ICHSS
THE 3rd INTERNATIONAL CONFERENCE OF HUMANITIES AND SOCIAL SCIENCE
Examining Socio-Cultural Problems, Language, Literature, and Art to Uplift The Nation's Civilization

INDIVIDUAL VULNERABILITY DURING COVID USING THE PRINCIPAL COMPONENT ANALYSIS METHOD

Ruth Meilianna
{ruthmeilianna56@gmail.com}

Badan Pusat Riset dan Inovasi Nasional (BRIN), Jakarta

Abstract. The Covid-19 pandemic affects almost all aspects globally, including health, economic, educational aspects, and also affects individual vulnerability can be affected. This research wants to examine worker vulnerability which is formed using a worker vulnerability index which is formed from various dimensions. The data used is the World Bank High Frequency Household Survey (HIFY) data which is specifically aimed at looking at aspects affected during Covid-19 until now, namely 2019 – 2023. The method used is Principal Component analysis. The results of the analysis show that female individuals tend to have higher vulnerability than men. Apart from that, there is a tendency for individuals with higher education, have lower vulnerability than individuals with low education. There is also a trend towards an improvement in the individual vulnerability index after Covid-19.

Keywords: covid-19, PCA, vulnerability, gender, education

INTRODUCTION

The Covid-19 pandemic has affected almost all aspects globally, including health, economy, education, and has also affected various aspects in Indonesia. Kansime (2021) examined how income and food security in two countries, East Africa and Urganda when Covid-19 came. The results showed that two-thirds of the respondents faced their income and food security deteriorating. In addition, ADB (2021) found that the Covid-19 pandemic had an impact on the reduction of working hours, loss of working hours, financial difficulties and the cessation of schooling for children due to not having digital devices and the difficulty of internet connection signals in Asian countries. On the other hand, Adriani (2021) stated that the Covid 19 Pandemic has encouraged people's consumption patterns to become more consumptive to meet their needs, while the lower middle class choose to diversify their food with substitutes. On average, changes in consumption patterns are more about increasing consumption allocations that pr ioritize food quality and food diversity. Not only Covid-19 shocks, several previous studies have examined other shocks. Torres (2015) examined the effect of international food price shocks on consumption and urban households in Mexico. Several previous studies illustrate that shocks tend to exacerbate the vulnerability of individuals or low-income households.

Moreover, there are several previous articles that discuss worker vulnerability. Bocquier et al. (2010) examined worker vulnerability in West Africa and its relationship with income using the European Social Survey. This study formed an index built from several indicators in measuring the vulnerability index. Furthermore, this study uses two least stage square to determine the impact of worker vulnerability on economic growth. More in-depth, this study divides the sample of workers into three parts, first formal private, informal private and total private sector. The results show that 85 percent of private sector workers in all capitals are vulnerable. Bazillier et al. (2015) examined worker vulnerability in Europe and examined the effect of migration on worker vulnerability. In line with Bocquier et al. (2010) this study also formed a vulnerability index formed from several indicators. The difference between the two studies is in the indicators used to form the vulnerability index. In addition, this study also uses survey data in its research, namely using the European Social Survey in 2008. In addition, another difference between this study and Bocquier et al. (2010) is in the method. This study estimates the model with propensity score matching (PSM). The results of the study indicate that migration can be seen as a strategy to reduce the vulnerability of workers for workers with low income. Based on this background, this research aims to measure the vulnerability of individuals in the household.

LITERATURE REVIEW

Vulnerability contributes to future poverty because it leads to lower income compared to current income due to shocks, ultimately increasing the depth of poverty. Sources of risk that can affect vulnerability include natural disasters (such as droughts, floods, cyclones, earthquakes), health shocks (such as disease, accidents, epidemics), social shocks (such as theft, assault, civil war, extortion), economic shocks (such as international price shocks, unemployment and inflation), political events (policy changes, termination of social programs), and social harms (such as air pollution from forest policies, emissions from neighboring companies). Reducing risk and mitigating the consequences of risk exposure will be a challenge for policymakers. Risk reduction consists of actions that reduce the likelihood of severity, such as medicine, education, vaccination, and savings. Risk reduction helps to protect income from shocks. Risk reduction can also be achieved through risk management in the form of self-insurance, mutual insurance, formal insurance (Haughton & Khandker, 2009).

