Effects of Flooding on Labor Market - Evidence from Malaysia

Mingxuan Huang *

United World College South East Asia, Singapore

* Corresponding Author Email: robinhuang2022@hotmail.com

Abstract. This study examines the relationship between flooding and labor market dynamics in Malaysia, focusing on labor force participation rate and employment rate. Using data from the Emergency Events Database (EM-DAT) and the Department of Statistics, Malaysia (DOSM) and applying the Ordinary Least Squares (OLS) model, we find that for every thousand individuals affected by floods, employment decreases by 2.5795 people, while LFPR is reduced by 0.0408\%.

Keywords: flooding, ols model, labor force.

1. Introduction

Natural disasters have always been a pertinent topic when concerning economics. Natural disasters like typhoons or earthquakes could lead to huge losses in wealth and life and it is important to understand how it affects people and what we should do about it.

In Malaysia, the most common type of natural disaster is flooding. It accounts for 85\% of all the natural disasters since 2000.[1] The water itself could cause economic losses as personal items or parts of buildings can be washed away or broken during floods. Houses with weak foundations could be completely demolished, leaving its owners homeless. Estimates show that "1-in-20-year flood can cost Malaysia up to 4.1 percent of GDP in 2030 and lead to up to a 2.2 percentage point increase in Malaysia's unemployment rate".[1] Some people would lose their jobs due to these economic losses. In a flood in 2022, estimated economic losses went up to 1.5 billion dollars, leaving around 120,000 people homeless. [2]

Some would choose to move away from flood prone areas. The mass relocation of people and capital could result in an increase of poverty, as suggested by a study on relocating the capital in Indonesia. [3] Both countries lie in southeast Asia and have similar levels of development, making this case applicable. Others find new jobs locally through apps or job offer posters, which could take a few days. With rising populations, these decisions by individuals affect more and more citizens of Malaysia.

In the last twenty years, there has been a significant amount of flooding. This could greatly effect the local labor market in Malaysia considering the economic losses of floods that occur each year as shown in the graph above. Hence, it is important for Malaysia, as a country with a huge amount of flooding each year, to estimate how flooding affects its labor force.

This leads us to the topic of how flooding affects employment rates and labor force participation rates. The effects of flooding could vary from place to place or from time to time. This article would focus on analyzing different aspects including time, location, and number of affected people and how they correlate with the employment rate and the labor force.

2. Literature Review

There is a lot of research concerning the effects of flooding on economic losses and migration. A study analyzes the pecuniary and non-pecuniary costs of flooding, including relief, cleanup, and capital damage.[4] Results show that net output loss has a positive correlation with capital damage and has a negative correspondence with reconstruction speed.

Another study by Gould, Wright, Collison, Ruto, Bosworth, and Pearson aims to develop a universal framework to evaluate the economic impact of coastal flooding on the agriculture sector.

[5] The study finds that in their case study, financial loses could go up to £4,887/ha. This is higher than previously thought since this study considered the longterm impacts of salt in soil.

Another common topic that past researchers have focused on was climate change, a potential cause of flooding. A study points out that Malaysia's agricultural sector is quite unprepared for climate change. The high costs of modern farming, lack of education, and lack of accessibility have set back adaptions to climate change. [6] This conclusion explains just how crucial learning more about the effects of flooding could be for Malaysia.

To summarize, past research mainly focused on the direct costs of flooding or climate change. All of these research results do not dive deep into the topic of the effects of flooding on the labor market. This paper focuses on the labor market, which is quite different.

3. Methodology

The model used for this article is OLS. It finds the best fitting coefficients for a linear model and a set of data. The method used to determine which group of coefficients is best is least squares, which squares each of the differences between the line of best fit and the points of data and adds them together.

For this particular article, there will be two different models, assessing the effect of the location and number of effected people due to flooding on the number of employed people and the labor force participation rate.

The effect of flooding on each state during each flood was represented by the estimated number of effected people of each flood in each state. This could be demonstrated with the following equation:

$$effected = toteffected \times \frac{spop}{tpop} \tag{1}$$

Here, "effected" and "tot effected" stands for estimated state effected and total effected. "Spop" and "tpop" stand for state population and total population of all the states effected. This was the only possible choice since there was missing data for all the other categories. Since there is no state level data for total effected people, we assume that the effect of floods is proportional to the population of the state. Then based on this, we calculated the estimated effected people by state.

