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Determinants of unemployment rate in an open economy: Malaysian evidence

Nurul Ghafar¹ and Mansur Masih²

Abstract

The focus of this paper is on the determinants of unemployment rate and economic variables in an open economy. Malaysia is taken as a case study. The standard time series techniques such as, VECM and VDC are used for the analysis. The results based mostly on variance decompositions (VDC) tend to indicate that in an open economy like Malaysia, the unemployment rate appears to be an endogenous (i.e., dependent) variable driven mostly by the inflation rate followed by private consumption and population variables. The results are plausible and intuitive and have strong policy implications for the developing countries like Malaysia.

Keywords: unemployment rate, macroeconomic variables, open economy, VECM, VDC, Malaysia

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1. INTRODUCTION

Unemployment in general is defined as the total number of adults (aged above 16 years old) who are willing and able to work and who are actively looking for work but have not found a job. Accordingly, unemployment rate is defined as the proportion of the measured labour force that is unemployed.¹

On the other hand, open economy is an economy in which people trade goods and services with other people in the international community at large.

2. OBJECTIVE AND MOTIVATION OF RESEARCH

The interrelation among economics variables makes it hard to identify which variable has the most influence on the others. Thus, this study aims to determine the influence of open economy variables on unemployment rate in Malaysia.

The overall study should cover the following objectives:

- i. To analyse how an economic well-being could significantly act as an indicator for the level of unemployment rate.
- ii. To explore the economic variables in an open economy.
- iii. To explore the relationship between the unemployment rate and the economic variables.

The study is important to policy makers mainly because it helps discover which variable has the most significant effect on the unemployment rate in Malaysia so that necessary amendment could be addressed.

3. LITERATURE AND THEORETICAL FRAMEWORK

Unemployment issues are among the main discussion in the economics field around the world. Research papers on this area are easily obtained. However, most previous empirical studies rely on the regression model and not on the time-series analysis.

Based on the 2008 Index of Economic Freedom Assessment, Malaysia was rated 6.5% of freedom and was ranked world's 51st most open economy, (Kueh *et al.*, 2008).

¹ According to Department of Statistics of Malaysia, unemployment rate is computed as: (Number of unemployed persons / Number of persons in labour force) x 100.

Economies that are more open have higher rates of industrial concentration, which tend to promote higher unionization, greater scope of collective bargaining and stronger labour confederation. Thus, unemployment rate is expected to decrease.

Unemployment received public attention for the first time as an important issue in Malaysia merely in the early 1960s. For that reason, to date this study was carried out, only up to 40 years observation of unemployment was reported by the Department of Statistics of Malaysia.

Figure 1 shows the behaviour of unemployment rate since 1976 to 2010. Malaysia recorded the worst unemployment rate in 1980's but then showed an impressive sign of decrease starting from 1991. In 1996, unemployment reached the lowest rate of 2.5.² Following the financial turmoil in 1997, the unemployment rate started to increase gradually. Ten years after the recession, the unemployment still showed no improvement in its rate.

