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Determining Long-Term Probabilities for Labor Absorption from the Realization of Domestic Investment (PMDN) and Foreign Investment (PMA) in Indonesia Using Markov Chain Analysis

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Abstract

The government through President Joko Widodo in a press conference stated that the Job Creation Law is very urgent to be passed immediately, even though it has received a lot of resistance in society. The government stated that the bureaucracy in investing in Indonesia is still convoluted, so the possibility of a decrease in employment in the future is very high. However, this was denied by Faisal Basri. This reason is not in accordance with the current state of investment, he concluded. Realization of Domestic Investment (PMDN) and Foreign Investment (PMA) in Indonesia tends to always increase every year, so it is not the investment bureaucracy that is the cause of decreased employment. Abdul Malik said that, the reason for the decrease in absorption labor is the lack of competitiveness of the local workforce and the government's lack of selectiveness in choosing investments that enter Indonesia. This study aims to provide consideration for the government, in the form of long-term employment probabilities from the realization of PMDN and PMA in Indonesia which are calculated using Markov chain analysis. The calculation results obtained are that the long-term probability of increasing the amount of labor absorption from the realization of PMDN and PMA is 0.56 or 56%, while the long-term probability of decreasing is 0.44 or 44%. Then, in specific intervals, the possibility of an increase in the workforce of at most 93 thousand people is very high, namely 0.42 or 42%. This value is greater than the possibility of a decrease in the workforce of at most 93 thousand people, namely 0.27 or 27%. This value is contrary to the government's assumption which states that the possibility of a decrease in labor absorption is very high. Therefore, the results of this research can be used as one of the considerations for the government to rethink the urgency of issuing the Job Creation Law.

Keywords: Job Creation Law, PMDN and PMA Realization, Long-Term Probability, Employment, Markov Chain Analysis

1. Introduction

President Joko Widodo in a press conference stated that it was very urgent for the Job Creation Law to be ratified immediately. According to Imelda Freddy, a researcher from the Center for Indonesian Policy Studies (CIPS), currently obtaining business licenses in Indonesia is still very difficult, thus closing the gate for the rapid flow of investment coming into Indonesia. If this is allowed to continue, it is possible that the number of available jobs will decrease in the future. He hopes that the issuance of this law can help open a swift flow of investment which will lead to increased employment which is projected to decrease in the future (Aswindo et al. [1]).

Indonesia's current investment condition is not bad. This can be seen from the investment growth (Gross Fixed Capital Formation/PMTB) in the last five years which is still above the Gross Domestic Product (GDP). This investment growth is still higher than Malaysia, South Africa, and Brazil so that it can be said that Indonesia's share of investment is already very high (Oyelola et al. [2]). In addition, in terms of investment realization that has entered Indonesia in the last five years, it has always increased, so that it can be said that there are no problems in the flow of investment into Indonesia.

This research was conducted to determine the long-term probabilities for employment from the realization of PMDN and PMA in Indonesia. To calculate these probabilities, the authors use Markov chain analysis (Muda [4]). Markov chain analysis can provide long-term probabilities of a situation based on available past data (Karlin [5]). The result of this research is to obtain long-term probabilities for employment from the realization of PMDN and PMA in Indonesia without the enactment of the Job Creation Law. These results will later be compared with the government's assumption which states that the amount of employment from the realization of PMDN and PMA in the future will decrease if it is not assisted by the issuance of the Job Creation Law. The results of this research can also be used as a consideration for the government to rethink the urgency of issuing this law.

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2. Materials and Methods

2.1. Materials

The data used in this study are quarterly PMDN and PMA data from 2010 to 2020. The data is obtained and can be accessed openly on the official website of the Ministry of Finance.

2.2. Methods

The discrete-time Markov chain is a special form of a stochastic process. Mathematically, for example $\{X(t), t = 0,1,2,3,\ldots\}$ is a discrete time stochastic process with states i and i_k, $k = 0, 1, \ldots, t-1$. If applicable:

$$\begin{aligned} P\{X(t-1) = j | X(0) = i_0, X(1) = i_1, \ldots, X(t-1) = i_{t-1}, X(t) = i\} \\ = P\{X(t+1) = j | X(t) = i\} \\ = p_{ij} \end{aligned} \tag{1}$$

for each j, t, i and i_k with $k = 0, 1, \ldots, t-1$, then the process is called a discrete time Markov chain and p_{ij} is called the 1-step transition probability from state i to state j (Osaki [3]).