There are several articles that discuss the concept of worker vulnerability. Saunders (2003) defines worker vulnerability as workers who fall outside the scope of labor laws. Ginneken (2005) categorizes vulnerable workers as those whose welfare declines because they are unable to cope with risks in the face of threats. Adger (2006) defines worker vulnerability as a concept where there is an interaction between the level of sensitivity of certain groups to exposure due to external shocks. The impact felt depends on the adaptive capacity of the group exposed to the shock. DIT (2006) defines worker vulnerability as a function of adverse risk, and a vulnerable worker is one who works in an unprotected environment. O'Brien (2007) states that the level of vulnerability depends on the social, political, governance, economic and cultural environment in which the community is located. ILO (2009) explains that workers can be said to be vulnerable if they do not receive adequate wages and do not enjoy basic labor rights. Fashoyin & Tiraboschi (2013) state that someone who works in a high-risk environment and does not have the ability to protect themselves can be categorized as a vulnerable worker. Generally, the vulnerability of workers is categorized from several indicators such as worker protection, income level, social, economic and political risks, work environment risks, and capacity to face risks.

There are several studies that discuss the impact of shocks on worker vulnerability. Bocquier et al. (2010) examined the vulnerability of workers in West Africa and its relationship with income using the European Social Survey. Bocquaier et al. (2010) used an approach of indicators that can summarize workers' vulnerabilities to explain the concept of worker vulnerability approach. This study formed an index built from several indicators in measuring the vulnerability index. The indicators used by Bocquier et al. (2010) to build the vulnerability index are contract, worker independence, working conditions, casual work, visible underemployment, instability in employment and remuneration. In addition, this study uses two least squares to determine the impact of worker vulnerability on economic growth. In more detail, this study divides the sample of workers into three parts, first formal private, informal private and total private sector. The results show that 85 percent of private sector workers in all capitals are vulnerable. Bazillier et al. (2015) studied the vulnerability of workers in Europe and examined the impact of migration on the vulnerability of workers. The agreement used by Bazilier et al. (2015) to explain the concept of worker vulnerability is the difficulty of individuals to manage risks or cope with losses and costs associated with risky events or situations, so worker vulnerability is workers who are exposed to risks under inadequate conditions or the risk of not having a good job. Bazilier et al. (2015) formed an index of vulnerability, which is composed of several indicators. The indicators used are: employment relationship, permanent employment contract, size of establishment, type of organization, responsible for supervising other employees, allowed to influence policy decisions about the organization's activities, and occupation. This study also uses survey data in its research, namely using the European Social Survey in 2008. This study estimates the model using propensity score matching (PSM). The results indicate that migration can be seen as a strategy to reduce the vulnerability of low-skilled workers.

RESEARCH METHOD

This study uses the World Bank's High Frequency Monitoring of Covid 19 Impact (HIFY) wave 2 in 2021 data. The World Bank has launched a rapidly-deployed high-frequency household monitoring survey to generate near real-time insights into the socio-economic impacts of COVID-19 on households that are then used to support evidence-based responses to the crisis. The breakdown of the mechanics of socio-economic impacts, identifying gaps in the public policy response along with the Government's response, yields insights that can be useful in scaling up or redirecting resources where necessary for affected communities to survive and ultimately regain economic footing. This data provides micro data that provides multiple aspects or variables. Moreover, this data has the advantage of having multiple rounds so that changes over time can be seen.

