DEVELOPING AN ALTERNATIVE ESTIMATION MODEL FOR THE NON-ACCELERATING INFLATION RATE OF UNEMPLOYMENT (NAIRU) IN MALAYSIA

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Abstract

The concept of the "non-accelerating inflation rate of unemployment" (NAIRU) is central to the conventional understanding of the relationship between the labour market and inflation, which, in turn, is essential for macroeconomic assessments and policy guidance. The problem is that the NAIRU is an unobserved or latent variable inferred from a mathematical model based on other observable variables. Estimates from unobserved component models are subject to end-point sensitivity or "pro-cyclicality," where there is a high dependence between the NAIRU estimate and actual unemployment at the end of the sample period. While many such models have been proposed based on developed economy priors in Western economies, they are often difficult to estimate or interpret consistently in developing economy labour markets. In Malaysia, a direct link between inflation and unemployment is often not found without inclusion of other cost-push indicators. Once these other factors are included, the influence of unemployment is often statistically insignificant. Drawing on an intuitive first principles approach, this paper aims to uncover some alternative estimates of the NAIRU in Malaysia. These suggest that there was significant time variation during the COVID-19 period and a higher estimated NAIRU post-COVID. The estimate for the long-run NAIRU is 3.18% pre-COVID and 3.40% post-COVID, and for the short-run NAIRU it is 3.17% pre-COVID and 3.49% post-COVID.

Keywords:

NAIRU, estimation, time variation, structural change, structural labour market indicators

JEL Classification:

C1, E1, E2, E3, J3

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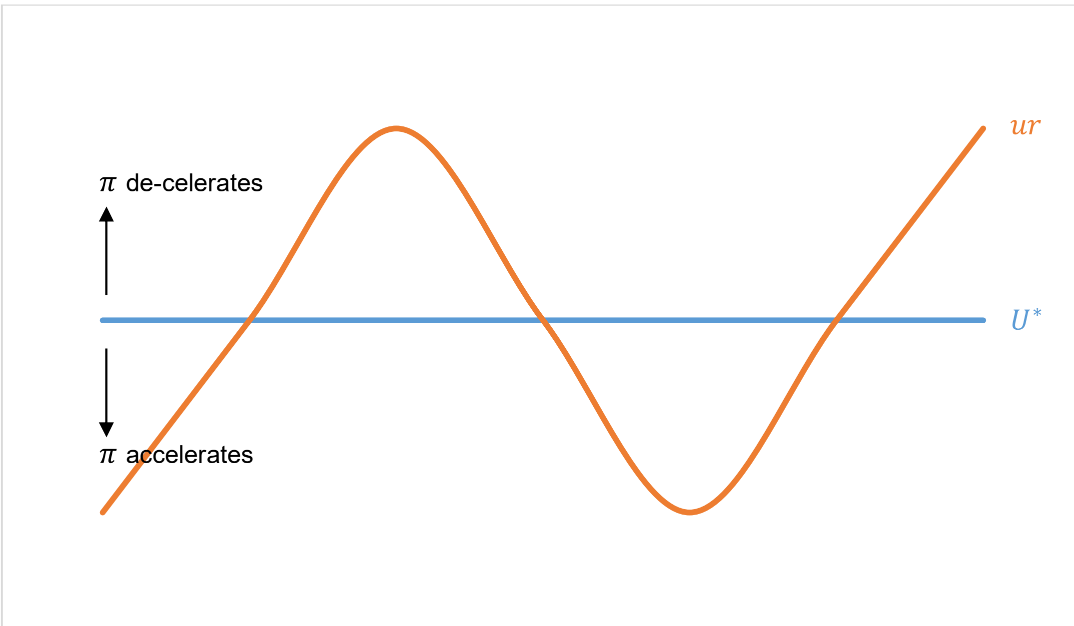
I. Introduction

The non-accelerating inflation rate of unemployment (NAIRU) is the structural rate of unemployment at which the rate of inflation is stable or, equivalently, the threshold rate of unemployment below which inflation would be expected to rise or above which inflation would be expected to fall (Modigliani and Lucas 1975).

Illustration: The NAIRU (U^*), the actual unemployment rate (ur), and inflation (π)



The concept of the NAIRU has been widely used and for many decades but is also subject to significant debate among economists (Espinosa-Vega and Russell 1997, Galbraith 1997, Ball and Mankiw 2002). The strengths of the NAIRU are that it provides a possible menu of optimal choices between unemployment and inflation for policymakers and used as a trend rate of optimal unemployment for comparative modelling. Some criticisms of the approach are that the theoretical underpinnings are at best very specific or at worst not fully articulated (Espinosa-Vega and Russell 1997, Galbraith 1997, Ball and Mankiw 2002). Despite the stability of inflation, the NAIRU is still consistent with a rising price level which has wider economic and welfare implications (Case, Fair and Oster, 2016). One material criticism which is the focus of this study is that the NAIRU may change or vary over time, which has significant implications for the measurement of the NAIRU and its use in policy (Gordon 1997).

The current study addresses possible solutions to the limitations of NAIRU estimates from alternative estimation methods recently suggested (Rusticelli, 2014, Turner et. al. 2016, Hristov et. al. 2017, Chalaux and Guillemette 2019, Guillemette 2021). Temporal variation in the NAIRU cause estimates to be inefficient, leading to a wide interval of possible values for the estimates. One way to mitigate this is to incorporate other variables that can affect equilibrium unemployment, such as structural labour market indicators and demand shocks, (Turner et. al. 2016, Hristov 2017). Another way is to use non-structural methods based on a time-varying estimator such as the Kalman filter.

II. Problem Statement

Estimates of the NAIRU are considered useful for macroeconomic assessments and policy guidance. The problem is that they vary over time due to structural changes in the economy, especially in the labour market. Unobserved component models like state-space models which are widely used to estimate the NAIRU are also prone to end-point sensitivity, in which the estimates become wider at the end of the sample period, or “pro-cyclicality”, in which estimates become wider due to the business cycle, especially around turning points. In these cases, there is a high dependence between the NAIRU estimate and the actual unemployment rates observed. This presents a problem particularly around periods of business cycle fluctuations and shocks, such as the COVID-19 crisis in 2020-2021, which led to a sharp increase in unemployment rates around the world and in Malaysia. In this case, using the same unobserved components models may lead to distortions in the NAIRU estimation and large upward revisions throughout the entire sample.

Time-varying estimators such as the Kalman filter offer one possible statistical solution but also tend to be inefficient especially around turning points and at the end of the estimation sample period, which is the period we are often most interested in for policy assessment and forecasts. Other approaches, which look for structural causes of the temporal variation also offer a potential solution but the variables causing the time-variation may be specific to the labour market conditions in particular countries and so must be identified on a case-by-case basis. The focus of the current study will therefore be to evaluate an alternative to statistical and structural approaches based on first principles in the context of Malaysia. That is, we will use a simple theoretical derivation of the NAIRU and estimate the unobserved components from known data as in Ball and Mankiw (2002). As a purely statistical approach structural and temporary shocks are not identified *a priori*.[3] Research on the usefulness of this approach in Malaysia, or more generally in ASEAN or Asian markets, is lacking and this paper aims to address this gap in research on the Malaysian labour market.

Based on the problem statement, the primary research question is: Can we estimate a NAIRU for Malaysia based on first principles rather than more complicated statistical or structural models which is justified theoretically and meaningful in empirical terms? The second research question would be: Do estimates of the NAIRU for Malaysia vary over time? The third would be: What is the nature of any such variation in terms of the level, volatility and long-term stationarity of the NAIRU? The final research question is: What are the implications for macroeconomic assessments and policy as well as future research areas?

III. Literature Review

The antecedents of the NAIRU can be found in the Phillips Curve (Phillips, 1958) which identified a negative relationship between changes in money wages and the unemployment rate in data from the United Kingdom over the period 1861-1957. Higher money wages were found to be associated with lower unemployment and vice versa. We call this a "simple Phillips Curve." Even in this early formulation, the relationship between changes in money wages and the unemployment rate was seen to change between sub-periods with the slope of the curve fitted to the scatter of data being steeper or flatter at different times. The rate of unemployment at which money wage growth is zero can be identified straightforwardly from the postulated relationship and is termed the "natural rate" of unemployment, (Friedman 1968).

Assuming a close correlation between money wages and inflation, which is a non-trivial restriction on the model, allows a generalisation to an inflation-based Phillips Curve, which in turn generalises to the NAIRU if the change in inflation is substituted

[3] This method is a 'first principles' approach because it starts with the observation that the inflation-unemployment relationship is a purely statistical relationship, hence we do not impose a structural relationship for the purpose of this working paper.

for the rate of inflation. This is the essential difference between the Phillips curve and the NAIRU. The former looks at the level of inflation, which is the rate of change in prices while the latter looks at the rate of change in inflation, whether inflation is speeding up or slowing down. The concept of the NAIRU originated in the 1970s from the work of Franco Modigliani and Lucas Papademos (Modigliani and Papademos 1975). The NAIRU is often considered a development of the long-term concern about inflation, unemployment and economic activity (Hayek 1950) and the idea of the natural rate of unemployment in relation to the Phillips curve.

The concept has been made more specific to wages and labour market conditions in a variation called the non-accelerating wage rate of unemployment (NAWRU) (Elemskov and MacFarland, 1993; Elemskov, 1994). By contrast, where employment and unemployment are related to the level of economic activity or gross domestic product (GDP), a generalisation is possible to allow for the direct relationship between growth and inflation, or equivalently the optimisation of a model with minimum inflation and unemployment solved jointly with maximum GDP growth and employment rates (Espinosa-Vega and Russell 1997, Galbraith 1997, Ball and Mankiw 2002). The NAIRU is not generally considered as a theory to explain inflation or unemployment (Espinosa-Vega and Russell 1997, Galbraith 1997, Ball and Mankiw 2002) but is interpreted more as an empirical regularity, not unlike the Phillips Curve (Phillips 1958), which offers a combination of policy choices of inflation and unemployment. As such, most of the attention given to the NAIRU focusses on estimation and the identification of empirical regularities (Laubach 2001).