The value of the probability of transition from each state to another can be expressed in the form of a matrix. This matrix is called the transition opportunity matrix. The 1 step transition probability matrix from $X_t, t = 0, 1, 2, 3, \ldots$ denoted by $P = [p_{ij}]$ is expressed as follows:

$$\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} & p_{02} & \cdots \\ p_{10} & p_{11} & p_{12} & \cdots \\ p_{20} & p_{21} & p_{22} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{2}$$

with $p_{ij} \geq 0$ and $\sum_{j=0}^{\infty} p_{ij} = 1$, $(i, j = 0,1,2,3,\ldots)$. If the state space i is finite, $i = 0, 1, 2, \ldots, m$, then the 1 step transition probability matrix is as follows:

$$\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} & \cdots & p_{0m} \\ p_{10} & p_{11} & \cdots & p_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m0} & p_{m1} & \cdots & p_{mm} \end{bmatrix} \tag{3}$$

with $p_{ij} \geq 0$ and $\sum_{j=0}^{m} p_{ij} = 1$, $(i, j = 0,1,2,\ldots,m)$.

The probability value of the transition from each state to another can be expressed in a graph with the state space as the set of vertices and each transition probability value as the weight of the arrows directed at each vertex. This graph is called a probability transition diagram. If for example $\{X(t) = i, i = 1,2\}$, then the transition probability diagram is as follows:

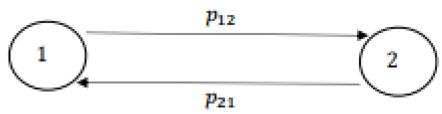


Figure1: Transition Opportunity Diagram

State j is said to be accessible from state i, denoted by $i \to j$, if there is a positive integer t so that the transition probability of t-step from state i to state j is positive or $p_{ij}^t > 0$. In general, if there are positife integers t and u such that $p_{ij}^t > 0$ and $p_{ji}^u > 0$, then state i and state j are called two states that communicate with each other. To make it easier to understand, if state j is accessible from state i and state i is accessible from state j, then state i and state j are called states that communicate with each other, denoted by $i \leftrightarrow j$.

A state in a Markov chain is called a recurrent state if when it transitions to any state, it returns to its initial state. If for example $\{X(t) = i, i = 1,2,3\}$, then the transition probability diagram is as follows:

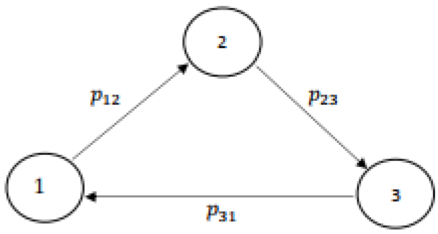


Figure 2: Recurrent States

A state in a Markov chain is called aperiodic if all the paths (directed arrows) leading to that state are a multiple of one in length. Mathematically, state i is called aperiodic if it behaves as follows:

$$d(i) = \gcd\{t > 1 | p_{ii}^{t} > 0\} = 1 \tag{4}$$

A state is said to be positively recurring if the average number of repetitions it takes for the state to reach itself the first time has a finite value. Mathematically, state i is called positive recurrence if it applies as follows:

$$\mu_i = \sum_{t=1}^{\infty} t f_{ii}^{t} < \infty. \tag{5}$$

To determine the long-run probability of a state in a Markov chain, the condition that must be met is that the Markov chain must be an ergodic Markov chain. A Markov chain is said to be ergodic if it includes irreducible, aperiodic, and positively repeating Markov chains.

The set of long-run probabilities for each state is called the stationary distribution of an ergodic Markov chain. Mathematically, the above statement can be expressed as follows:

$$\pi_j = \lim_{t\to\infty} p_{ij}^{t} \,;\, j = 0,1,2,3, \ldots \text{ (independent of } i\text{)}, \tag{6}$$

The Chapman-Kolmogorov equation is an equation used to calculate the probability of the t-step transition for each state in the Markov chain. Mathematically, the Chapman-Kolmogorov equation can be expressed as follows:

$$p_{ij}^{(t)} = \sum_{k=1}^{\infty} p_{ik}^{(r)}\, p_{kj}^{(t-r)}. \tag{7}$$

If expressed in matrix form, then equation (7) can be expressed as follows:

$$P^{(t)} = P^{(r)} P^{(t-r)} = P^{r} P^{t-r} = P^{t}. \tag{8}$$

3. Results and Discussion

The following is a visualization of the data under study which is given in Figure 3.