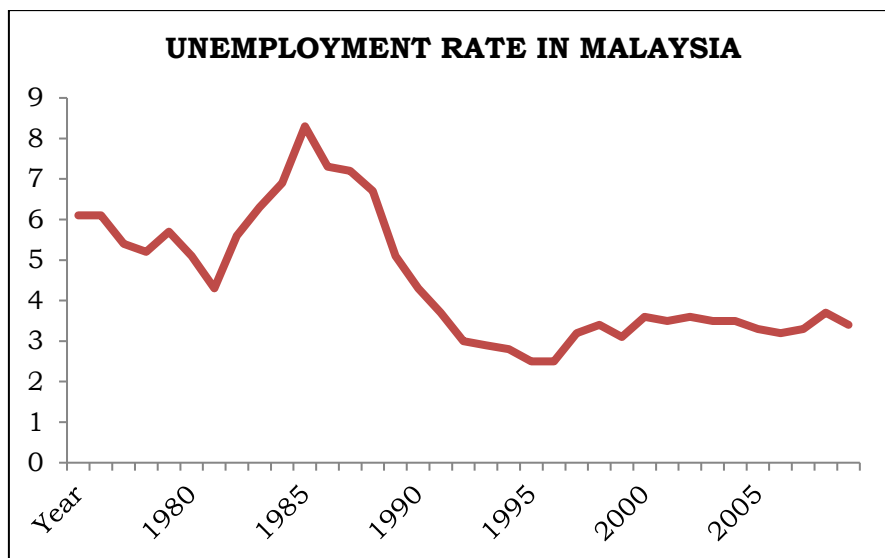


Figure 1: Unemployment rate in Malaysia (1976-2010)

² The rate in 1996 was almost one third of the rate in 1990.

4. RESEARCH METHODOLOGY, RESULTS AND INTERPRETATION

The study will be conducted with respect to Malaysia as the focus study. The study also underscores the importance and relevance factors that affect unemployment rate.

The sample data are in the form of annual secondary retrieved from Datastream for 35 years starting from 1976 . At first, authors were keen to examine longer sample data in order to examine whether the theory reflects real economic condition in long-term period. Nevertheless, only 35 observations were successfully obtained.

Open economy variables used in the study including private consumption (PCON), government expenditure (GOVEXP)³, annual consumer price index (CPIA) and population (POP). CPIA is used as the proxy to represent the inflation rate. The authors also had in mind to include net export in the study since it also a part of economic variables and previous study showed net export had significant effect on unemployment rate. However inconsistency in number of observation had forced the variable to be dropped from the study.

4.1 TESTING STATIONARITY OF VARIABLES

The study started by determining the stationarity of the variables used. In order to proceed with the testing of cointegration later, ideally, our variables should be I(1), in that in their original level form, they are non-stationary and in their first differenced form, they are stationary. The differenced form for each variable used is created by taking the difference of their log forms. For example, $DUNEM = LUNEM - LUNEM_{t-1}$. Consequently, the Augmented Dickey-Fuller (ADF) test was conducted on each variable for both level and differenced form. Table 1 and Table 2 below recapitulate the results.

Table 1: Summary of Stationarity of Variables in Level Form

Variables in Level Form			
Variable	Test Statistic	Critical Value	Implication
LUNEM	-3.2713	-3.5731	Variable is non-stationary
LPCON	-3.6846 (AIC)	-3.5731	Variable is non-stationary

³ Government expenditure is computed as: (government consumption + government investment) where government consumption refers to all government purchase of goods and services for current use and government investment refers to government purchase of goods and services to create future benefits.

	-3.33229 (SBC)		
LGOVEXP	-3.4687	-3.5731	Variable is non-stationary
LCPIA	-2.5040 (AIC)	-3.5731	Variable is non-stationary
	-2.7328 (SBC)		
LPOP	0.21335	-3.5731	Variable is non-stationary

Table 2: Summary of Stationarity of Variables in Differenced Form

Variables in Differenced Form			
Variable	Test Statistic	Critical Value	Implication
DUNEM	-2.4029 (AIC)	-2.9706	Variable is stationary
	-4.1215 (SBC)		
DPCON	-4.4358 (AIC)	-2.9706	Variable is stationary
	-4.1587 (SBC)		
DGOVEXP	-3.5371 (AIC)	-2.9706	Variable is stationary
	-4.2282 (SBC)		
DCPIA	-3.0606 (AIC)	-2.9706	Variable is stationary
	-3.4615 (SBC)		
DPOP	0.21774	-2.9706	Variable is non-stationary

Refer to Table 2, we realized that one of the variable is still non-stationary in differenced form where it was supposed to be stationary to indicates I(1). In order to correct this problem, we conduct another test called Phillips-Perron test. The result showed in Table 3 indicates that the p -value is smaller than 0.05. Thus we reject the null hypothesis saying that the variable is now stationary. ⁴

Table 3: Phillips-Perron Test

Variables in Differenced Form		
Variable	p -Value	Implication
DPOP	0.009	Variable is stationary

Based on above findings, we may now proceed to the next step of time-series analysis which is the determination of order of the VAR models.