Recent empirical studies have renewed interest in the estimation of the NAIRU by attempting to account for factors that might cause the temporal and geographical variation in estimates (Gordon 1997, Gianella et. al 2008). Rusticelli (2014), for example, proposes a refinement to the standard OECD approach of using a Kalman filter, or time-varying estimator to measure the NAIRU. In this case, the NAIRU is considered as a trend rate of unemployment and the time varying estimator using the Kalman filter is an attempt to capture the variation in the trend over time, without structural explanation (Fronckova, Prazak and Soukal, 2019). The revised methodology gives mixed results on a selection of OECD countries. For smaller euro area countries (Greece, Ireland, Italy, Portugal and Spain) the magnitude and statistical significance of the unemployment gap increases, and the NAIRU is revised upward on average by 1.75%, which is a significant upward revision with large implications for the inflation and unemployment trade-off. The revised methodology provides less improvement to the standard OECD methodology for larger G7 countries excluding Italy. Finally for the United States, while the statistical evidence for the Kalman filter method is marginal, the policy implications of the new point estimate of the NAIRU are significant because they are higher than those previously estimated.

Chalaux and Guillemette (2019) describes a further revision to the methodology used by the OECD as a starting point for long-run scenarios with three main inputs; labour, fixed capital excluding housing and labour efficiency, which is obtained as a decomposition residual. The trend unemployment rate is estimated by Kalman filtering within a forward-looking Phillips curve (Rusticelli 2014) and other trend components are obtained by using the Hodrick-Prescott filter (HP filter). The labour efficiency and the labour force participation rate are cyclically adjusted before filtering, as a remedy for the end-point problem associated with filters. This pre-filtering cyclical adjustment also helps mitigate the cyclical turning points problem and lowers the cyclicality of potential output. Future revisions are less likely as a result.[4] Guillemette (2021) presents the results of an exercise to apply the OECD methodology in the context of the most recent COVID-19 structural shock, where the NAIRU is taken as a time-varying trend estimated with a Kalman filter and the “unemployment gap” is estimated as the difference between actual unemployment and this time-varying NAIRU estimate. The estimated equations predict a larger increase in the NAIRU for countries with less flexible labour markets, but the differences are small (between 0 and 0.2 percentage points), suggesting that there is not much impact on the NAIRU from the COVID-19 shock.

Turner et. al (2016) investigate an alternative modification to the standard OECD methodology which adds a cyclical adjustment measure to trend labour efficiency, which helps to reduce large end-point revisions The significant variables in the cyclical

[4] A similar methodological approach has been used in another context to estimate the impact of temporal variation in financial liberalization (FLIB) on the consumption function in the United Kingdom (Caporale and Williams, 2001). In this approach FLIB is measured as an index instrument constructed using indicators of financial liberalization which is added to a standard consumption function with the coefficient on FLIB estimated using a Kalman filter approach.

adjustment of labour efficiency are manufacturing capacity utilisation, and the investment share, for a sample of countries, additional variables such as house prices and credit are used. They conclude that re-specifications of the Phillips curve incorporating structural determinants suggest a tighter fit between the unemployment gap and inflation and might reduce future end-point revisions to the NAIRU estimates In a similar search for structural causes in the variation of the NAIRU, Hristov et. al. (2017) evaluate the criticism of unobserved component models to estimate the NAWRU variant of the NAIRU, which has been shown to suffer from excessive pro-cyclicality at the sample end, especially around turning points such as crisis periods and recovery periods. They present the European Commission model-based approach, which adds a structural indicator of the labour market as a convergence point for the NAWRU. The revised estimates of the NAWRU combines indicators of the business cycle and the labour market and when applied to data from the EU Member States, appears to moderate pro-cyclicality and reduces the need to revise to the one- and two-year-ahead forecasts of the NAWRU in eighty percent of the countries in the sample group.

For Malaysia, studies of the relationship between inflation and unemployment tend to focus on Phillips Curve and “Phillips Curve” relationships augmented with other macroeconomic indicators. Most find evidence for a stable relationship between the unemployment rate and inflation rate in Malaysia in both the short and long-run (Tang and Lean 2007; Furuoka 2007), and equilibrium relationships using standard co-integration and error correction modelling (ECMs) can also be identified (Fumitaka and Munir, 2014). Estimation of so-called New Keynesian Phillips Curves in Malaysia, which are augmented by various addition indicators such as the output gap or exchange rates have also been identified (Furuoka, and Harvey 2015). Similar results are found across Asian economies, despite very different economic structures and labour market conditions (Furouka and Munir, 2009) using standard linear and nonlinear methods (Baharumshah, Soon and Wohar 2021).

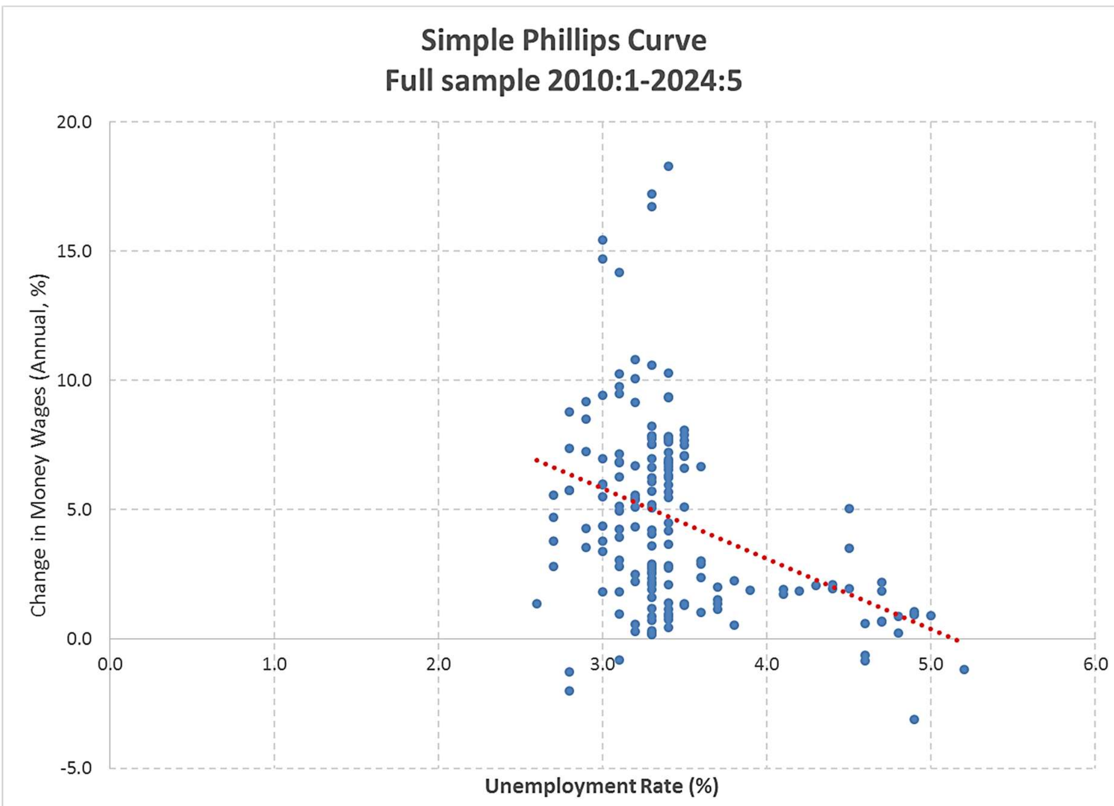
The most recent evidence from Malaysia (Leong, 2024) using a hybrid New Keynesian Phillips curve suggest that forward-looking expectations have a greater effect on the relationship between unemployment rate and inflation rate, which has steepened in the post-COVID period compared to pre-COVID. That is, that a smaller change in the unemployment rate will have a larger effect on changes in inflation, when inflation expectations are more binding. This latter result is consistent with studies in other countries which also find that the relationship between the unemployment rate and inflation becomes stronger and weaker under different circumstances (Kuttner and Robinson, 2010; Hazell, Herreno Nakamura and Steinsson, 2022; Hobijn, Miles, Royal and Zhang, 2023). This is a phenomenon identified by Phillips himself in his 1958 article.