High Frequency Monitoring of Covid 19 Impact (HIFY) is available for 8 rounds. Round 1 starts in May 2020 and ends in the same month. Round 2 starts in Month 5 of 2020 and ends in June 2020. Then Round 3 starts in July 2020 through August 2020. Round 4 begins in November 2020 and ends in the same month. Round 5 begins in March 2021 and ends in the same month. Round 6 is conducted in October. Round 7 is in April 2022 and Round 8 starts in March 2023 and ends in April 20023. Each Round discusses a different round of topics. Table 1. shows the topics available at each Round. For example, Knowledge and behavior caps are only available in Round 1 & 3. Digital transactions are only available in Round 2 and 4. Not every aspect is available in every Round. However, there are also aspects that are available in many rounds such as household roster which is available in Round 1,2,3,4,5,6,7, and 8.

Table 1. High Frequency Monitoring of Covid 19 Impact (HIFY)

Start	End	Cycle
2020-05-01	2020-05-17	Round 1
2020-05-26	2020-06-05	Round 2
2020-07-20	2020-08-02	Round 3
2020-11-03	2020-11-15	Round 4
2021-03-11	2021-03-24	Round 5
2021-10-18	2021-10-31	Round 6
2022-04-07	2022-04-20	Round 7
2023-03-13	2023-04-03	Round 8

This research uses high frequency monitoring of covid 19 impact (HFIY) wave 2 in 2021 from the World Bank. This study uses several indicators to form a worker vulnerability index formed from several indicators and variables used (Table 2). Some of the indicators used are food security, health and income indicators. Each indicator consists of variables that can explain it. The variable lack of money to buy food and the variable reducing food consumption are used to explain the food security indicator. To explain the health indicator, the variable whether households have access to medical care to buy food is used. Furthermore, the variable of additional income from additional activities is a variable that explains the income indicator. All these indicators are used to form a worker vulnerability index. Then, this worker vulnerability index becomes the dependent variable. The independent variables used are the Covid-19 aspect, finance and banking, and other independent variables. The Covid-19 aspect can be explained by the variable of how Covid-19 affects household finances. This variable contains several levels of responses. The first is not affected, affected and very affected. The financial and banking aspects are explained by several variables that can explain workers' access to financial technology, such as the use of digital payment methods and the use of loans from financial institutions. The next variable used is the savings dependent variable. This variable can explain the ownership of savings by workers. Furthermore, other independent variables used are the variables of credit purchase, government assistance, and age of workers. This credit purchase variable can explain the consumption of workers in the Covid-19 situation and this study wants to see whether this credit consumption behavior encourages these workers to be more vulnerable or not. In addition, the age variable is also used as an independent variable.

Table 2. Indicators and Variables Forming the Vulnerability Index

Indicator	Variables
Food security	Ps5a_8 Past week, did you/hh have to eat less cause of lack of money or other resources Yes, often................1 Yes, sometimes............2 Yes seldom................3 No........................4 Ps5a_9 Past month, did you/any other adult in your household, were hungry but did not e Ps5a_10 Past month, did you/any adult in your household, went without eating for a whole
Health	Ps5b_1 In the last week, has your hh been able to buy Medicine? Yes …….. 1 => 1 No ……... 2 => 2 Not Tried …. 3 => 3 Ps5b_3 Were you or the member of your household able to access the medical treatment? Yes …….. 1 => 1 No ……... 2 => 2
Income	Ps8_3 How much of a threat would you say the coronavirus outbreak is to your household's finances? A substantial threat ....1 =>4 A moderate threat ....2 => 3 Not much of a threat ....3 => 2 Not a threat at all .....4 => 1
Concerns	ps8_1 How worried are you about the possibility that you or someone in your immediate family might become ill from COVID-19 (coronavirus disease)? Very worried ....1 => 4 Somewhat worried ....2 => 3 Not too worried .....3=> 2 Not worried at all ..4 => 1 ps8_2

How worried are you about having enough to eat in the next week?
Very worried ....1 => 4
Somewhat worried ....2 => 3
Not too worried .....3 => 2
Not worried at all ..4 => 1

ps8_4
How worried are you with your household's finances in the next month?
Very worried ....1 => 4
Somewhat worried ....2=>3
Not too worried .....3 =>2
Not worried at all ..4 =>1