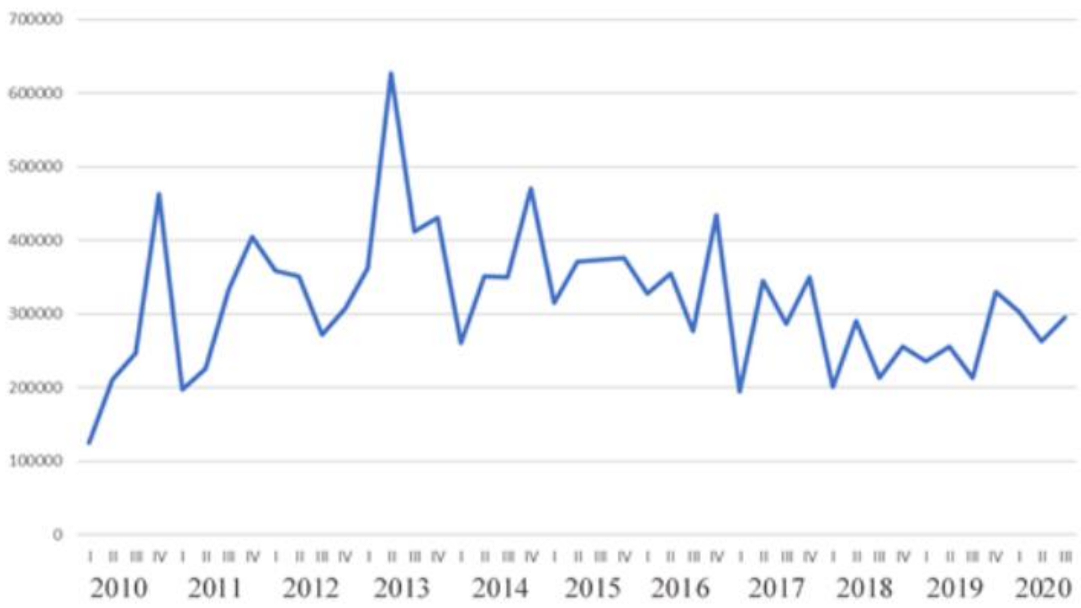


Figure 3: Diagram of the Labor Absorption Line from the Realization of PMDN and PMA in Indonesia from 2010 to the third quarter of 2020

Data descriptive statistics function to provide general data information. The following are descriptive statistics from data on employment from the realization of PMDN and PMA in Indonesia from 2010 to the third quarter of 2020:

Table 1: Data Descriptive Statistics

Descriptive Statistics	Value
Average	316.639,44
Median	315.229
Diversity	8.495.790.332,44
Standard Deviation	92.172,61
Slope	0,76
Kurtosis	1,83

3.1. Determination of the State of the Markov Chain

In this study, the researcher makes two cases of Markov chains, the following are the conditions of each Markov chain:

Table 2: State of the First Case Markov Chain

State	Explanation
1	The amount of labour absorption increased
2	The amount of labour absorption decreased

Table 3: State of the Second Case Markov Chain

State	Explanation
1	The number of employments increased by more than 93 thousand people
2	The number of workers absorbed increased by a maximum of 93 thousand people
3	The number of labour absorption decreased by a maximum of 93 thousand people
4	Total employment decreased to less than 93 thousand people

3.2. Defining Transition Opportunity Matrix and Diagrams

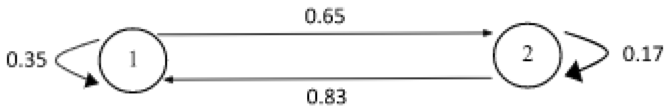
The following is the state transition matrix of each Markov chain created with the help of Maple software:

$$K_1 = \begin{bmatrix} 8 & 15 \\ 15 & 3 \end{bmatrix} \text{ and } K_2 = \begin{bmatrix} 0 & 1 & 2 & 4 \\ 3 & 4 & 7 & 2 \\ 3 & 6 & 3 & 0 \\ 1 & 5 & 0 & 0 \end{bmatrix}.$$

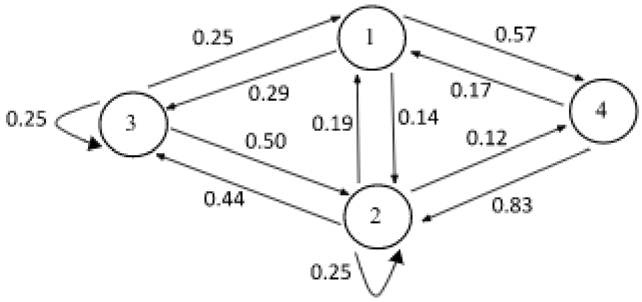
Then, each element in each matrix is divided by the number of elements in each row, so that by using Maple, the transition probability matrices for each Markov chain are obtained as follows:

$$P_1 = \begin{bmatrix} 0.3478 & 0.6522 \\ 0.8333 & 0.1667 \end{bmatrix} \text{ and } P_2 = \begin{bmatrix} 0 & 0.1429 & 0.2857 & 0.5714 \\ 0.1875 & 0.2500 & 0.4375 & 0.1250 \\ 0.2500 & 0.5000 & 0.2500 & 0 \\ 0.1667 & 0.8333 & 0 & 0 \end{bmatrix}.$$