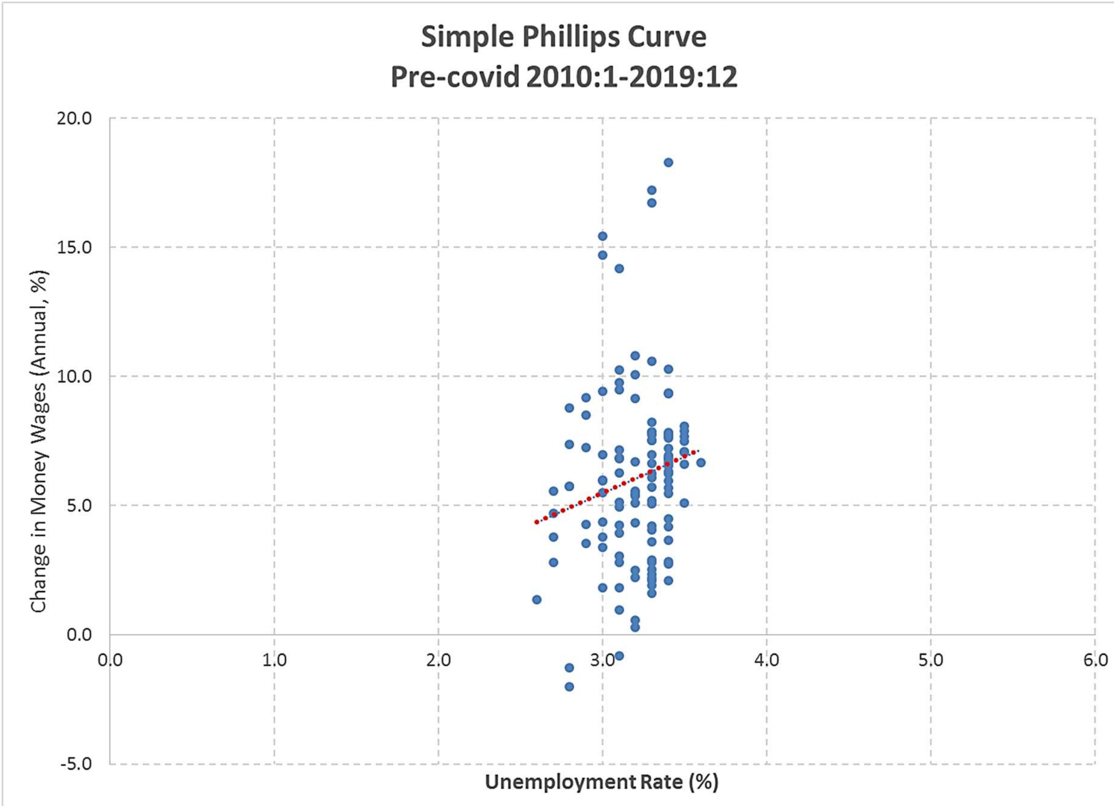
Based on the above it appears that approaches to the relationship between unemployment and inflation have departed from the original idea that the NAIRU and its antecedent in the Phillips Curve are not generally considered as theories to explain inflation or unemployment but are empirical regularities which, if they exist, can offer a guide to macroeconomic assessments and policy choices. Many approaches appear to mistake the NAIRU and the Phillips Curve as the same thing and estimates of the relationships augmented by other variables, within a New Keynesian Phillips Curve for example, are the reduced form of a full structural model rather than the estimate of an independent empirical regularity.

IV. Stylised Facts on the NAIRU in Malaysia

This section presents labour market and inflation dynamics in various configurations in Malaysia. Figure 1 shows a series of simple scatter plots of data for the rate of unemployment against the change in money wages for Malaysia, which we call the simple Phillips Curve, as in the original formulation in Phillips (1958). A simple Phillips Curve only appears in the full sample including the COVID-19 period. In the pre-COVID period, the simple fitted curve has the wrong slope and in the post-COVID period, the simple fitted curve is almost flat.

Figure 1: Simple Phillips Curve: Unemployment and Money Wages and Inflation




Simple Phillips Curve
Pre-covid 2010:1-2019:12
Change in Money Wages (Annual, %)
20.0
15.0
10.0
5.0
0.0
-5.0
0.0
1.0
2.0
3.0
4.0
5.0
6.0
Unemployment Rate (%)

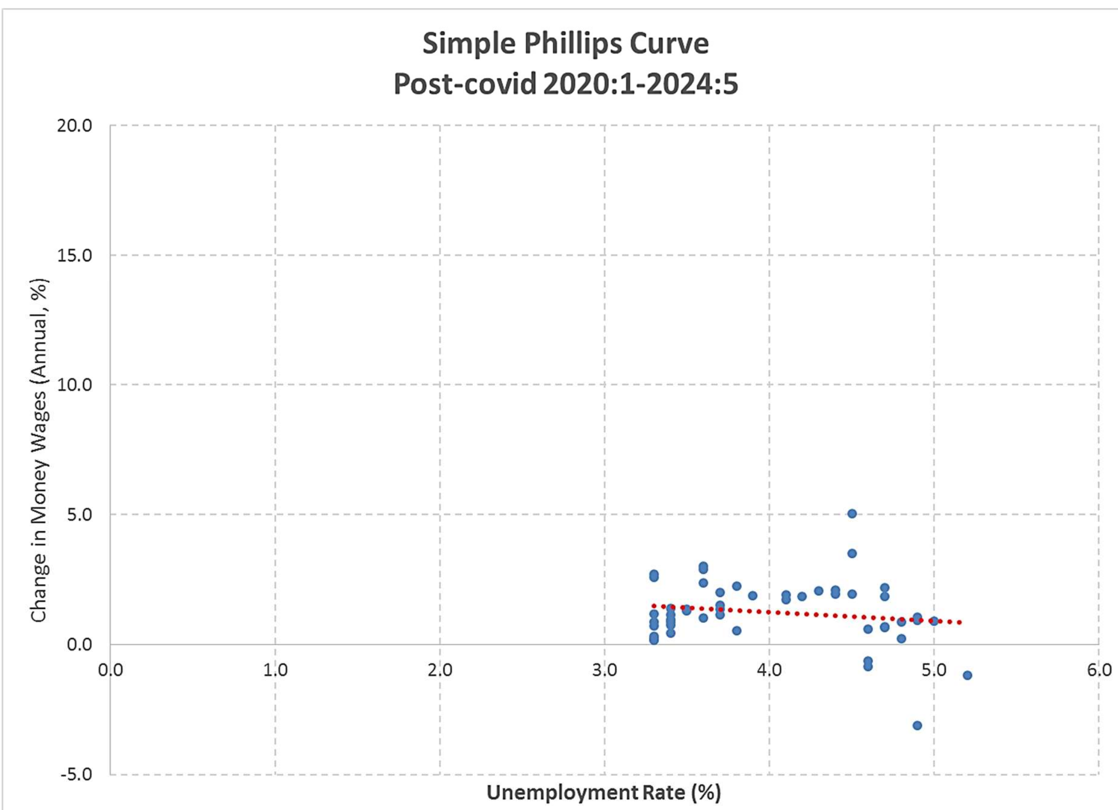
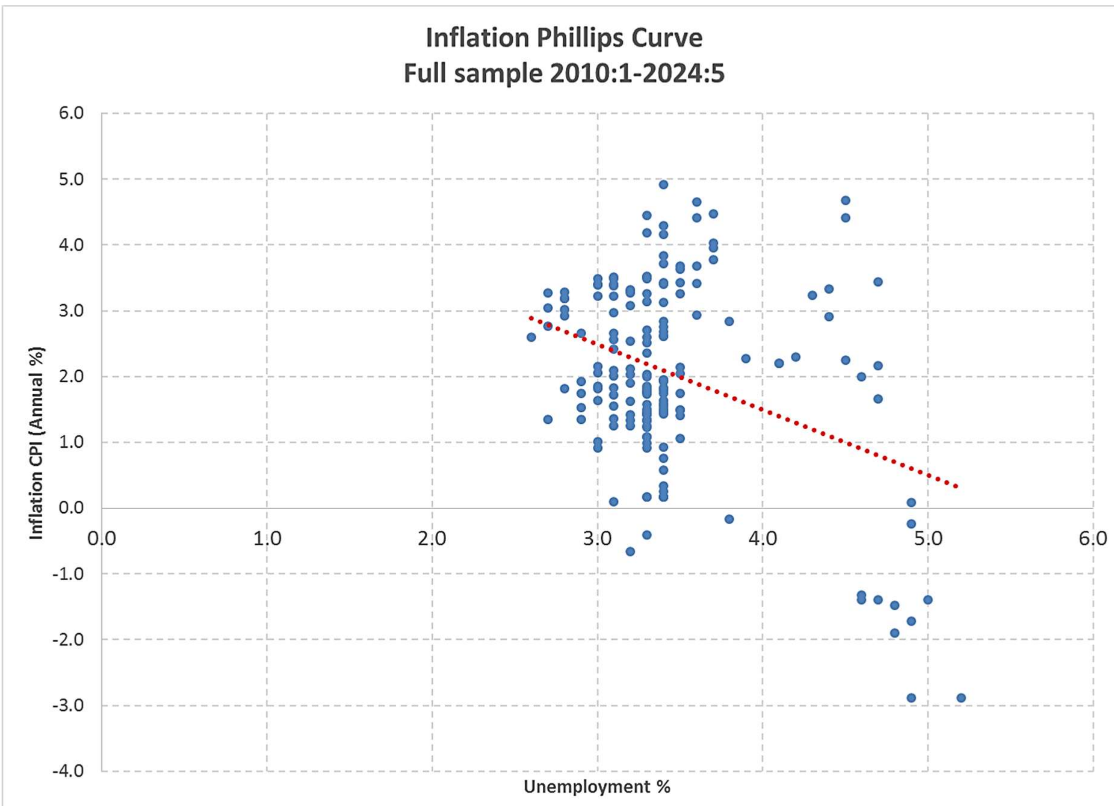
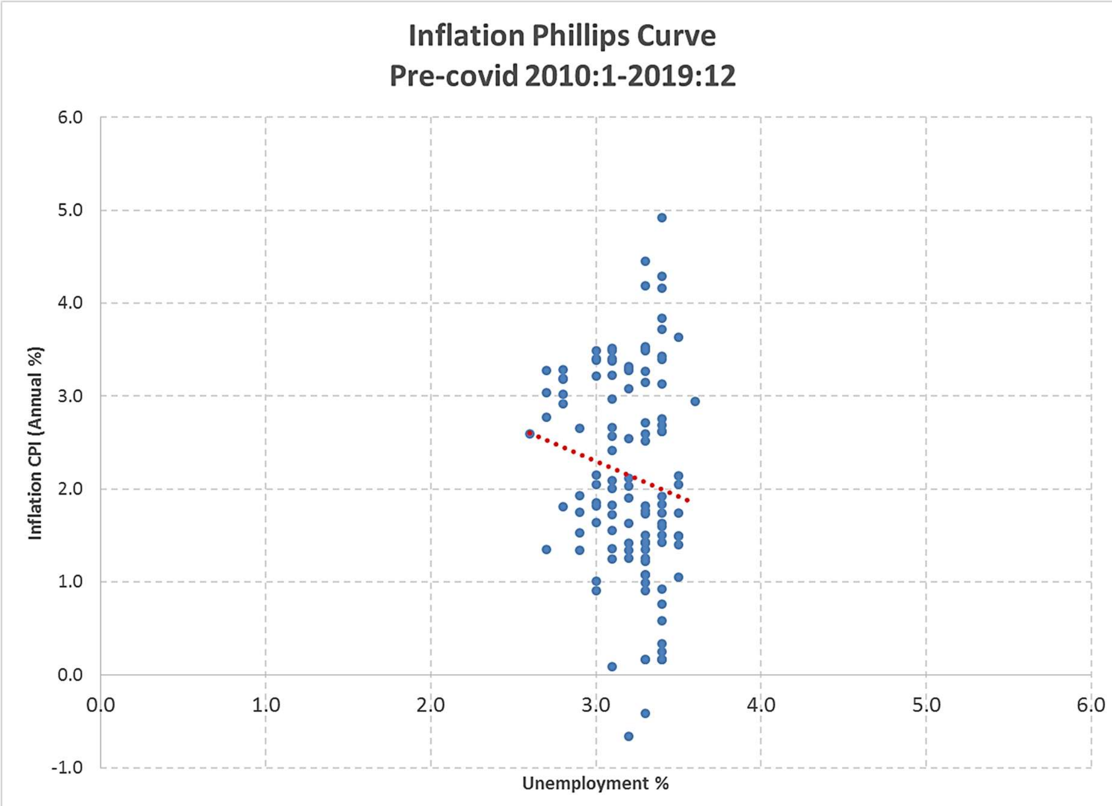