Vulnerability Index

This research uses Principal Component Analysis (PCA) to construct a worker vulnerability index from several predetermined variables. Principal component analysis (PCA) is used to find relationships between variables from a set of variables (Tabachnick, 2001). Principal component analysis (PCA) aims to explain some of the variation in a set of observed variables on the basis of several dimensions, while the specific purpose of principal component analysis (PCA) is to summarize the correlation pattern between observed variables and reduce a large number of variables to a small number of factors. In addition, another specific purpose is to provide an operational definition of the main dimensions of the use of observed variables, and the final objective is to test the underlying theory (Tabachnick, 2001). Amaluddin (2017) states that Principal Component Analysis (PCA) is used to transform data in a linear way on a correlated variables into a new data structure with new variables (called principal components) that are not correlated. The principal component analysis process produces eigenvalues, factor loadings, loadings and factor scores. In terms of selecting the factor scores, the eigenvalues should be greater than 1 and the total diversity should be greater than or equal to 70% (Gozali, 2013). In addition, it is necessary to test with KMO, where the KMO value must be > 0.50, which indicates that there is a sufficient sample for the feasibility of this PCA analysis. Then, from the results of this PCA, the weight of each variable indicator that will be used is obtained using Kaiser-Meyer-Olkin and Barlet's Test of Spbericity.

RESULT AND ANALYSIS

1.1 Indeks Kerentanan Individu

The first step we need to do in Principal Component Analysis (PCA) test is to test KMO and Bartlett's test (Table 3). The results show that the Kaiser-Meyer-Olkin test value is 0.757, which indicates that this study has sufficient data and is suitable for further testing. When the Kaiser-Meyer-Olkin test value is <0.5, the data is insufficient and additional data must be added to make it suitable for research. The results of Bartlett's test of sphericity indicate that the data used are good for use in factor analysis and that the data are well correlated.

Tabel 3. KMO dan Barlett's Test

Kaiser-Mayer-Oklin Measure of Sampling Adequacy		0.757
Barlett's Test of Sphericity	Approx. Chi-Square	25153.715
	Df	36
	Sig	0.000

In addition, when measuring Principal Component Analysis (PCA), we must also pay attention to the R-square in the regression analysis available in Table Y. Variables that have low correlation communalities are considered red flags or the factor is not good to use. The value considered low is 0.3. Table Y shows that all variables have correlation communalities that are all above 0.5, so all factors or variables can be included in the analysis and no factors or variables need to be removed from the model. These results may indicate that all the variables used are appropriate and all the variables are significant variables that form the worker vulnerability index.

After determining which variables are appropriate to use, the Principal Component Analysis (PCA) process extracts variables or components into multiple variables. In this model, Principal Component Analysis (PCA) extracts factors into 3 components (Table 4). In Table 4, there is an eigenvalue where this eigenvalue explains the total variation that can be explained in the data. The results show that only three new components have been extracted, with the largest total variation being in component 1, which is 31.08%. In other words, the newly created component is able to explain 31.084%. Furthermore, the second component is able to explain 16.196% of the total variation and the third component is able to explain 12.036% of the total variation.

Table 4. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	2.798	31.084	31.084	2.798	31.084	31.084	2.57
2	1.458	16.196	47.279	1.458	16.196	47.279	1.784
3	1.083	12.036	59.316	1.083	12.036	59.316	1.391
4	0.857	9.526	68.841				
5	0.723	8.032	76.873				
6	0.673	7.479	84.352				
7	0.551	6.12	90.472				
8	0.498	5.529	96.001				
9	0.36	3.999	100				

The number of new components created by Principal Component Analysis (PCA) can also be seen in the scree plot (Figure A). The vertical plane shows the eigenvalues for the components, which originally totaled 9. Only components 1, 2, and 3 have eigenvalues greater than 0.5, so the new components total 3.