4.2 DETERMINATION OF ORDER OF THE VAR MODELS

Before proceeding with test of cointegration, we need to first determine the order of the vector auto regression (VAR), that is, the number of lags to be used. Table 4 showed that AIC recommends order of 4 whereas SBC favours 1 lag.

⁴ The null hypothesis is the variable is non-stationary.

Table 4: Optimal Order of VAR

Choice of Criteria	
AIC	SBC
4	1

Given this obvious conflict between recommendation of AIC and SBC, we address this in the following manner.⁵ First we checked for serial correlation for each variable and obtained the following results in Table 5.

Table 5: Serial Correlation Diagnostics Test

Variable	Chi-sq p-value	Implications (at 10%)
DUNEM	0.747	There is no serial correlation
DPCON	0.794	There is no serial correlation
DGOVEXP	0.041	There is serial correlation
DCPIA	0.786	There is no serial correlation
DPOP	0.937	There is no serial correlation

Table 5 showed that one out of five of the variable suffers from serial correlation problem. Thus, considering lower order, we may encounter the effects of serial correlation. However taking higher order is not a good option for this study since we may risk over-parameterization due to a short number of observations. Taking into account the trade-off of lower and higher orders, we decided to *choose lower order of 1*. By choosing order of 1, we already bear in mind that later in step 5: Vector Error Correction Model (VECM), we would not be able to display the response of each variable in short-term.

4.3 TESTING COINTEGRATION

Once we have established that the variables are I(1) and determined the optimal VAR order as 2, we are ready to test for cointegration. Table 6 illustrates the number of cointegrating vector suggested by Maximal Eigenvalue, Trace, AIC, SBC and HQC.

⁵ Note that AIC will tends to give higher order while SBC act in opposite manner. This is because SBC is more concerned with the problem of over-parameterization (more parsimonious) compared to the use of AIC.

The number suggested varies with each other; make it difficult for the author to conduct a wise decision.

Table 6: Number of Cointegrating Vector

Criteria	Number of cointegrating vector
Maximal Eigenvalue	2
Trace	1
AIC	5
SBC	2
HQC	4

Despite the varies suggestion showed in Table 6, we inclined to believe there is one cointegrating vector as intuition as well as knowing the facts that economic variables are typically “connected” to each other. Based on the above statistical result as well as our intuition, for the purpose of this study, we *shall assume that there is one cointegrating vector*.

Cointegrating relationship tells us that the relationships among variables are not spurious, that is, there is theoretical relationship among them and they are in equilibrium in long run. It also indicates that each variable contains information for the prediction of other variables. However, cointegration does not reveal any information on the direction of Granger-causation; which variables is the leader and which is the follower (exogenous and endogenous).

4.4 LONG RUN STRUCTURAL MODELLING (LRSM)

Subsequently, we attempt to quantify this apparent theoretical relationship among the indices. We do this in order to compare our statistical findings with theoretical (or intuitive) expectations. We then normalize our variable of interest, the CPIA and obtained the results in the Table 7.⁶ Calculating the *t*-ratios manually, we found two variables to be significant (UNEM and POP).⁷

Table 7: Normalize UNEM

Variable	Coefficient	Standard Error	t-ratio	Implication
LUNEM	1.8469	0.70043	2.6368	Variable is significant
LPCON	-2.9357	2.5121	-1.1686	Variable is insignificant
LGOVEXP	-1.1889	1.1625	-1,0227	Variable is insignificant
LCPIA	-	-	-	-
LPOP	1.9469	0.61159	3.1833	Variable is significant

⁶ In order to proceed to next step, we should have at least one significant variable.