Data on flooding, employment by state, and state population every year was needed to complete the first model. Four databases were used, one from the Emergency Events Database and three from the Department of Statistics, Malaysia. [7, 8, 9] The first database includes data on all the floods in Malaysia throughout the years, the areas they effected, the number of effected people, and other less relevant information. However, the data needed intense cleaning. There was a place in the location column called the peninsula states. This was replaced by a list of states that are in this peninsula area as searched on the internet. Finally, extra words and symbols were taken out by matching phrases with a list of state names from another database. This second database contained data on state populations for each year from 2000 to 2023. Using equation (1) as described above, the number of effected people in each state was estimated and put into OLS for fitting with a third database from DOSM containing employment data for each state in the years 2000-2017.

For the second model, similar data cleaning was also required. Extra symbols and words were taken out and a fourth database from DOSM on labor force participation rate was used.

After such data cleaning, I made two different equations for the two models as shown below.

$$employed = \alpha_0 + \alpha_1 \times effected + \delta \times location \tag{2}$$

$$LFPR = \beta_0 + \beta_1 \times effected + \delta \times location \tag{3}$$

For the first model, there are three different variables. "Employed" simply means the number of employed people in a certain state in a certain year. "Effected" means the number of effected people in a certain flood in a certain state. The $\delta \times location$ part of both equations are categorical variables. In this regression, it will be represented as a dummy variable. Johor, Kedah, Kelantan, Malacca, Negeri Sembilan, Pahang, Penang, Perak, Perlis, Selangor and Terengganu are the dummy variables while Johor is the omitted variable. The same applies for the second model.

For the second model, there are also three variables. “LFPR” is the short the labor force participation rate. This is the number of people in a working age that are employed or actively seeking jobs divided by the number of people at a working age. “Effected” and the dummy variable for location are the same as the first equation.

OLS is a method where you have a function with unknown coefficients and the function fits the coefficients with data for the variables. The goal is to find the correlation between the effected people in a flood and the number of employed people or labor force participation rate.

Table 1. The summary statistics for both models

	effected	Employed	LFPR	Total Affected	population	tot_pop
count	188.00	188.00	121.00	178.00	188.00	188.00
mean	11.23	4185.91	63.31	33.01	2317.08	10889.36
std	15.84	4384.89	2.73	54.07	1402.80	7473.25
min	0.00	0.00	58.55	0.20	221.60	1040.70
25%	2.06	0.00	60.24	3.00	1387.55	4606.93
50%	5.76	3415.60	64.55	10.50	1829.00	7291.60
75%	13.50	7358.68	65.74	28.25	2926.40	20440.40
max	107.67	12690.90	68.40	230.00	7205.30	24715.80

4. Discussion

Table 2. Detailed Model Outcome of Flooding Study

	Model 1	Model 2
	1	2
Kedah	-821.36***	-5.54***
	(80.44)	(1.10)
Kelantan	-1042.42***	-10.26***
	(66.44)	(0.90)
Kuala Lumpur	-784.49***	1.03
	(122.59)	(1.67)
Melaka	-1241.26***	-4.38**
	(122.69)	(1.67)
Negeri Sembilan	-1142.26***	-3.53**
	(122.40)	(1.67)
Pahang	-950.21***	-3.62***
	(66.72)	(0.91)
Perak	-671.38***	-6.84***
	(76.31)	(1.04)
Perlis	-1497.11***	-7.73***
	(106.07)	(1.44)
Pulau Pinang	-808.63***	2.31
	(122.97)	(1.67)
Sabah	-86.55	0.29
	(78.42)	(1.07)
Sarawak	-425.54***	-0.56
	(80.26)	(1.09)
Selangor	1732.53***	7.15***
	(91.89)	(1.25)
Terengganu	-1195.50***	-8.05***
	(66.29)	(0.90)
Intercept	1592.93***	68.04***
	(55.94)	(0.76)
effected	-2.58**	-0.04**
	(1.16)	(0.02)
Observations	99	99
R^2	0.95	0.83
Adjusted R^2	0.94	0.80
Residual Std. Error	156.92 (df=84)	2.14 (df=84)
F Statistic	117.01*** (df=14; 84)	29.32*** (df=14; 84)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2 presents the results for both models. The R squared for both models are quite high, meaning that the model accounts for most of the variation in labor force participation rate and employment.