Simple Phillips Curve
Post-covid 2020:1-2024:5
Change in Money Wages (Annual, %)
20.0
15.0
10.0
5.0
0.0
-5.0
0.0
1.0
2.0
3.0
4.0
5.0
6.0
Unemployment Rate (%)

Figure 2 shows the inflation-based Phillips Curve using the consumer price index (CPI) as the measure of changes in prices. An inflation-based Phillips Curve appears in all subsamples but is stronger in the post-Covid-19 period. In both the simple Phillips Curve and the inflation-based Phillips Curve there is clustering of the inflation-unemployment relationship around +/-3% unemployment and it is clear from the scatter that this is largely due to outliers above or below this range.

Figure 2: Inflation-based Phillips Curve: Unemployment and Inflation




Inflation Phillips Curve
Pre-covid 2010:1-2019:12
Inflation CPI (Annual %)
Unemployment %
6.0
5.0
4.0
3.0
2.0
1.0
0.0
-1.0
0.0
1.0
2.0
3.0
4.0
5.0
6.0

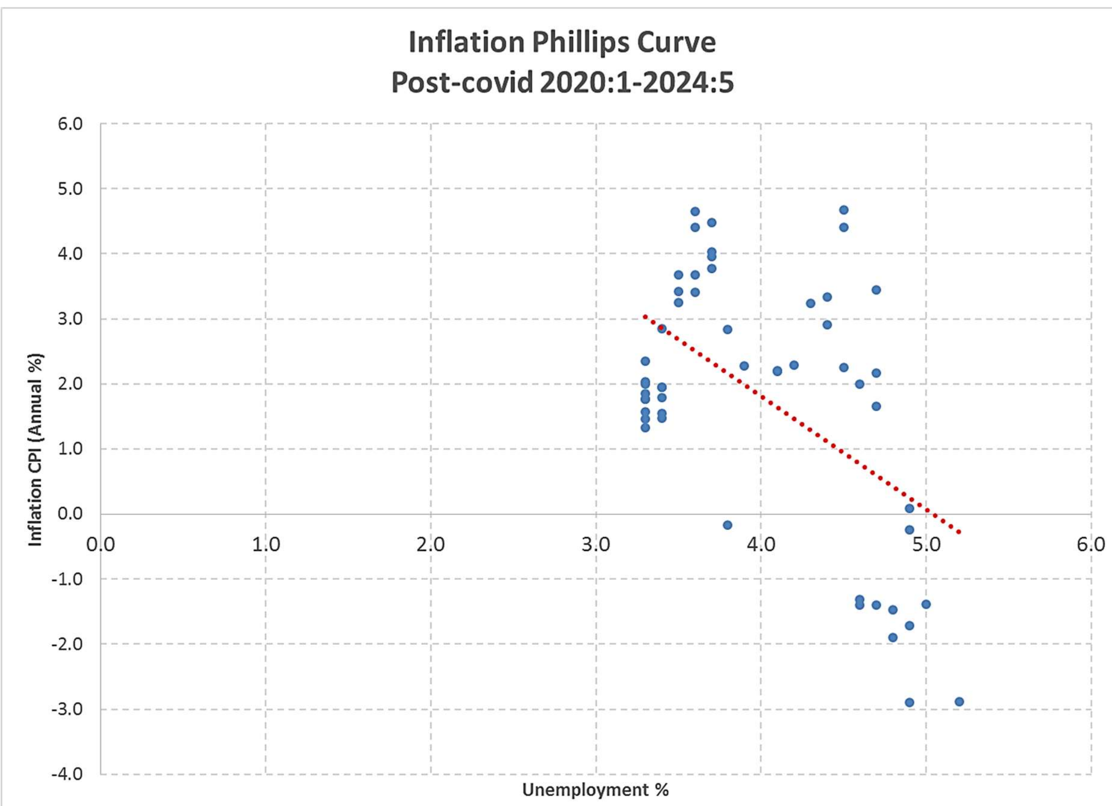
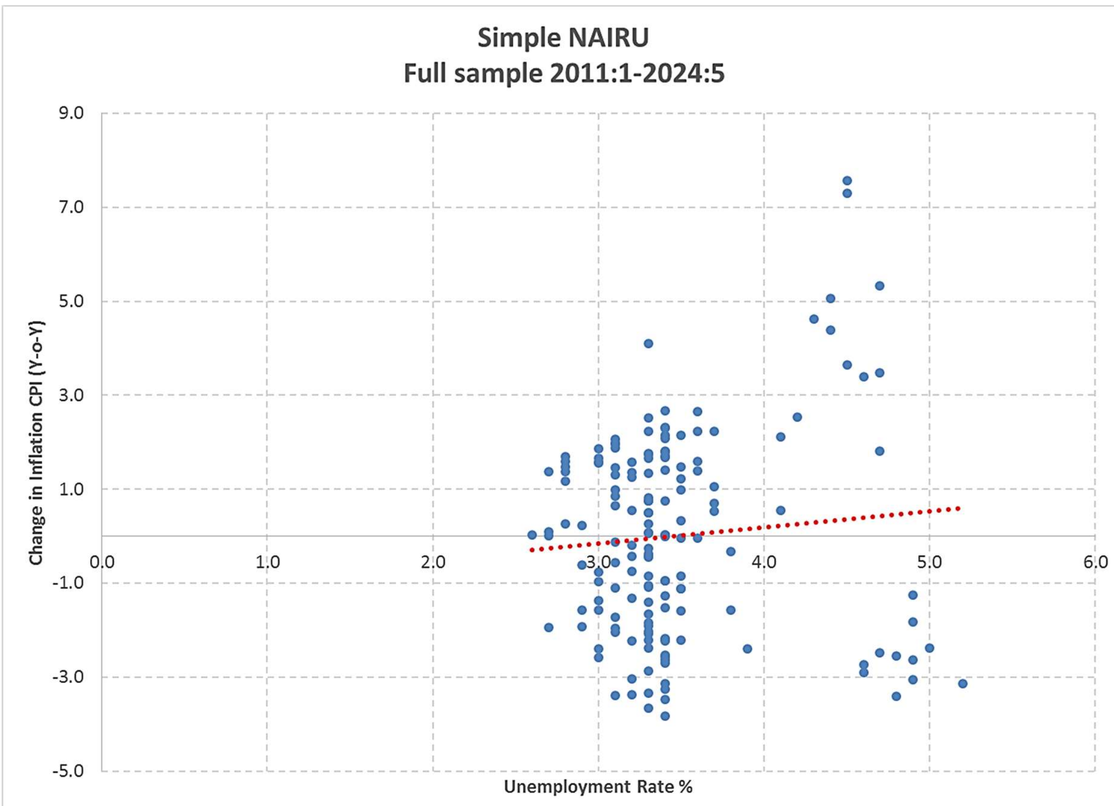
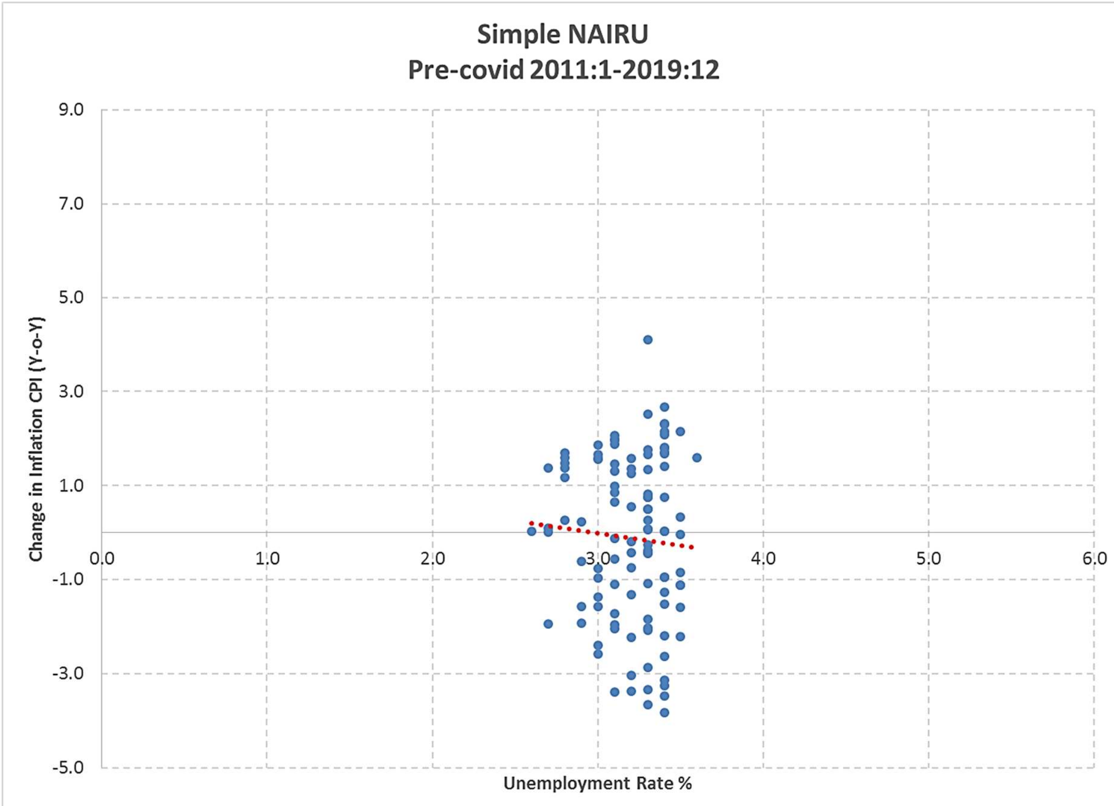
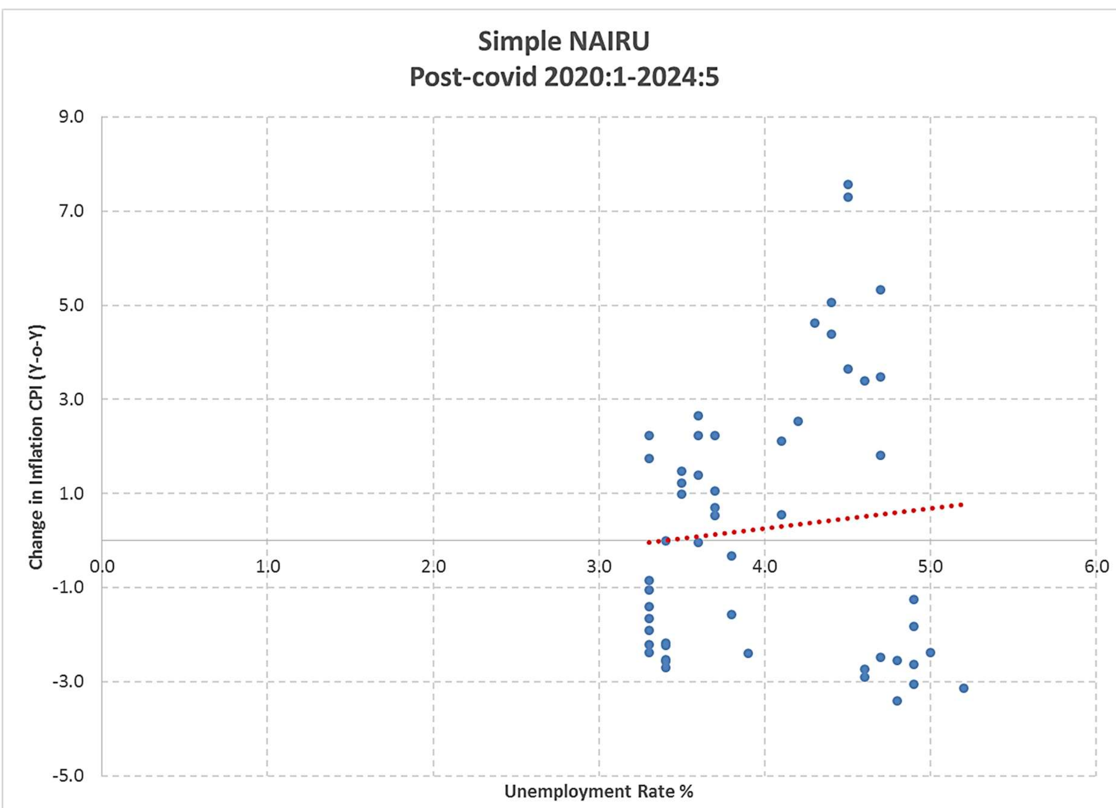