⁷ If the *t*-ratio computed is less than 2, we reject the null hypothesis saying that the variable is insignificant and vice versa.

Following these findings, we decided to verify the significance of the variables by subjecting the estimates to over-identifying restrictions. We did this for all the variables; making one over-identifying at a time.⁸ Interestingly, we found that all variables are significant (see Table 8) and this contradicts Table 7 from earlier findings.

Table 8: Normalize UNEM, Over-Identifying Restriction

Variable	Chi-sq p-value	Implication
LUNEM	0.028	Variable is significant
LPCON	0.000	Variable is significant
LGOVEXP	0.000	Variable is significant
LCPIA	-	-
LPOP	0.000	Variable is significant

However, later we did the same procedure on UNEM. We first normalize UNEM and conduct over-identifying restrictions for all the variables. But then we encounter problem in the middle of doing over-identifying restrictions (A1 = 1; A4 = 0) where Microfit bumped up a warning message saying that “no convergences after 50 iterations”. We tried to increase number of iterations but there is still no convergence up to 1000 iterations. For that reason, we stick to findings in Table 8.

Afterwards, we made over-indentifying restriction all at once, on the variables we found insignificant when doing exact-identifying, which are PCON and GOVEXP. Again, we found contradict findings that both PCON and GOVEXP were actually significant variables.

From the above analysis, we arrive at the following cointegrating equation (numbers in parentheses are standard deviations):

$\text{CPIA} + 1.8469\text{UNEM} - 2.9357\text{PCON} - 1.1889\text{GOVEXP} - 56.5165\text{POP}$			
	(0.70043)	(2.5121)	(1.1625)
			(19.9781)

⁸ If the p-value obtained less than 0.10, we reject the null hypothesis saying that the restriction implied is incorrect and vice versa. In other words, the variable is significant.

4.5. VECTOR ERROR CORRECTION MODEL (VECM)

From our analysis thus far, we have established that all five indices are cointegrated to a significant degree. However, the cointegrating equation reveals nothing about the Granger-causality relationship, that is, which variable is the leader (exogenous) and which is the follower (endogenous). Information on direction of Granger-causality can be particularly useful for policymaker in order to capture the main factors that contribute to unemployment. By knowing which variable is exogenous and endogenous, policymakers can better planned accurate amendment action to overcome unemployment in the future. In general, they would be likely to know which variable is the exogenous variable because then they would closely monitor the implementation of that particular variable as it would have significant influence on the expected movement of other variable.

The next part of our analysis is the Vector Error Correction Model (VECM) step. Here, in addition to decomposing the change in each variable to short-term and long-term components, we are able to establish which variables are in fact exogenous and which are endogenous. In our case, we would not be able to display the response of each variable in short-term basis. Basically, it was because we decided only one order of VAR.⁹ In order to view the response in short-term; we should at least choose two order of VAR. The 'd' or Δ in front of the variables indicates the change in short-term. For example: dUNEM indicates change of unemployment rate in short-run, as well as dPCON indicates change of private consumption in short-run. Table 9 gives the summary of Error-correction model estimates.

Table 9: Summary of Error Correction Model¹⁰

Dependent Variable	dUNEM	dPCON	dGOVEXP	dCPIA	dPOP
ECM(-1)	-0.0597 [0.0324]	0.0266 [0.0164]	0.0287 [0.0257]	-0.7231 [0.1852]	0.0013 [0.0012]
Chi-sq SC (1)	1.7277 [0.189]	1.2045 [0.272]	3.0034 [0.083]	1.0756 [0.300]	27.3111 [0.000]
Chi-sq FF(1)	2.5253 [0.112]	0.29874 [0.585]	0.15845 [0.691]	0.43233 [0.511]	0.24217 [.623]
Chi-sq N (2)	1.6102 [0.447]	4.5272 [0.104]	8.2594 [0.016]	9.7787 [0.008]	15.6311 [0.000]
Chi-sq Het (1)	0.9414	3.5967	0.15897	0.0082346	0.69935

⁹ As explained in Section 4.2.