Based on the transition probability matrices for the two cases of the Markov chain above, the respective transition probability diagrams are as follows:



(a)



(b)

Figure 3: Transition Probability Diagram in the First Case (a) and (b)

The value of the transition probability for each state is rounded to two numbers behind to make it easier to describe the visualization and processing of the data.

3.3. Checking the Ergodicity of the Markov Chain

3.3.1. Checking Irreducible Markov Chains

For the first case Markov chain. Since every state in the first case Markov chain communicates with each other, the first case Markov chain is irreducible. For the second case Markov chain. Because every state in the second case Markov chain communicates with each other, the second case Markov chain is irreducible.

3.3.2. Examining the Aperiodicity of the Markov Chain

For the first case Markov chain. Since all states in the first case Markov chain are aperiodic, the first case Markov chain is aperiodic. For the second case Markov chain. Since all states in the second case Markov chain are aperiodic, the second case Markov chain is aperiodic.

3.3.3. Checking the Markov Chain Repetition Classification

For the first case Markov chain. The average repeat time of each state which is calculated is as follows:

$$\mu_1 = \sum_{t=1}^{\infty} t f_{11}^t,$$

$$(t+2)(0.17)^t = 0 \rightarrow \sum_{t=0}^{\infty} (t+2)(0.17)^t < \infty$$

$$\mu_2 = \sum_{t=1}^{\infty} t f_{22}^t,$$

$$(t+2)(0.35)^t = 0 \rightarrow \sum_{t=0}^{\infty} (t+2)(0.35)^t < \infty$$

For the second case Markov chain. The following is the average repeat time for each state:

$$\mu_1 = \sum_{t=1}^{\infty} t f_{11}^t,$$

$$(t+1)(0.25)^t = 0 \to \sum_{t=0}^{\infty}(t+1)(0.25)^t < \infty$$

$$\mu_2 = \sum_{t=1}^{\infty} t f_{22}^{t},$$

$$(t+2)(0.25)^t = 0 \to \sum_{t=0}^{\infty}(t+2)(0.25)^t < \infty$$

$$\mu_3 = \sum_{t=1}^{\infty} t f_{33}^{t},$$

$$(t+2)(0.25)^t = 0 \to \sum_{t=0}^{\infty}(t+2)(0.25)^t < \infty$$

$$\mu_4 = \sum_{t=1}^{\infty} t f_{44}^{t},$$

$$(t+2)(0.25)^t = 0 \to \sum_{t=0}^{\infty}(t+2)(0.25)^t < \infty$$

Since all the conditions in the second case Markov chain are repeated positive, the second case Markov chain is repeated positive.

3.3.4. Checking the Ergodicity of the Markov Chain

Since the first and second case Markov chains are irreducible, aperiodic, and positively repeating, respectively, the first and second case Markov chains are ergodic.

3.4. Determine the Chapman Kolmogorov Equation

For the first case and second case Markov chain, each Chapman-Kolmogorov equation is obtained, namely as follows:

$$P_1^{(t)} = \begin{bmatrix} 0.3478 & 0.6522 \\ 0.8333 & 0.1667 \end{bmatrix}^t \text{ and } P_2^{(t)} = \begin{bmatrix} 0 & 0.1429 & 0.2857 & 0.5714 \\ 0.1875 & 0.2500 & 0.4375 & 0.1250 \\ 0.2500 & 0.5000 & 0.2500 & 0 \\ 0.1667 & 0.8333 & 0 & 0 \end{bmatrix}^t.$$

3.5. Determining the Stationary Distribution of the Markov Chain with the Chapman-Kolmogorov Equation

The stationary distribution of the Markov chain can be determined using the Chapman-Kolmogorov equation. The stationary distribution is obtained until the result of the multiplication of the transition probability matrix is obtained by itself where each element in the column converges to a real number. For the first case Markov chain, with the help of Maple software, the following is the t-step transition probability matrix for each t:

Table 4: First Case Markov Chain t-Step Transition Matrix on First Case

t	$P_1^{(t)}$
1	$\begin{bmatrix} 0.6645 & 0.3355 \\ 0.4287 & 0.5712 \end{bmatrix}$
2	$\begin{bmatrix} 0.5107 & 0.4893 \\ 0.6252 & 0.3748 \end{bmatrix}$

3	$\begin{bmatrix} 05854 & 0.4146 \\ 0.5298 & 0.4702 \end{bmatrix}$
⋮	⋮
34	$\begin{bmatrix} 05610 & 0.4390 \\ 0.5610 & 0.4390 \end{bmatrix}$
⋮	⋮
100	$\begin{bmatrix} 05610 & 0.4390 \\ 0.5610 & 0.4390 \end{bmatrix}$

From the table above, the long-term transition opportunity matrix is obtained, which is as follows:

$$\begin{bmatrix} 05610 & 0.4390 \\ 0.5610 & 0.4390 \end{bmatrix}$$

From the matrix above, a stationary distribution is obtained for each state, which is as follows:

$$\pi_j = \{\pi_1, \pi_2\} = \{0.5609756098, 0.4390243902\}$$

For the second case Markov chain, with the help of Maple software, the following is the t-step transition probability matrix for each t:

Table 5: Transition Matrix t-Step Markov Chain Second Case

t	$P_2^{(t)}$
1	$\begin{bmatrix} 0.1934 & 0.6548 & 0.1339 & 0.0179 \\ 0.1771 & 0.4122 & 0.2723 & 0.1384 \\ 0.1562 & 0.2857 & 0.3527 & 0.2053 \\ 0.1562 & 0.2321 & 0.4122 & 0.1994 \end{bmatrix}$
2	$\begin{bmatrix} 0.1592 & 0.2731 & 0.3752 & 0.1924 \\ 0.1684 & 0.3798 & 0.2990 & 0.1527 \\ 0.1760 & 0.4412 & 0.2578 & 0.1250 \\ 0.1798 & 0.4526 & 0.2492 & 0.1183 \end{bmatrix}$
⋮	⋮
30	$\begin{bmatrix} 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \end{bmatrix}$
⋮	⋮
100	$\begin{bmatrix} 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \end{bmatrix}$

From the table above, the long-term transition opportunity matrix is obtained, which is as follows:

$$\begin{bmatrix} 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \\ 0.1707 & 0.3902 & 0.2927 & 0.1463 \end{bmatrix}.$$

From the matrix above, a stationary distribution is obtained for each state, which is as follows:

$$\pi_j = \{\pi_1, \pi_2, \pi_3, \pi_4\} = \{0.1707317, 0.3902439, 0.2926829, 0.1463415\}$$

4. Conclussion

Based on the stationary distribution above, information is obtained that the long-term opportunity for an increase in employment from the realization of PMDN and FDI of more than 93 thousand people is 0.1707317≈0.17=17%. Meanwhile, the long-term opportunity for an increase in employment from the realization of PMDN and FDI is at most 93 thousand people, which is 0.3902439≈0.39=39%. Then, the long-term chance of a decrease in employment from the realization of PMDN and FDI at most 93 thousand people is 0.2926829≈0.29=29%. Finally, the long-term probability of a decrease in employment from the realization of PMDN and FDI of more than 93 thousand people is 0.1463415≈0.15=15%. From this value, it can be interpreted that without the issuance of the Job Creation Law, employment from the realization of PMDN and FDI is likely to increase in the future. This is contrary to the government's assumption which states that the amount of employment from the realization of PMDN and FDI is likely to decrease in the future.

The results of this research can be used as a consideration for the government regarding the urgency of issuing the Job Creation Law. In accordance with Faisal Basri's statement, the state of investment in Indonesia is not bad, in fact it tends to increase from year to year. Therefore, bureaucratic investment problems should not be used as the main source of the decline in employment in recent years. Other causes as stated by Abdul Malik can also be considered, namely the low competitiveness of the Indonesian workforce and the lack of selective investment selection by the government. The low competitiveness of the domestic workforce causes investors to experience difficulties in finding workers according to their needs, forcing them to recruit foreign workers. Then, the government must be more selective in choosing incoming capital. The proportion between capital-intensive industries and labor-intensive industries must be calculated so that they are proportional, so that incoming capital is accompanied by the fulfillment of the community's need for employment.

This research only pays attention to the absorption of labor as a whole and does not pay attention specifically to which sectors the absorption of labor will increase. In order to obtain more specific results, long-term opportunity calculations can be carried out by considering employment with other methods, such as time series analysis or spatial analysis.

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