been able to create decent and productive jobs with adequate protection.

This study investigates the effect of PIL on the open unemployment rate in Indonesia. Data processing was carried out with R Studio with the results attached in Table 7.

**Table 7**. Parameter test results with covariate variable proportion of informal employment in provincial segmentation

| | **Estimation** | **Std. Error** | **p-value** |
|---|---|---|---|
| Intercept | 8,963 | 1,253 | 0.000*** |
| MTT KBM | -0.077 | 0. 021 | 0.001** |
| Time | 3,789 | 0.98 | 0.0005*** |
| MTT KBM Time | -0.043 | 0.016 | 0.017** |

Table 7 shows the p value for the covariate variable Proportion of Informal Employment (PIL) is less than the significance of α, indicating that this variable has a statistically significant effect on the open unemployment rate in the provincial segmentation in Indonesia. The coefficient for the PIL variable is also negative which indicates that the increase in the PIL rate is responsible for the decrease in the open unemployment rate in the province segmentation in Indonesia. A clear example that illustrates these figures is the reduction in small street vendors. The pandemic has destroyed their business and run out of capital. As a result, they are no longer able to build a business and increase the open unemployment rate in Indonesia.

The result also shows that the p-value for the time variable is less than significant $\alpha$, indicating that this variable has a statistically significant effect on the open unemployment rate in Indonesia's provincial segmentation. The coefficient for this variable is also positive, indicating that the change in time (before and after the pandemic) was also followed by an increase in the open unemployment rate in Indonesia's provincial segmentation. This is relevant to the example of the case of street vendors.

Furthermore, this model also shows the p value for the variable PIL: Time is less than the significance of α, indicating that this variable has a statistically significant effect on the open unemployment rate in the provincial segmentation in Indonesia. This shows that the pandemic has affected the proportion of informal employment and has resulted in a change in the open unemployment rate in Indonesia.

**Model (6) Modification with the Covariate Variable Level of Completion of High School Education**

Senior High School (SHS) Education Completion Rate (ECR) is an indicator that measures the percentage of children and adolescents who successfully complete SHS (High School) education according to their age range. Completion rates that reach or approach 100% indicate that almost all children and adolescents have completed the level of education that should be appropriate for their age, without significant or significant delays.

This study investigates the effect of SHS ECR on the open unemployment rate in Indonesia. Data processing was carried out with R Studio with the results attached in Table 8.

**Table 7**. Parameter test results with covariate variable level of high school education completion in province segmentation

| | **Estimation** | **Std. Error** | **p-value** |
|---|---|---|---|
| Intercept | 1971 | 1,357 | 0.156 |
| MTT KBM | 0.044 | 0.022 _ | 0.057 |
| Time | -1,492 | 0.948 | 0.125 |
| MTT KBM Time | 0.031 | 0.014 | 0.038 |

Table 8 shows the p-value for the covariate variable SHS Education Completion Rate not less than α significance, indicating that this variable has no statistically significant effect on the open unemployment rate in the provincial segmentation in Indonesia. The result also shows that the p-value for the time variable is not less than the significance of α, indicating that this variable has no statistically significant effect on the open unemployment rate in Indonesia's provincial segmentation.

**Summary and Implications**

Overall, a key contribution of this study lies in highlighting the role of regional heterogeneity as a central mechanism shaping labor market outcomes. The multilevel estimates reveal substantial variation across provinces and regions, suggesting that national-level aggregates may obscure critical subnational disparities. The empirical findings confirm that the COVID-19 pandemic generated a significant temporal shock to Indonesia's labor market, as evidenced by the consistently positive and statistically significant time effect across model specifications. The persistence of this effect, even after accounting for regional and provincial random components, indicates that the pandemic shock was structural and nationwide in scope. However, the variation in random effect estimates across provinces highlights that labor market responses were not uniform, reflecting underlying regional heterogeneity in adaptive capacity.