4.1. Employment Model

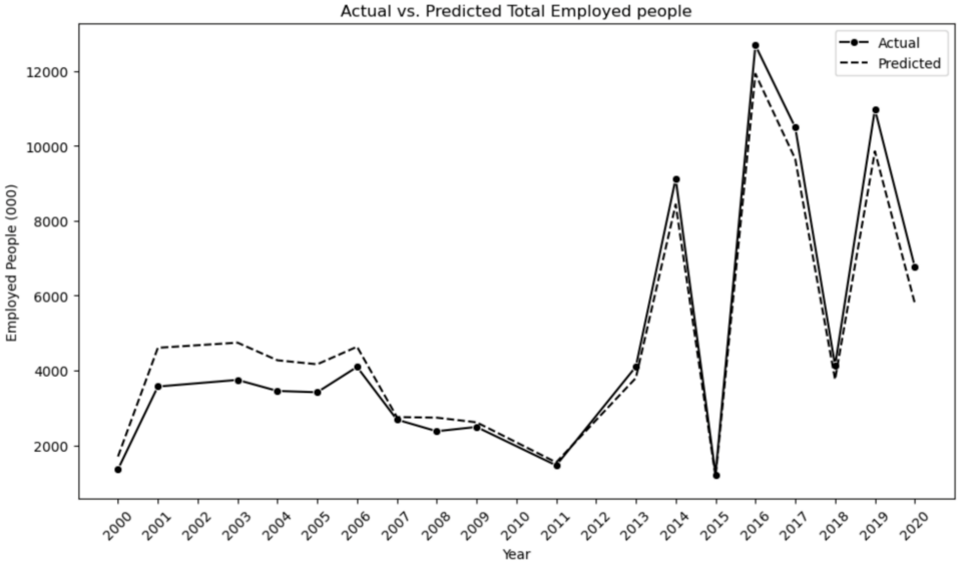

Figure 1. Employment Model Results

The results of the first OLS regression are shown in table 2. The coefficient for effected stand for keeping all other values constant, if the number of effected people in the state increases by one thousand people, the number of employed people decreases by 2.6 people. The dummy variable stands for the control variable locations. For example, if the location is T. Perak, keeping all other values constant, the number of employed people is 671.3794 thousand people less than the number of employed people if the location is Johor. 95 percent of the data variation can be expressed by the model. The p value of the coefficient is statistically significant under 0.05 level. Figure 1 is the result when we put the coefficients we have to the test matched up against the original data we had. It shows exactly how well the model has been able to find the relationship between the data given and the coefficients we have added. The two lines are quite close to each other for the whole 20-year time span.