Inflation Phillips Curve
Post-covid 2020:1-2024:5
Inflation CPI (Annual %)
Unemployment %
6.0
5.0
4.0
3.0
2.0
1.0
0.0
-1.0
-2.0
-3.0
-4.0
0.0
1.0
2.0
3.0
4.0
5.0
6.0

Figure 3 shows a series of plots of the scatter of data for the rate of unemployment against changes in the rate of inflation, measured by the difference in the CPI growth rates year-on-year. Weak evidence for the NAIRU only appears in the pre-COVID period - before and after this point the standard relationship breaks down. In all cases for the Phillips Curve and the NAIRU, the scatter plots suggest time variation *prima-facie* and this hypothesis shall be tested with the modelled estimates.

Figure 3: NAIRU: Unemployment and Changes in Inflation




Simple NAIRU
Pre-covid 2011:1-2019:12
Change in Inflation CPI (Y-o-Y)
Unemployment Rate %
9.0
7.0
5.0
3.0
1.0
-1.0
-3.0
-5.0
0.0
1.0
2.0
3.0
4.0
5.0
6.0


Simple NAIRU
Post-covid 2020:1-2024:5
Change in Inflation CPI (Y-o-Y)
Unemployment Rate %
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3.0
1.0
-1.0
-3.0
-5.0
0.0
1.0
2.0
3.0
4.0
5.0
6.0

To summarise, the scatter plots suggest that the Phillips curve is generally evident in Malaysia. Although the relationship for NAIRU appears weak, nevertheless they give sufficient basis to proceed with the research question identified for this paper.

V. Research Methodology

Theoretical Foundation

The discussions above indicate the complications that arise from over-parameterising the estimated equation for the NAIRU and the limitations of a non-parameterised statistical approach. Based on this our theoretical approach is to start with first principles and build a simple model to estimate the NAIRU with as few peripheral assumptions as possible.

To calculate the NAIRU as a latent variable we follow Ball and Mankiw (2002) who begin with the short-run trade-off between inflation, π and unemployment U as follows:

$$\pi = k - aU \tag{1}$$

where *k* and *a*>0 are parameters measuring the baseline inflation rate and the responsiveness of inflation to unemployment or slope of the Phillips Curve, respectively. This equation has the standard form of the inflation-based Phillips Curve and states that π and U are negatively related.

In most standard theories, we can write the inflation unemployment trade-off as:

$$\pi = \pi^e - a(U - U^*) \tag{2}$$

Where π^e is expected inflation and U^* is a parameter called the "natural rate of unemployment." The natural rate is the rate of unemployment that prevails when inflation expectations are confirmed. Seen in another light, the parameter U^* embeds all shifts in the inflation-unemployment trade-off previously represented by the parameter k, other than shifts arising from expected inflation.

The standard literature often adds a 'supply shock' term to capture disruptions to the economy outside of the of the normal inflation-unemployment dynamics, including oil-price shocks, policy shocks or exchange rate shocks. These are captured by a variable v as follows:

$$\pi = \pi^e - a(U - U^*) + v \tag{3}$$

In addition, the simplest way to incorporate inflation expectations is to assume that they rely on the previous period inflation rate so that $\pi^e = \pi_{t-1}$ as follows:

$$\pi = \pi_{t-1} - a(U - U^*) + v \tag{4}$$

This allows for simple rearrangement to find changes in inflation as:

$$\Delta\pi = aU^* - aU + v \tag{5}$$

This is the simplest way to find the NAIRU as the natural rate and the supply shocks which are unknown from the unemployment rate and the inflation rate which are known, with the parameter a estimated from equation (1), again using known variables:[5]

$$\underbrace{U^* + \frac{v}{a}}_{\substack{\text{Unobservable} \\ \text{/ Latent} \\ \text{Variables}}} = \underbrace{U + \frac{\Delta\pi}{a}}_{\substack{\text{Observable /} \\ \text{Known} \\ \text{Variables}}} \tag{6}$$

The final stage is to extract U^* as a long-run time varying measure from the left-hand side, which is calculated from known variables on the right-hand side. This can be done using standard trend tools such as the Hodrick-Prescott (1997) filter, which

[5] The parameter a in Equation 1 is estimated using an Autoregressive Distributed Lag (ARDL) model regressing $\Delta\pi$ on unemployment with the optimal lag determined using the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC/BIC) and the parameter stability tested with the CUSUM and CUSUMSQ post-estimation stability tests.

captures both the long-run trend features and possible time variation as noted in Ball and Mankiw (2002).[6]

VI. Empirical considerations

One empirical problem arises from this which is that Equation 1 is likely to be under-specified *a priori*, and so the "supply shock" variable υ captures variation which can be modelled from observed variables such as oil prices or policy shocks. It is also likely that inertia or hysteresis such as labour market rigidity, causes lags in expected inflation beyond just the previous period $\pi^e = \pi_{t-1}$

These would make the estimate inefficient. We experimented with this and found that it can be solved by including either oil prices (given by $bOIL$) or the policy rate (given by bi), but not both, incorporated in Equation 1 as follows:

$$U^* + \frac{v}{a} = U + \frac{\Delta\pi}{a} + \frac{bi}{a} \tag{7}$$

$$U^* + \frac{v}{a} = U + \frac{\Delta\pi}{a} + \frac{bOIL}{a} \tag{8}$$

The final estimate of the NAIRU is obtained from the arithmetic mean of estimates from Equation 6, 7 and 8, from which we also derive a range for the estimates.