¹⁰ Standard errors are given in parenthesis. The diagnostics of serial correlation (SC), functional form (FF), normality (N), and heteroscedasticity (Het) are based on LM version.

	[0.332]	[0.058]	[0.690]	[0.928]	[0.403]
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From Table 9, we come to conclusion which variable is the exogenous and which variable is the endogenous and represents it in Table 10.¹¹ The findings showed all variables are exogenous except one which is CPIA. However VECM does not provide information on which variable is the most exogenous and which one is the most endogenous. We will later rank the variables according to their exogeneity in the next step: Variance Decomposition (VDC).

Table 10: Exogenous and Endogenous Variables

Variable	ECM(-1) t-value	Implication
LUNEM	-1.84269	Variable is exogenous
LPCON	1.62195	Variable is exogenous
LGOVEXP	1.11673	Variable is exogenous
LCPIA	-3.90443	Variable is endogenous
LPOP	1.08333	Variable is exogenous

On top of above information, the VECM also provides a statistic that would probably interest the policymakers. The coefficient of e_{t-1} tells us how long it will take in long term to get back to equilibrium if that particular variable is shocked. The coefficient represents proportion of imbalance corrected in each period. For example, the coefficient of GOVEXP is 0.0287. This implies that, when there is a shock applied to this particular variable, it would take, on average, 2.87 years for the variable to get back to equilibrium.

4.6 VARIANCE DECOMPOSITIONS (VDC)

Up to this stage we have established that the CPIA is the only endogenous variable. Nonetheless, we have not been able to say anything about the relative endogeneity (or exogeneity) of the remaining variables. In other words, of the remaining variable, which is the most laggard variable compared to others, or, the least laggard. As the VECM is not able to assist us in this regard, we turn our attention to variance decomposition (VDC). Relative endogeneity can be ascertained in the following way. VDC decomposes the variance of forecast error of each variable into proportions attributable to shocks from each variable in the system, including its own. The least

¹¹ In order to determine the exogeneity or endogeneity of the corresponding variable, we check the t-test of the error-correction term.

endogenous variable is thus the variable whose variation is explained mostly by its own past variations.

In VDC we do both orthogonalized and generalized variance decompositions. There are mainly two differences between these two type of VDC. First, the orthogonalized VDCs are not unique (bias) and in general depend on particular ordering of variables in VAR whereas generalized VDCs invariant to the ordering of the variables. Second, orthogonalized VDCS assumes that when a particular variable in the sytem is shocked, all other variables are switched off whereas generalized VDCs do not make such assumption.

We purposely choose a very long time forecast according to the nature of the data itself. Economics data, compare to financial data do not act efficiently to information in short period. By applying orthogonalized VDCs, we obtained following findings illustrated in Table 11 and 12.

Table 11: Orthogonalized Variance Decompositions

Percentage of Forecast at Horizon = 50 (years)					
	UNEM	PCON	GOVEXP	CPIA	POP
UNEM	7.64%	4.09%	2.23%	83.70%	2.33%
PCON	34.51%	59.76%	0.14%	5.43%	0.15%
GOVEXP	11.47%	1.57%	7.43%	77.37%	2.16%
CPIA	11.65%	4.02%	2.09%	79.53%	2.71%
POP	9.34%	4.09%	2.16%	81.80%	2.61%

Table 12: Orthogonalized Variance Decompositions

Percentage of Forecast at Horizon = 100 (years)					
	UNEM	PCON	GOVEXP	CPIA	POP
UNEM	6.93%	4.12%	2.24%	84.35%	2.35%
PCON	26.07%	13.89%	1.51%	56.94%	1.59%
GOVEXP	9.92%	3.25%	1.29%	83.21%	2.32%
CPIA	9.71%	4.02%	2.17%	81.75%	2.35%
POP	9.39%	4.03%	2.18%	82.07%	2.34%

The VDC decomposes the variance of the forecast error of a particular variable into proportions attributable to shocks (or innovations) in other variables including itself.

