# The unemployment rate and its determinants: the Malaysian case

Ghafar, Aiman and Masih, Mansur

INCEIF, Malaysia, Business School, Universiti Kuala Lumpur, Kuala Lumpur, Malaysia

25 May 2017

# The unemployment rate and its determinants: the Malaysian case

Aiman Ghafar[1] and Mansur Masih[2]

**Abstract:**

The focus of this paper is on the determinants of unemployment rate. Malaysia is used as a case study. The standard time series techniques are used for the analysis. The variables are bound together by theoretical relation as evidenced in their being cointegrated. Based on the variance decomposition analysis, the unemployment rate is driven mostly by inflation rate followed by the growth of population and private consumption expenditures. The results are consistent with the well-known 'Phillips curve' (Phillips,1958). The results are plausible and contain strong policy implications for the emerging countries like Malaysia.

**Keywords:** Determinants of unemployment rate, VECM, VDC, Malaysia

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[1] INCEIF, Lorong Universiti A, 59100 Kuala Lumpur, Malaysia.

2 **Corresponding author**, Senior Professor, UniKL Business School, 50300, Kuala Lumpur, Malaysia.

Email: mansurmasih@unikl.edu.my

## 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]

## 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 find out the determinants of unemployment rate. Malaysia is taken as a case study.

The study is important to policy makers mainly because it helps us 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 were relying on the regression model, not time-series analysis. This paper now focuses on a brief literature review.

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). Economics 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 in the early 1960s. For that reason, to the date this study was carried out, only up to 40 years observation of unemployment rate. Figure 1 shows the behaviour of unemployment rate since 1976. Malaysia recorded the worst unemployment rate

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[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.

in the 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.

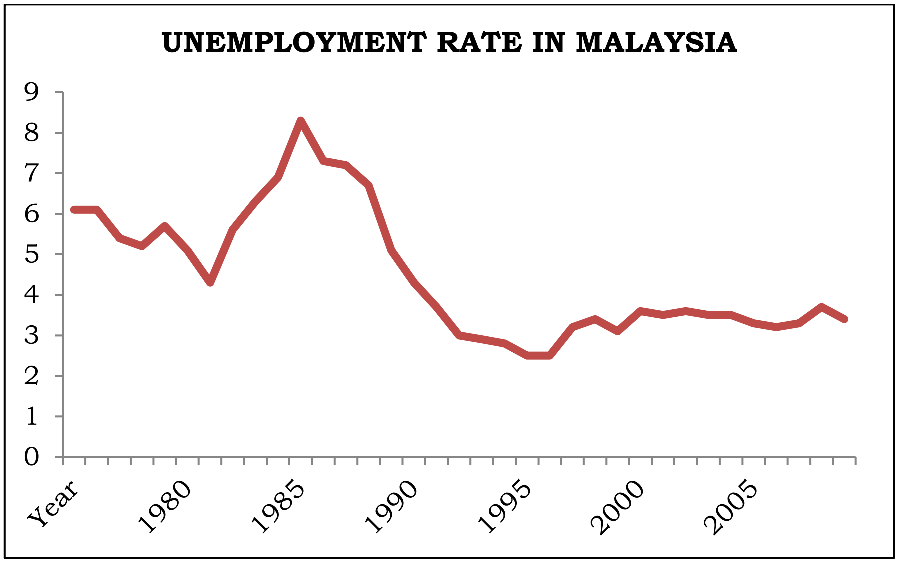


**Figure 1:** Unemployment rate in Malaysia (1976-2010)

## 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 relevant factors that affect unemployment rate.

The sample data are in form of annual secondary retrieved from Datastream for 35 years starting from1976. 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 include 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 is also a part of

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

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 |
| | -3.33229 (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 |

Referring 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.

**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 |

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

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. 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 |

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 massage saying that "no convergences after 50

[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.
[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.

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-identifying 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):

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

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 △ in front of the variables indicates the change in short-

[9] As explained in Section 4.2.

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 point up the summary

**Table 9:** Summary of Error Correction Model[10]

| 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 [0.332] | 3.5967 [0.058] | 0.15897 [0.690] | 0.0082346 [0.928] | 0.69935 [0.403] |

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

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

this particular variable, it would take, on average, 2.87 years for the variable to get back to equilibrium.

## 4.6 VARIANCE DECOMPOSITION (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 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 system 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 Decomposition

| | 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 Decomposition

| | 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 Decomposition

| 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. 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 limitations of Orthogonalized VDC, we decided to rely on Generalized VDC. Thus, we obtained following findings illustrated in Table 14 and 15.

**Table 14:** Generalized Variance Decomposition

| | 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 Decomposition

| | 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 Decomposition

| 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 does 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, etc.

## 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 included the various graphs of IRFs in Appendix 7A to 7J. The graphs show the behaviour of others 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.

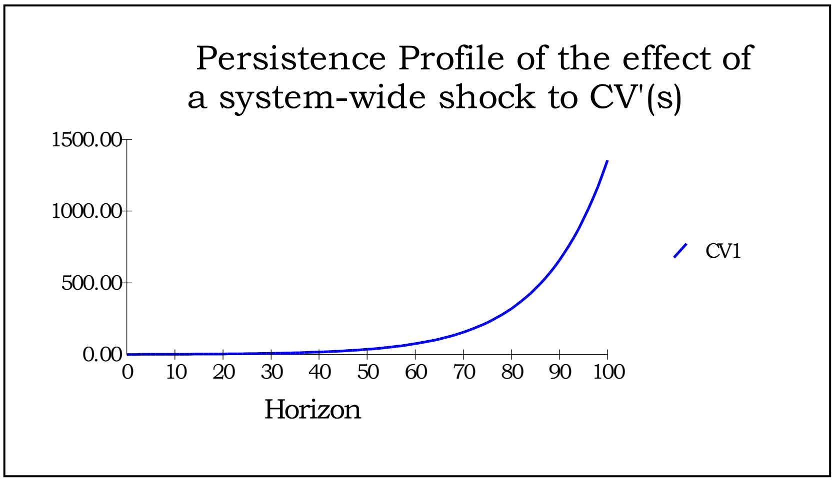


**Figure 2:** Persistence Profile

## 5. CONCLUSION

In conclusion, we revisit the research objective posed in the beginning of this study. Based on the variance decomposition analysis, we evidenced that the unemployment rate is driven mostly by inflation rate followed by the growth of population and private consumption expenditures. The findings have strong policy implications.

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 variable found to influence the unemployment rate most.

## 6. LIMITATIONS AND SUGESSTIONS 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 for 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 authors 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 are 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.

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