VII. Data and estimation

We use seasonally adjusted monthly data from the Department of Statistics Malaysia (DOSM) on money wages in the manufacturing sector, headline inflation using the consumer price index (CPI) and the rate of unemployment. Interest rates are the

[6] As noted by Ball and Mankiw (2002), the Hodrick-Prescott (HP) filter generalizes a linear time trend by allowing its slope to adapt gradually over time. Formally, the filter optimizes an objective function that minimizes the sum of squared deviations between the actual data and the estimated trend, subject to a penalty on curvature that enforces smoothness. The behaviour of the filter is governed entirely by the weight assigned to this penalty. A penalty of zero forces the filter to perfectly replicate the original data series, whereas an exceptionally high penalty restricts the output to a rigid, linear time trend.

monthly Overnight Policy Rate (OPR) from Bank Negara and oil prices are the West Texas monthly average from industry sources.[7]

The overall sample runs from January 2010 to May 2024 and is spilt into two main sub-periods the first is the pre- COVID period from January 2010 to December 2019 and the second is the post- COVID period from January 2020 to May 2024. This in turn is divided into a period of restrictions on movement and activity, under a series of Movement Control Orders (MCO) enforced from January 2020 to December 2021 and the post-MCO period from January 2022 to May 2024. The short-run NAIRU is the contemporaneous estimate without any smoothing, the left-hand side of Equation 6. This is useful to understand the impact of the shocks on in the short-run and to distinguish them from long-run, possibly structural changes in the long-run NAIRU which is the 'trend' derived from the HP-filter.

[7] Estimates were attempted using core inflation but the data series is very short. The availability of headline inflation data is longer and the results are clearer. In addition, we are interested in the volatility in inflation, there is much less in core inflation because the components are price-controlled and more variable prices are excluded due to the definition of this measure.

VIII. Results

Figure 4 shows the estimated statistical model for the long-run NAIRU which clearly suggests that there is time variation in the NAIRU before and after the COVID-19 period. The mean level and variation appear escalated at beginning of the COVID-19 period. It has moderated since then but is still higher at 3.40% vs 3.18%.

Figure 4: Estimates of the long-run NAIRU using CPI inflation (% of labour force)

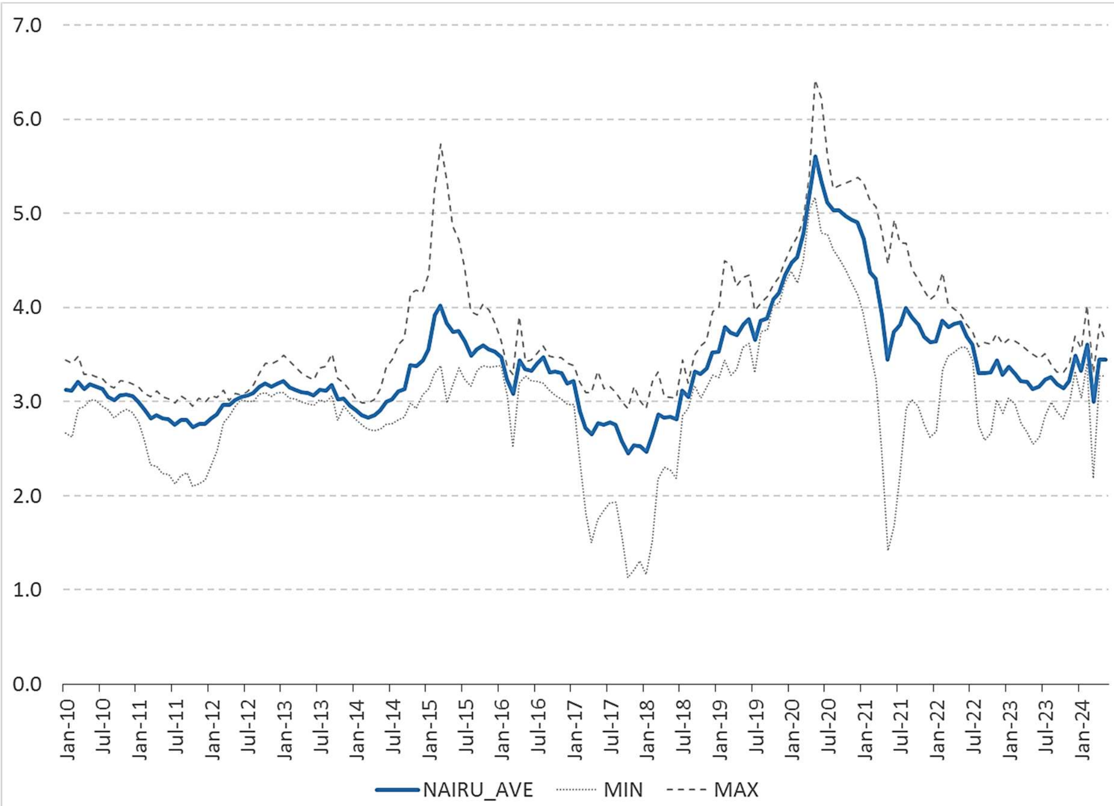

Table 1 shows the tests of difference in volatility measured as the variance in the long-run NAIRU across the various subsamples.[8] The results show that the volatility of the long-run NAIRU rose significantly between the pre-COVID and post-COVID periods, which includes the MCO period where the volatility peaked. After the end of movement restrictions, the volatility of the long-run NAIRU is significantly lower compared to the pre-COVID period. Table 2 shows the tests of the difference in the mean level of the long-run NAIRU across the various subsamples.[9] The results show that the level of

[8] The difference in volatility is an F-test on the variances in the two samples
[9] The difference in means is tested using a t-test for two samples assuming unequal variances

the long-run NAIRU rose significantly after the pre- COVID, peaking during the MCO period at 4.47% before falling to 3.40% after the movement restrictions were removed. Nonetheless, this is significantly higher than the average of 3.18% during the pre-COVID period.

Table 1: Difference in Volatility - Long-run time-varying NAIRU

	Pre-covid	*Post-covid*	*Pre-covid*	*MCO*	*Pre-covid*	*Post-MCO*	*Post-MCO*	*MCO*
	2010:1-2019:12	2020:1-2024:5	2010:1-2019:12	2020:1-2021:12	2010:1-2019:12	2022:1-2024:5	2022:1-2024:5	2020:1-2021:12
Mean	3.18	3.89	3.18	4.47	3.18	3.40	3.40	4.47
Var	0.15	0.49	0.15	0.39	0.15	0.06	0.06	0.39
Obs	120	53	120	24	120	29	29	24
df	119	52	119	23	119	28	28	23
F	0.2983		0.3735		2.5788		0.1448	
P(F<=f)*	0.0000		0.0003		0.0025		0.0000	
F Critical	0.6891		0.6171		1.7143		0.5196	

Table 2: Difference in Means - Long-run time-varying NAIRU

	Pre-covid	*Post-covid*	*Pre-covid*	*MCO*	*Pre-covid*	*Post-MCO*	*Post-MCO*	*MCO*
	2010:1-2019:12	2020:1-2024:5	2010:1-2019:12	2020:1-2021:12	2010:1-2019:12	2022:1-2024:5	2022:1-2024:5	2020:1-2021:12
Mean	3.18	3.89	3.18	4.47	3.18	3.40	3.40	4.47
Variance	0.15	0.49	0.15	0.39	0.15	0.06	0.06	0.39
Obs	120	53	120	24	120	29	29	24
df	66		27		68		29	
t Stat	-6.9338		-9.7595		-4.0309		-7.8806	
P(T<=t) *	0.0000		0.0000		0.0001		0.0000	
t Critical	1.6683		1.7033		1.6676		1.6991	
P(T<=t) **	0.0000		0.0000		0.0001		0.0000	
t Critical	1.9966		2.0518		1.9955		2.0452	

Figure 5 shows the estimated statistical model for the short-run NAIRU, which again suggests that there is time variation in the NAIRU before and after the COVID-19 period. The mean level and variation appears escalated at beginning of COVID-19. It has moderated since then but is still higher at 3.49% vs 3.17%.

Figure 5: Estimates of the Short-run NAIRU using CPI inflation (%)

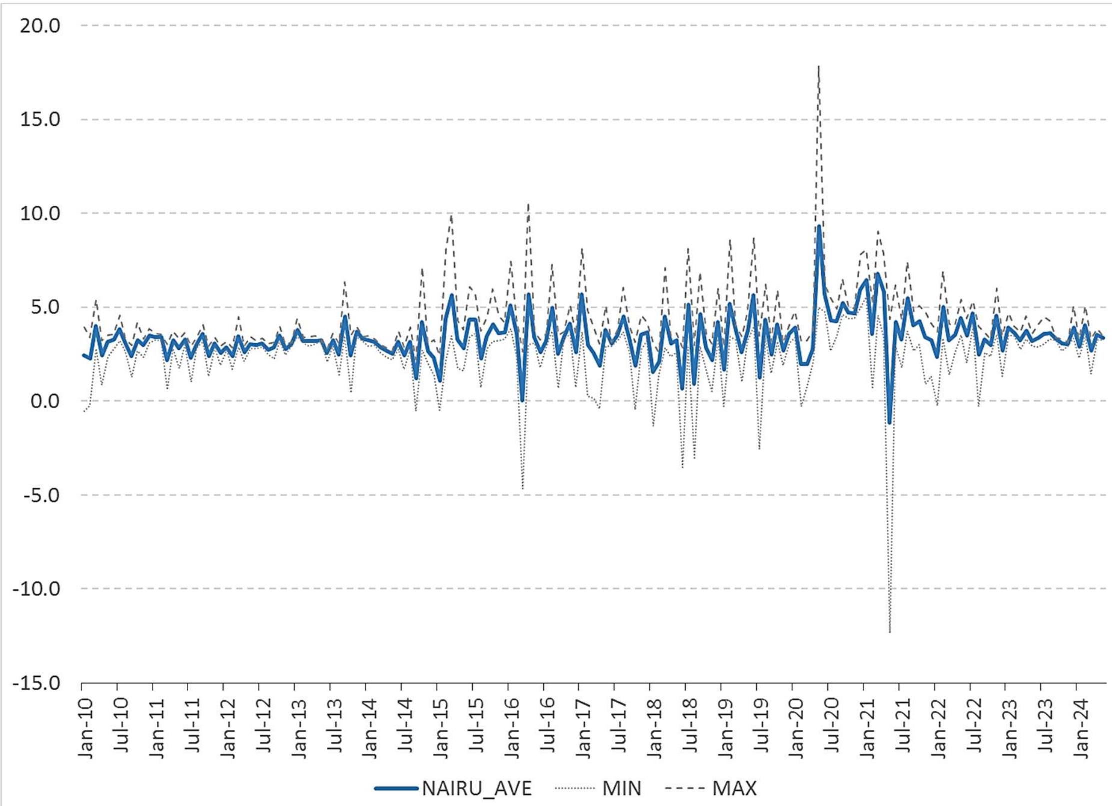

Table 3 shows the tests of difference in variance in the short-run NAIRU across the various subsamples. The results show that the volatility of the short-run NAIRU rose significantly between the pre- COVID and post- COVID, which includes the MCO period where the volatility peaked. After the end of movement restrictions the volatility of the short-run NAIRU is significantly lower compared to the pre- COVID period. Table 4 shows the tests of the difference in the mean level of the short-run NAIRU across the various subsamples. The results show that the level of the short-run NAIRU rose significantly after the pre- COVID, peaking during the MCO-period at 4.34% before falling to 3.49% after the movement restrictions were removed. Nonetheless this is significantly higher than the average of 3.17% during the pre- COVID period.