The variable which is explained mostly by its own self is considered to be the most exogenous of all. The diagonal line of the matrix (highlighted) represents the relative exogeneity. Based Table 11 and 12, we ranked all variables according to the degree of exogeneity. (Refer to Table 13). The most exogenous variable was ranked 1 and the most endogenous was ranked 5.

Table 13: Rank of exogeneity for Orthogonalized Variance Decompositions

RANK	VARIABLES	
	Forecast at Horizon = 50	Forecast at Horizon = 100
1	CPIA	CPIA
2	PCON	PCON
3	UNEM	UNEM
4	GOVEXP	POP
5	POP	GOVEXP

The findings in Table 13 had grown some confusion in the study. Previously, we found only one endogenous variable which is CPIA. Afterwards, in VDC, CPIA turns out the most exogenous variable of all other variables. To test out whether orthogonalized VDC is bias or not, we change the ordering of UNEM in VAR, which appears first, with CPIA which appears the second last, and redo the orthogonalized VDC. The discovery proved our suspicion (refer Appendix 6F). For forecast horizon of 50 weeks, for CPIA, the percentage of variation explained by its own past dropped from 79.53% to 56.39%.

Taking into account the shortage of Orthogonalized VDC, we decided to rely on Generalized VDC. Thus, we obtained following findings illustrated in Table 13 and 14.

Table 14: Generalized Variance Decompositions

	Percentage of Forecast at Horizon = 50 (years)				
	UNEM	PCON	GOVEXP	CPIA	POP
UNEM	5.41%	4.08%	3.69%	63.66%	23.16%
PCON	23.64%	63.95%	10.24%	1.47%	0.70%
GOVEXP	9.59%	2.69%	7.45%	55.08%	25.19%
CPIA	8.76%	0.04%	2.31%	60.36%	28.52%
POP	6.99%	0.00%	2.49%	62.18%	28.33%

Table 15: Generalized Variance Decompositions

	Percentage of Forecast at Horizon = 100 (years)				
	UNEM	PCON	GOVEXP	CPIA	POP
UNEM	5.17%	0.14%	2.73%	64.36%	27.60%
PCON	20.36%	23.95%	2.45%	37.33%	15.89%
GOVEXP	7.59%	0.08%	1.55%	62.86%	27.93%
CPIA	7.31%	0.00%	2.47%	62.37%	27.85%
POP	7.06%	0.00%	2.50%	62.63%	27.81%

We can now more reliably rank the variables by relative exogeneity, as shown in the Table 16 below.

Table 16: Rank of exogeneity for Generalized Variance Decompositions

RANK	VARIABLES	
	Forecast at Horizon = 50	Forecast at Horizon = 100
1	PCON	CPIA
2	CPIA	POP
3	POP	PCON
4	GOVEXP	UNEM
5	UNEM	GOVEXP

According to Table 16, we could see different ranking for 50 years forecast and as time increases the ranking of the variables also changing. From the above results, we can make the several interpretations. First, the Generalized VDCs does not support earlier findings in VECM where it picked CPIA as the only endogenous variable. Second, the relative rank in exogeneity in some way seem unstable as time passes. Between 50 years and 100 years, the rank totally changes in order. Third, we cannot say that the difference in exogeneity between the variables is not substantial. As we add more variables to the study, the difference in exogeneity will decrease.

The above results may interest the policymakers. Among the variables considered, it appears that somehow inflation rate (CPIA) has the highest influence in the open economies. This is followed by the private consumption and population. Even though population do not have that much influence in the open economies towards unemployed, policymaker may still need to plan amendment action to grab the issue such as increasing education level, awareness campaign.