Table 5. Rotation: Orthogona Varimax (Kaiser off)

Component	Variance	Difference	Proportion	Cumulative
Comp 1	2.5	0.91	0.27	0.27
Comp 2	1.58	0.33	0.17	0.45
Comp 3	1.24		0.13	0.59

After knowing which components or variables are included in the index model and which variables or components must be removed in the index calculation, and then knowing how many new components are formed, the index can be calculated. This calculation is done using the following formula

PCB = PCB1 * The proportion value of the component 1 + PCB2 * The proportion value of the component 2 + PCB3 * The proportion value of the component 3 / Cumulative value 3... (1)

So the value becomes

PCB = ((PC1B*0.2782)+(PC2B*0.1763)+(PC3B*0.1387))/0.5932.. (2)

Then we get the index value for each individual. The minimum and maximum values of the index depend on the highest value of the component. Next, we get an index value for each individual, which indicates the vulnerability value of the individual. In this research, the vulnerability value is divided into 5 levels, namely very not vulnerable, not vulnerable, medium, vulnerable and very vulnerable.

Figure 1 illustrates the results of the individual vulnerability data in 2020.The data shows that, on average, most individuals in 2020 have a medium vulnerability index.On average, the frequency table is spread in the middle and clustered on a scale between -2 and 2, and the largest frequency is in the range of index value 0. In general, the figure can show that the individual vulnerability index ranges on the scale of moderate vulnerability index and there are few individuals who have extreme vulnerability indices such as very good or very bad.

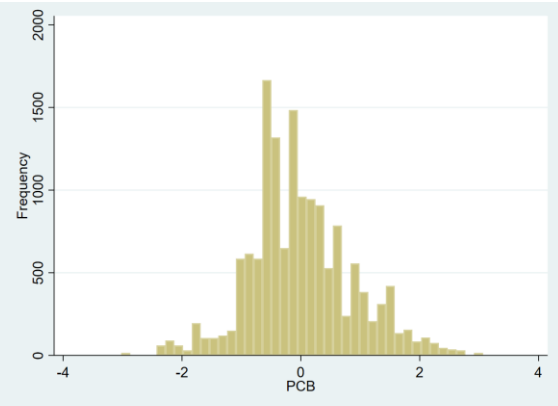

Fig. 1. Individual Vulnerability Index

Table 6. describes the maximum, minimum, mean and standard deviation values of the individual vulnerability index in Indonesia in 2020. The average value of the individual vulnerability index is 0.000, which can be said that on average the value of individual vulnerability is in a range that is still in the medium level category in 2020 The maximum and minimum values of the individual vulnerability index are 3.06 and -3.02. The maximum and minimum values of the individual vulnerability index are 3.06 and -3.02. The maximum and minimum values depend on the number of values in the category.

Table 6. Descriptive Statistic of Individual Vulnerable Index

	N	Minimum	Maximum	Mean	Std. Deviation
PCB	14757	-3.02	3.06	0	0.874

Furthermore, the overall overview of the state of the community vulnerability index in Indonesia can be illustrated by Table 7. The category with the highest frequency is the category of moderate vulnerability index, which amounted to 52749 of the total data. The next most frequent category is the category of poor vulnerability index, which amounted to 2096 and. These results indicate that the state of vulnerability of Indonesian society in 2020 tends to be moderate to poor. The frequency of the community vulnerability index with the good category is 2645. Furthermore, the frequency of the number of people who have very bad and very good vulnerability index categories is relatively small compared to the frequency of other vulnerability categories.

Tabel 7. Frequency of Individual Vulnerability Index Categories

Kategori	Frequency

Very Bad	270
Bad	3630
Medium	52749
Good	2645
Very Good	428

1.2 Women's Vulnerability to Covid-19 Shock

While we can measure vulnerability indices broadly, we can also measure gender-specific vulnerability indices and use the data to analyze whether there are differences in the vulnerability indices of women and men.