The analysis further demonstrates that structural characteristics play a decisive role in shaping regional resilience. Disruptions in commodity distribution, proxied by the Margin of Trade and Transportation (MTT) of shallots, are associated with higher unemployment pressures, suggesting that inefficiencies in supply chain systems may amplify economic vulnerability during crisis conditions. In contrast, the proportion of informal employment exhibits a mitigating effect, indicating that informal labor absorption can function as a short-term buffer against unemployment shocks. Nevertheless, while informality enhances immediate flexibility, its structural limitations may constrain long-term resilience if not supported by institutional and productivity improvements. Clearly, while informal employment reduces short-term unemployment pressures, it may undermine long-term resilience due to limited job security and productivity constraints. This highlights an important trade-off between short-term absorptive capacity and long-term adaptive resilience.

These findings together indicate that employment resilience during systemic crises depends not just on the size of external shocks but comes from the dynamic interaction between temporary disruptions and existing regional structural characteristics. The pandemic did not simply raise unemployment levels; it revealed existing disparities in economic structure, labor flexibility, and distribution systems across provinces. Understanding unemployment dynamics therefore requires incorporating both temporal shocks and regional differences into the resilience framework, especially when examining economic resilience.

## CONCLUSION

Overall, this study advances the understanding of economic resilience by demonstrating that unemployment dynamics during crisis periods are shaped by the interaction of structural, spatial, and market-based factors. By integrating regional heterogeneity, labor market dualism, and supply chain efficiency within a multilevel analytical framework, the study offers a more holistic account of how economies respond to systemic shocks. This study demonstrates the importance of incorporating multilevel regional dynamics in assessing national economic resilience.The findings indicate that the COVID-19 pandemic had a significant effect on the open unemployment rate in Indonesia (p-value: 0.0365, coefficient: 0.884). This study shows that residence in certain regions and provinces also affects the unemployment rate during the pandemic. This means that the geographical, locational, cultural, economic, and other characteristics specific to a region or province will affect resilience to the COVID-19 pandemic. This study also shows that the percentage of MTT for shallots has an impact on the open unemployment rate with a p-value of 0.017 and a variable coefficient of 0.021. In addition, it was also found that the proportion of informal workers in the national labor force also has a significant impact on changes in the open unemployment rate (p-value: 0.001, coefficient: -0.077). Another insight generated in this research is that the level of completion of high school education does not significantly affect the open unemployment rate. This study confirms that the COVID-19 pandemic generated a significant temporal shock to Indonesia's employment, leading to a

systematic increase in open unemployment rates across provinces. Although the shock was nationwide, its magnitude varied across regions, reflecting structural heterogeneity in economic composition, labor market flexibility, and distribution systems. These differences demonstrate that regional characteristics play a critical role in shaping economic resilience during crisis conditions. Therefore, understanding the dynamics of unemployment requires integrating the analysis of temporal shocks and regional heterogeneity into the resilience framework, particularly in economic resilience. Policies should focus on strengthening regional supply chains and formalizing informal sectors.

Future research should extend the temporal scope to capture long-term recovery trajectories and post-pandemic adjustment dynamics. Incorporating additional structural variables such as fiscal capacity, industrial diversification, and social protection coverage would allow for a more comprehensive assessment of resilience determinants. Moreover, comparative cross-country or cross-regional studies could provide broader insights into how institutional frameworks and governance quality influence labor market adaptability under systemic shocks. Integrating spatial econometric approaches may also deepen understanding of spillover effects and interregional dependencies in times of crisis.

## AUTHOR CONTRIBUTIONS

N.: Conceptualization, investigation, methodology, resources, funding acquisition, and writing – review & editing. B.R.: Data collection, data curation, formal analysis, visualization, and writing – original draft. K.C.P.: Data curation, formal analysis, and writing – review & editing. A.N.B.: Supervision and writing – review & editing. S.S.: Supervision and formal analysis.

## CONFLICT OF INTEREST

The authors declare that have no conflict of interest.

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