4.2. LFPR Model

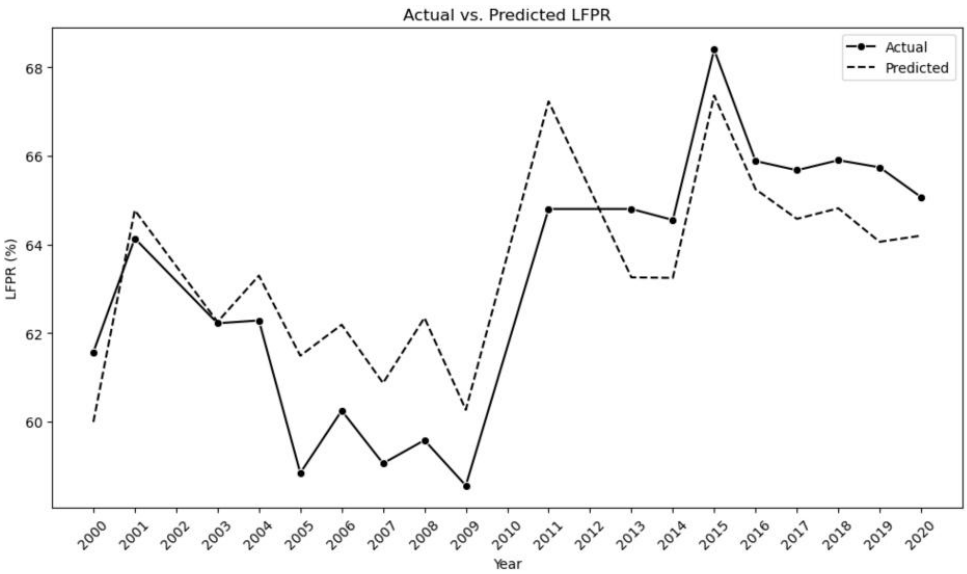

Figure 2. Average Labor Force Participation Rate Model Results

The results for this model are also listed in table 2. For this second regression, the coefficient for effected stands for keeping all other values constant, if the number of effected people in the state increases by 1 thousand people, the LFPR decreases by 0.04075 percent. The dummy variable is still the location. If the location is T. Perak, keeping all other values constant, the LFPR is 6.8386 percent less than the LFPR if the location is Johor. 79 percent of the data variation can be expressed by the model. The p value of the coefficient is statistically significant under 0.05 level. Figure 2 is the depiction of the data against our model. Though it is not as similar as the first model, there is still quite a clear correspondence between the two.

5. Conclusion

This study provides evidence of a significant correlation between flooding and labor market outcomes in Malaysia. Our findings indicate that floods lead to a reduction in employment and labor force participation rate, by 2.5795 people and 0.0408 percent every thousand people affected.

Though significant progress has been made in this article, there is still huge potential for future improvement. For example, it is impossible to account for the scenario where multiple floods happen in the same state in the same year. In this situation, we can only add up the number of effected people, which might not be the actual case. This might involve another much more complex model.

There could also be some extra control variables including the year, but adding that in made the coefficients make no sense. A better model is needed to completely fathom the correlation between flooding and the labor market.

Overall, this paper could be used as a pedestal for further research on the topic. These two models could help calculate the labor market distortions in each area, and governments could utilize the numbers here to create policies to help flooded areas like providing job opportunities or assign rebuilding projects, though more rigorous analysis is needed to find the optimal policy for each case.

References

[1] "Flood Risk Management: Leveraging Finance for Business Resilience in Malaysia." World Bank, World Bank Group, 27 Mar. 2024, www.worldbank.org/en/country/malaysia/publication/flood-risk-management-leveraging-finance-for-business-resilience-in-malaysia. Accessed 16 Dec. 2024.

[2] Malaysia Floods Caused Nearly $1.5 Billion in Losses, Government Report Says | Reuters, www.reuters.com/world/asia-pacific/malaysia-floods-caused-nearly-15-bln-losses-govt-report-2022-01-28/. Accessed 16 Dec. 2024.

[3] Anzor, et al. "The Effect of Relocation the Country's Capital on Poverty Rates Using System Dynamics (Case Study: Balikpapan City)." International Journal of Information Engineering and Electronic Business, vol. 16, no. 3, 8 June 2024, pp. 57 – 65, doi:10.5815/ijieeb.2024.03.06.

[4] Davies, J.B. "Economic Analysis of the Costs of Flooding." Canadian Water Resources Journal / Revue Canadienne Des Ressources Hydriques, vol. 41, no. 1 – 2, 9 July 2015, pp. 204 – 219, doi: 10.1080/07011784.2015.1055804.

[5] Gould, Iain J., et al. "The Impact of Coastal Flooding on Agriculture: A Case-study of Lincolnshire, United Kingdom." Land Degradation & Development, vol. 31, no. 12, 19 Feb. 2020, pp. 1545 – 1559, doi: 10.1002/ldr.3551.

[6] Tang, Kuok Ho, et al. "Perceptions of Agriculture-Related Agencies and Farmers in the Malaysian Borneo on Climate Change: An Exploratory Qualitative Study." International Journal of Global Warming, vol. 32, no. 2, 2024, pp. 245 – 265, doi:10.1504/ijgw.2024.135988.

[7] Cred. "Dat - The International Disaster Database." EM, www.emdat.be/. Accessed 16 Dec. 2024.

[8] "Department of Statistics Malaysia." Open DOSM, open.dosm.gov.my/. Accessed 16 Dec. 2024.

[9] Malaysia, Department of Statistics. "Population Table: States." OpenDOSM, open.dosm.gov.my/data-catalogue/population_state. Accessed 16 Dec. 2024.