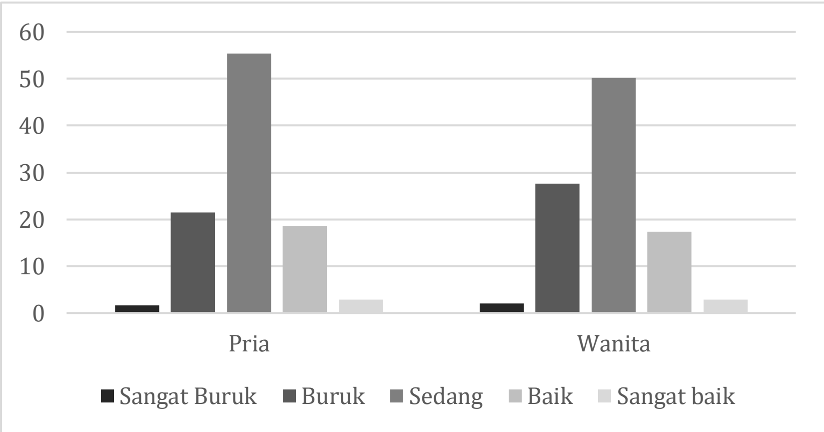

Fig. 2. Percentage Frequency of Vulnerability Categories by Gender

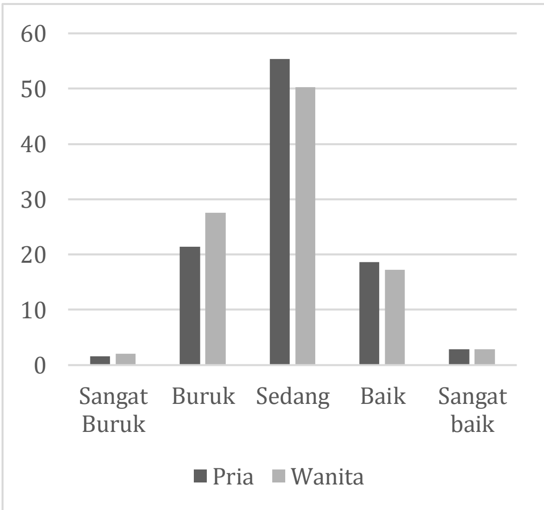

Fig. 3. Vulnerability of Women and Men by Vulnerability Index Category

Figure 2. and Figure 3. show that the vulnerability of women is worse than that of men, with a greater percentage frequency of the individual vulnerability index in the bad category, while in the poor category, the percentage frequency of women is less than that of men. In the medium category, there are more men than women. In the very good and very bad categories, both are relatively equal in frequency.

Tabel 8. Frequency of Women and Men in Vulnerability Categories

Male		Female	
Very Bad	118	Very Bad	152
Bad	1534	Bad	2096
Medium	3966	Medium	3818
Good	1331	Good	1314
Very Good	209	Very Good	219

Table 8. shows the frequency for each category of the individual vulnerability index for women and men. The category with the highest frequency for both men and women is the moderate category, which is 3966 for men and 52746 for women. The number of female individuals with a moderate vulnerability index is lower than the number of male individuals. Moreover, in terms of frequency or number of bad categories, the vulnerability index of women is higher than that of men.

1.3 Higher Education and Lower Individual Vulnerability Index.

Education is one of the most important aspects to consider when analyzing an individual's Vulnerability Index. Although there is not a strong relationship between education and the Vulnerability Index, education can affect a person's vulnerability. A person with higher education tends to have a good level of knowledge about risk management, so when the shock comes, they are more vulnerable than those with lower education.

Figures 4 and 5 illustrate how education affects a person's vulnerability. The good and excellent vulnerability index categories are dominated by those with a college degree (Figure 4). Furthermore, the lower the level of education, the lower the relative frequency or number of individuals with a good vulnerability index. In addition, those with higher education tend to have a very low frequency in the very poor vulnerability index category.