Table 3: Difference in Volatility - Short-run time-varying NAIRU

	Pre-covid	*Post-covid*	*Pre-covid*	*MCO*	*Post-MCO*	*Pre-covid*	*Post-MCO*	*MCO*
	2010:1-2019:12	2020:1-2024:5	2010:1-2019:12	2020:1-2021:12	2022:1-2024:5	2010:1-2019:12	2022:1-2024:5	2020:1-2021:12
Mean	3.17	3.87	3.17	4.34	3.49	3.17	3.49	4.34
Var	1.01	2.17	1.01	4.00	0.40	1.01	0.40	4.00
Obs	120	53	120	24	29	120	29	24
df	119	52	119	23	28	119	28	23
F	0.4638		0.2518		0.4013		0.101	
P(F<=f)*	0.0003		0.0000		0.0033		0.000	
F Critical	0.6891		0.6171		0.5833		0.520	

Table 4: Difference in Means - Short-run time-varying NAIRU

	Pre-covid	*Post-covid*	*Pre-covid*	*MCO*	*Pre-covid*	*Post-MCO*	*Post-MCO*	*MCO*
	2010:1-2019:12	2020:1-2024:5	2010:1-2019:12	2020:1-2021:12	2010:1-2019:12	2022:1-2024:5	2022:1-2024:5	2020:1-2021:12
Mean	3.17	3.87	3.17	4.34	3.17	3.49	3.49	4.34
Variance	1.01	2.17	1.01	4.00	1.01	0.40	0.40	4.00
Obs	120	53	120	24	120	29	29	24
df	74		25		66		27	
t Stat	-3.139		-2.7853		-2.0768		-2.0120	
P(T<=t) *	0.001		0.0050		0.0209		0.0271	
t Critical	1.666		1.7081		1.6683		1.7033	
P(T<=t) **	0.002		0.0101		0.0417		0.0543	
t Critical	1.993		2.0595		1.9966		2.0518	

Figure 6 shows the estimated statistical model for the shocks to the NAIRU measured as the difference between the short-run and long-run NAIRU estimates. The mean level of the shocks appears stable around zero throughout the sample and between the subsamples.

Figure 6: Estimates of the shocks to the time-varying NAIRU using CPI inflation (%)

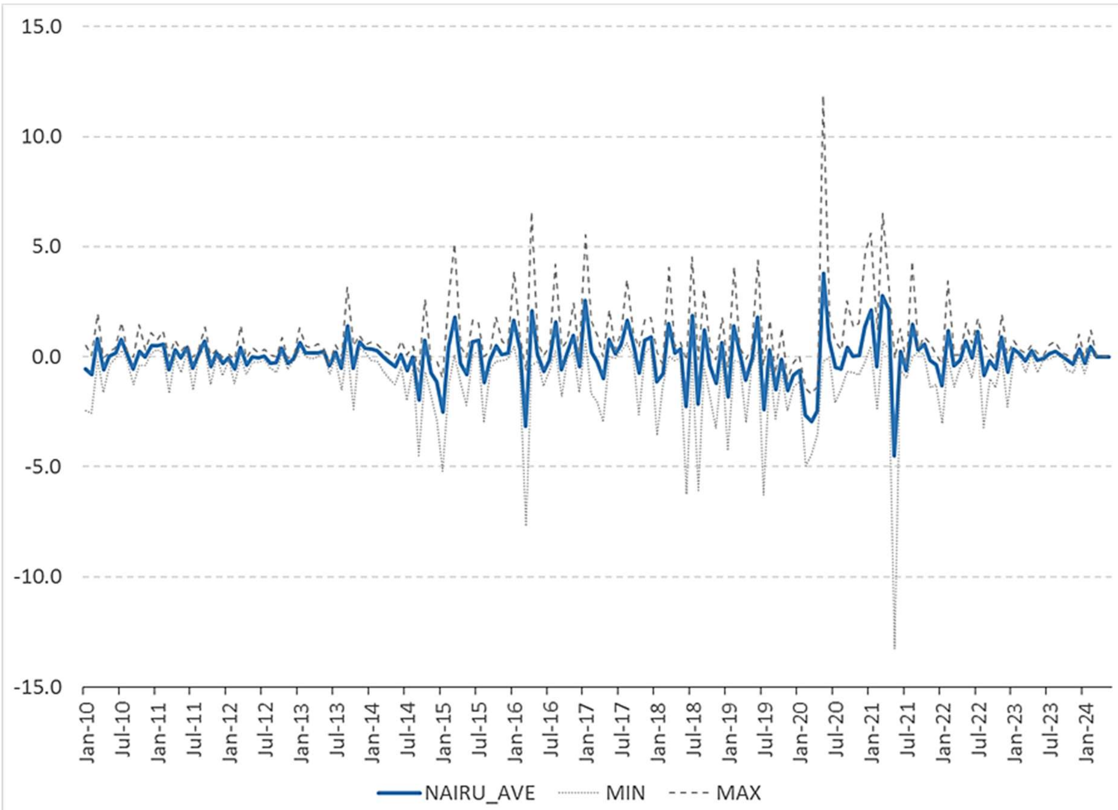

Table 5 shows the tests of difference in variance of the shocks across the various subsamples. The results show that the variance of the shocks has changed significantly between the subsamples, peaking during the MCO period. The volatility of shocks is significantly lower after the removal of movement restrictions compared to the pre- COVID period. Table 6 shows the tests of the difference in the mean level of the NAIRU across the various subsamples. The results show that the mean value of the shocks is not significantly different between subsamples.

Table 5: Difference in Volatility – Shocks to the time-varying NAIRU

	Pre-covid	*Post-covid*	*Pre-covid*	*MCO*	*Post-MCO*	*Pre-covid*	*Post-MCO*	*MCO*
	2010:1-2019:12	2020:1-2024:5	2010:1-2019:12	2020:1-2021:12	2022:1-2024:5	2010:1-2019:12	2022:1-2024:5	2020:1-2021:12
Mean	-0.01	0.01	-0.01	0.00	0.01	-0.01	0.01	0.00
Var	0.91	1.70	0.91	3.49	0.30	0.91	0.30	3.49
Obs	120	53	120	24	29	120	29	24
df	119	52	119	23	28	119	28	23
F	0.5318		0.2595		0.3275		0.0850	
P(F<=f)*	0.0025		0.0000		0.0006		0.0000	
F Critical	0.6891		0.6171		0.5833		0.5196	

Table 6: Difference in Means – Shocks to the time-varying NAIRU

	Pre-covid	*Post-covid*	*Pre-covid*	*MCO*	*Pre-covid*	*Post-MCO*	*Post-MCO*	*MCO*
	2010:1-2019:12	2020:1-2024:5	2010:1-2019:12	2020:1-2021:12	2010:1-2019:12	2022:1-2024:5	2022:1-2024:5	2020:1-2021:12
Mean	-0.01	0.01	-0.01	0.00	-0.01	0.01	0.01	0.00
Variance	0.91	1.70	0.91	3.49	0.91	0.30	0.30	3.49
Obs	120	53	120	24	120	29	29	24
df	77		25		75		26	
t Stat	-0.1244		-0.0495		-0.2194		0.0251	
P(T<=t) *	0.4507		0.4805		0.4135		0.4901	
t Critical	1.6649		1.7081		1.6654		1.7056	
P(T<=t) **	0.9014		0.9609		0.8269		0.9802	
t Critical	1.9913		2.0595		1.9921		2.0555	

Table 7 and Table 8 shows the descriptive statistics for the short-run and long-run NAIRU across the various subsamples. The results show that there has been significant time variation in the NAIRU due to supply shocks of the COVID period. The long-run and short-run NAIRU measures have now reverted to closer to the pre-COVID levels but remain elevated although the volatility has fallen in both cases. Table 9 shows the unit root tests of stationarity for both the long-run and short-run NAIRU estimates in levels and first differences across the various subsamples. The results show that the long-run NAIRU is non-stationary in levels but stationary (mean-reverting) in first differences. The short-run NAIRU is stationary (mean-reverting) in both levels and first differences. The shocks to both NAIRU measures are stationary in levels and first differences and mean reverting around zero that is, they are stochastic, white noise.