4.7 IMPULSE RESPONSE FUNCTIONS (IRF)

The Impulse Response Functions (IRF) essentially produces the consistent information as the VDCs, except that they can be presented in graphical form. For the sake of completeness, we have done the various graphs of IRFs. The graphs show the behaviour of other variables (as well as its own self) in long-run when a variable is shocked. We expect all variables would become equilibrium over time in long-run. However, from our observation, we could see that the same particular variable (CPIA) behave weirdly throughout the test. We could conduct several detection and correction actions in order to address this problem, yet as time is limited we are unable to do so.

4.8 PERSISTENCE PROFILE

The persistence profile (PP) illustrates the situation when the entire cointegrating equation is shocked, and indicates the time it would take for the relationship to get back to equilibrium. The main difference between persistence profile (PP) and IRFs is that PP trace out the effects of a system-wide shock on the long-run relation whereas IRF trace out the effect of a variable-specific shock on long run relations.

Figure 2 shows the persistence profile for the cointegrating equation of this study. Again, we discovered a weird behaviour in graph. Instead of dying out (become equilibrium) as expectation, the CV deviates over time. This indicates something had gone wrong throughout the conduct of the study.

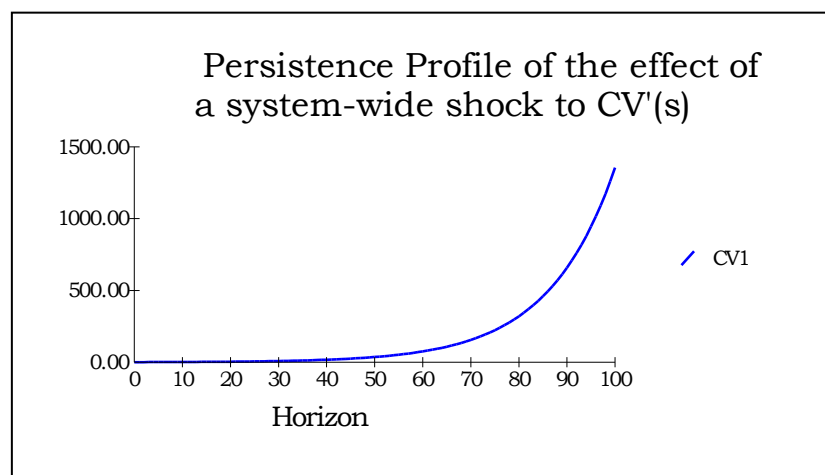


Figure 2: Persistence Profile

5. CONCLUSION

In conclusion, we revisit the three research objectives posed in the beginning of this study. Based on the above descriptive analysis, we found that:

- i. Economic well-being has some influence on unemployment rate.
- ii. We also explore the relationship between the unemployment rate and the economic variables.

In order to achieve a stable economic and unemployment condition, the policymaker should take drastic action to increase awareness among the communities. In a study conducted by Dr. M. Breaner (1979), it is found that for every increase of 10% in unemployed, there is a 1.2% rise in mortality, 1.7% increase in cardiovascular disease, 1.3% more cirrhosis case, 1.7% suicidal cases, 0.4% arrests and 0.8% more assault. Besides that, the policymaker should take good care of the variables found to be most influential to affect the unemployment rate.

6. LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

The following are some possible limitations of this study and hence presents opportunities for future research:

- i. Even though there are strong theory and literature support the conduct of this study, yet, it is difficult to carry out the study in respect of Malaysia as the focus study due to limited data available. The author would like to propose similar study being conducted in respect of other country (i.e., USA, England, Australia) as focus study where longer period of data available and easily to be accessed.
- ii. The main hindrance of this study is the short period of observations available.
- iii. Choice of variables should be consistent to the objective of the study. For that reason, we would like to suggest other variables to be included in the study for further study such as literacy rate (proxy of education level), migration rate, GDP etc.

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