Furthermore, in the bad vulnerability index category, there is a tendency that the higher the education, the lower the number/frequency. In Figure 5 the highly educated category is dominated by those in the medium category, then good then bad. Interestingly, there is a tendency that the higher a person's education, the number of those in the medium category is actually lower, but the number of those in the good category is getting higher while the number in the bad category is getting lower. However, there is another interesting thing, at the Not in school/never attend education level and the primary school/similar education level, the percentage in the medium category is relatively large besides the percentage in the bad category which is also high.

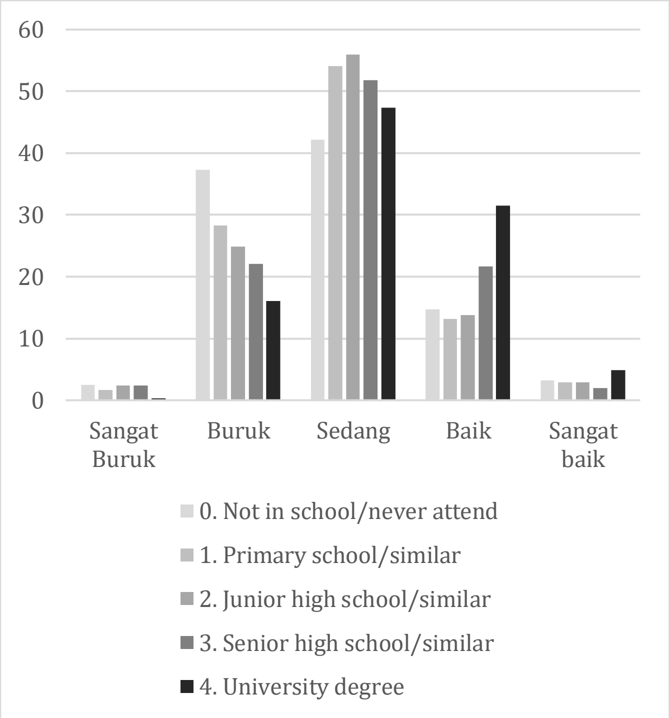

Fig. 4. Percentage of Vulnerability Index Based on Education Level

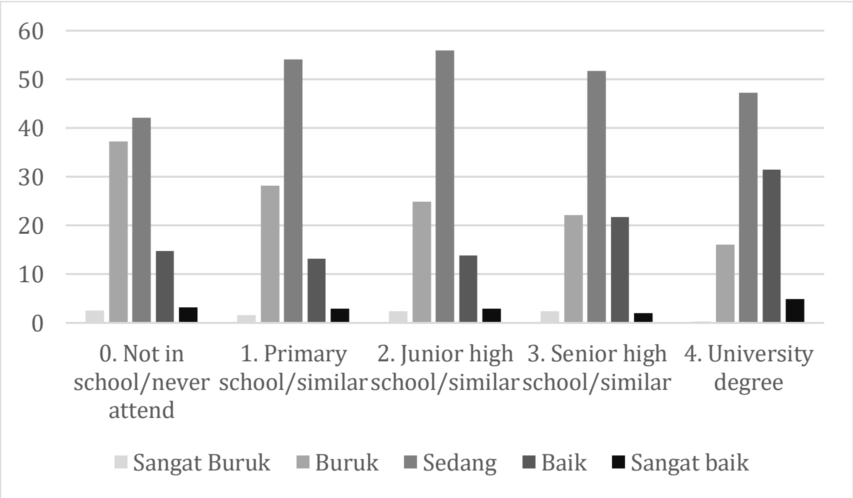

Fig. 5. Percentage of Individuals from Each Education Level Based on Vulnerability Category

CONCLUSION

This research analyzes the condition of the individual vulnerability index in Indonesia during Covid-19, specifically in 2020. By using several aspects such as health, food security, income and concern, this research forms a community vulnerability index in Indonesia which is measured from multiple aspects. By using Principal Component Analysis (PCA), this research found that health aspects, food security aspects, income aspects and concern aspects were aspects that were significantly proven to be able to measure workers' vulnerability index.