Table 7: Descriptive Statistics for Estimates of the NAIRU using CPI inflation: Long-run

	Whole Sample	Pre-covid	Post-covid	MCO	Post-MCO
	2010:1-2024:5	2010:1-2019:12	2020:1-2024:5	2020:1-2021:12	2022:1-2024:5
Mean	3.39	3.18	3.89	4.47	3.40
St. Error	0.05	0.03	0.09	0.13	0.04
Median	3.22	3.12	3.69	4.50	3.31
St. Dev	0.60	0.38	0.70	0.63	0.24
Variance	0.36	0.15	0.49	0.39	0.06
Kurtosis	2.12	0.18	-0.50	-1.30	-0.63
Skewness	1.40	0.67	0.84	-0.02	0.60
Range	3.15	1.90	2.61	2.16	0.87
Minimum	2.45	2.45	2.99	3.45	2.99
Maximum	5.61	4.35	5.61	5.61	3.86
Sum	586.93	381.01	210.27	107.25	98.67
Count	173	120	54	24	29
95% CI Mean	0.09	0.07	0.19	0.26	0.09

Table 8: Descriptive Statistics for Estimates of the NAIRU using CPI inflation: Short-run

	Whole Sample	Pre-covid	Post-covid	MCO	Post-MCO
	2010:1-2024:5	2010:1-2019:12	2020:1-2024:5	2020:1-2021:12	2022:1-2024:5
Mean	3.39	3.17	3.87	4.34	3.49
St. Error	0.09	0.09	0.20	0.41	0.12
Median	3.26	3.17	3.59	4.25	3.37
St. Dev	1.21	1.00	1.47	2.00	0.64
Variance	1.46	1.01	2.17	4.00	0.40
Kurtosis	4.17	1.06	4.76	2.47	0.28
Skewness	0.60	0.09	0.49	-0.25	0.56
Range	10.47	5.66	10.47	10.47	2.66
Minimum	-1.16	0.04	-1.16	-1.16	2.36
Maximum	9.31	5.70	9.31	9.31	5.02
Sum	586.23	381.00	205.23	104.16	101.07
Count	173	120	53	24	29
95% CI Mean	0.18	0.18	0.41	0.84	0.24

Table 9: Unit Root Tests for Stationarity

		Levels			First Difference		
		NAIRU_LR	NAIRU_SR	NAIRU_SHOCK	NAIRU_LR	NAIRU_SR	NAIRU_SHOCK
Whole Sample:	ADF	0.4524	0.0000	0.0000	0.0000	0.0000	0.0000
2010:01-2024:05	PP	0.3186	0.0000	0.0000	0.0000	0.0001	0.0001
Pre-covid:	ADF	0.9463	0.0000	0.0000	0.0000	0.0000	0.0000
2010:01-2019:12	PP	0.8394	0.0000	0.0000	0.0000	0.0001	0.0001
Post-covid:	ADF	0.6937	0.0000	0.0000	0.0000	0.0000	0.1132
2020:01-2024:05	PP	0.6795	0.0000	0.0000	0.0000	0.0001	0.0001
MCO:	ADF	0.9045	0.0031	0.0029	0.0381	0.0005	0.0004
2020:01-2021:12	PP	0.8595	0.0032	0.0031	0.0374	0.0000	0.0000
Post-MCO:	ADF	0.1537	0.0000	0.0000	0.0000	0.0000	0.0017
2022:01-2024:05	PP	0.2299	0.0000	0.0001	0.0000	0.0001	0.0001

Null Hypothesis: Unit root (individual unit root process); Includes constant but no trend
P-values for the PP = Phillips-Perron Test and ADF=Augmented Dickey-Fuller Test

In summary, the long-run NAIRU mean level and volatility appears escalated at beginning of COVID-19. The level has moderated since then but is still higher at 3.40% post MCO compared to 3.18% pre-COVID although the volatility is lower in the post-MCO period. The long-run NAIRU is non-stationary in levels but stationary (mean-reverting) in first differences and has reverted to closer to pre-COVID levels by mid-2024. The short-run NAIRU mean and volatility also appears escalated at beginning of COVID-19 and has moderated since then, but the level is still higher at 3.49% vs 3.17% even though the volatility is significantly lower. Similar results are found for the shocks to the NAIRU across the subsamples.

IX. Implications and significance

The results suggest that the NAIRU changes over time due to shocks and as such we cannot expect to estimate a single, stable value for the rate of unemployment below which inflation will speed up and above which inflation will slow down. In the real world and during normal business cycles, it is unlikely that transitory fluctuations in the exchange rate would feed directly to inflation conditions. Nevertheless, greater variation in the estimated NAIRU would be useful during turning points in the business cycle, or after supply or demand shocks. The results also show that shocks to the economy can cause persistence in changes both to the level and the volatility of the NAIRU. We found the level of the NAIRU rose significantly during the MCO period and continued to remain high afterwards even though the volatility of shocks had fallen and the environment was more stable. This means that the structural rate of unemployment at which the rate of inflation in Malaysia is stable is now higher than it was before the COVID-19 pandemic and the lockdown policies adopted in response. Equivalently, the threshold rate of unemployment in Malaysia below which inflation would be expected to rise or above which inflation would be expected to fall is now higher both in the short-run and the long-run.

Finally, for policy, the relatively more volatile estimates produced by the approach outlined in this paper may somewhat complicate the use-case. Prevailing state-space and structural models tend to produce relatively stable estimates of the NAIRU, which increases confidence in estimating the extent of spare capacity in the economy. Nevertheless, the more volatile estimates utilising the approach outlined in this paper suggest the NAIRU may be more dynamic than previously thought and provides a good argument for frequently revisiting NAIRU estimates, particularly after shocks. There has been a significant change in the NAIRU since COVID-19, which affects the assessment and policy environment which deserves further attention and monitoring. Additionally, utilising more than one model or approach in gauging the extent of spare capacity and its potential implications on inflation momentum or trajectory is always prudent.

X. Limitations and further research

The results presented above provide evidence that the NAIRU in Malaysia can be estimated from first principles and that it shows significant variation in the estimates over time. While these results are interesting, they raise questions as to what is causing the time variation. The answer to that question may be the fact that the data sample used in the current study includes developments and distortions arising from the COVID-19 crisis itself i.e., that unemployment (which tends to be rather stable) increased significantly following imposition of lockdown measures and movement controls, while inflation rose rapidly (albeit temporarily) following re-opening of economies due to continued disruptions in supply chains and relatively robust pent-up demand. Nonetheless, there may be other underlying structural labour market factors at play, such as the extent of informality, limited bargaining power among Malaysian workers, and price controls, which have not been considered in the current study.

The purely statistical approach based on first principles has the advantages of allowing the date to speak for itself without over-parametrising the model or assuming too many theoretical priors. This avoids and address the end-point bias and the over-specification problems often found with conventional methods. The virtue of this estimation approach is that it is more in-line with the original observations of the Phillips Curve as a statistical regularity and the time variations as an inherent feature of that relationship in different sub-samples. The estimates are not designed to draw causal/structural relationships to explain either changes or variation but to establish that whether these statistical regularities are evident before imposing an explanation *a priori*.

Based on the recent empirical studies described in the literature review above there are two approaches of interest in understanding the estimation of the NAIRU as a trend rate of unemployment. The first is a statistical solution which takes the temporal variation as an observed regularity and uses a time-varying estimator such as the Kalman filter to measure it, with or without other statistical adjustments such as the HP filter (Rusticelli 2014, Chalaux and Guillemette 2019, Guillemette 2021). The second approach seeks to find variables that might explain the time variation, such as indicators of labour market conditions and to test the significance of these possible explanatory variables in the context of a reduced form equation (Turner et. al. 2016, Hristov et. al. 2017).

Future research could be useful to test both approaches in the context of Malaysia and, if data allows, across a sample of ASEAN and other Asian countries. The main emphasis might be on the second methodological approach because there is potentially more information content in this method which can inform policy decisions more clearly. The model would incorporate information about structural labour market characteristics and the business cycle, in addition to the concurrent unemployment rate. The end-point sensitivity will ideally be moderated so that the model is applicable to all periods including crises and recovery years. The structural labour market indicators should be designed to reflect structural issues in labour markets in emerging economies (including Malaysia) with comparative estimates for other non-structural approaches and for countries in ASEAN and Asia as whole. These might distinguish the effect of wages and other sources of formal or informal income on inflation.

Further research avenues would include: How are wages determined? Is there a mark-up model? What is the impact of labour market participation on the percent of waged or salaried jobs? What is the impact of formal and informal employment measured by the percentage of formal employment contracts rather than informal gig-economy contracts? What is the impact of differentiating unemployment and underemployment? What is the impact of a reserve cohort of foreign workers with less wage negation power? What is the role of labour market structure, sector dynamics and segmentation? How does employment law and market power measured by unionisation and contract enforcement affect pass-through of wages to inflation? How are expectations formed? What is the role of adaptive and rational expectations and information asymmetry? These lines of inquiry could provide useful insights to illuminate the causes of time variance, changes in the slope of the relationship between inflation and unemployment, reversal of that relationship and structural changes in the dynamics of the labour market leading to changes in the impact on inflation and vice-versa.

Conclusions

This study adopts the original approach in interpreting the NAIRU and its antecedent in the Phillips Curve as empirical regularities rather than theoretical constructs. Using a first principles approach we estimate the NAIRU from observable data with as little parameterisation as possible. This aims to obtain an estimate of the NAIRU as a simple relationship between the rate of unemployment and the rate of change in inflation rather than as an artefact of a reduced form of a larger structural equation. Based on the problem statement the research in this study shows that we can indeed estimate the NAIRU for Malaysia based on first principles rather than more complicated models. We also answer second research question in the affirmative, namely, that estimates of the NAIRU for Malaysia do vary over time. In response to the third research question, we find that the estimate for the long-run NAIRU has risen from 3.18% pre-COVID to 3.40% post-MCO. The estimate for the short-run NAIRU has risen from 3.17% pre-COVID to 3.49% post-MCO. In both cases the estimate is less volatile after the lockdowns.

The implications for macroeconomic assessments and policy are important and suggest that inflation may begin to accelerate at higher rates of unemployment in the period immediately following the COVID-19 crisis, and as such, inflation dynamics may be more responsive to labour market developments going forward. The current very-low unemployment rate of 2.9-3% and continued low inflation rate of 1.5-2%, however, raises the need for updated estimates and models on prevailing NAIRU dynamics, particularly given rising risk of rising inflationary pressures.

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