This research found that the vulnerability index in Indonesia was on average in the moderate to poor category. The percentage of people who have very bad and very good vulnerability index categories is small compared to the number of good and bad vulnerability categories. Even in the Covid-19 situation, it is proven that Indonesian society has a vulnerability that is not too high or is still in the medium category and there are relatively few people with extreme vulnerability, namely very vulnerable but also a few who are not vulnerable.

Not only does it analyze the big picture of community vulnerability during Covid-19, this research also measures gender aspects in analyzing community vulnerability in Indonesia. The research results showed that women's vulnerability was higher than men's during Covid 19. This was indicated by a larger percentage of women than men in the poor vulnerability category, whereas the percentage of women was smaller than men in the good vulnerability category. The results of this research show that women need more attention and assistance when facing shocks such as Covid-19 than men.

Furthermore, this research also examines how education influences a person's vulnerability. The results show that the worker vulnerability index turns out to depend on a person's education. The higher a person's education, the less vulnerable a person is when facing risks. The percentage of the poor vulnerability index category is greater for those with low education than for those with low education. The results of this research show that education is an important aspect that needs to be considered to mitigate risks when shocks such as Covid-19 occur so that individuals have a lower level of vulnerability when facing shocks.

Of course, this research has shortcomings in terms of comparisons between before and after Covid-19, but there are shortcomings in terms of the available data considering that the available data is not consistent every year with the same variables. Comparisons cannot be made using variables that are not the same between time comparisons. Apart from that, the selection of variables that form aspects of the worker vulnerability index depends on the availability of data and variables in World Bank data.

References

Adger. W. N. (2006). Vulnerability. Global Enviromental Change, 16, 268-281. http://dx.doi.org/10.1016/j.gloenvcha.2006.02.006

Adriani, A. (2021). Changes in community consumption patterns due to the covid-19 pandemic. Jurnal Riset dan Ekonomi dan Bisnis, 16(1), 29-40.

Amaluddin (2017)

Bazillier, R., Bobog, C., & Calavrezo, O. (2014). Employment vulnerability in Europe: Is there a migration effect? Orleans: Laboratoire d’Economie d’Orleans.

Bocquier, P., Nordman, C. J., & Vescovo, A. (2010). Employment vulnerability in urban west Africa. Dauphine Universite Paris Working Paper DT No 05.

Bocquier, P., Nordman, C. J., & Vescovo, A. (2010). Employment vulnerability in urban west Africa. Dauphine Universite Paris Working Paper DT No 05.

Fashoyin, T., & Tiraboschi, M. (2013). Vulnerability worker and precarious working. Newcastle: Cambridge Scholars Publishing.

Ghozali, Imam. (2013). “Aplikasi Analisis Multivariate Dengan Program SPSS.”. Semarang: Badan Penerbit Universitas Dipenogoro

Ginneken, Van Wouten. (2005). Managing risk and minimizing vulnerability: the role of social protection in pro-poor growth. Geneva: ILO

Haughton, J., & Khandker, S. R. (2009). Handbook on Poverty + Inequality. New York: The International Bank for Reconstruction and Develpoment/The World Bank

Kansiime, M. K., Tambo, A. J., Mugambi, I., Bundi, M., Kara, A., & Ouwor, C. (2021). Covid-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment, World Develpoment, 137, 1-10, https://doi.org/10.1016/j.worlddev.2020.105199

O’Brien, K., Erisken, S., Nygaard, L. (2007). Why different interpretation matter in climate change dicourses. Climate Policy, 7(1), 73-88.

Tabachnick B 7 Fidell L.S (2001). UsingMultivariate Statistics,4rd ed. Boston :Allyn & Bacon.

Torres, M. J. (2015). The impact of food price shocks on consumption nutritional patterns of urban Mexican household. Banco de Mexico Working Papers No 2015-16

Umar, H. B. (2009). Principal Component Analysis (PCA) dan Aplikasinya dengan SPSS. Jrunal Kesehatan Masyarakat