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Job Market Efficiencies During Pre- & Post-Movement Control Order (MCO) in Malaysia

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Abstract

Motivation and aim: Key policy initiatives taken by the Malaysian government in response to the disruptions to the labour market caused by the coronavirus (COVID-19) pandemic have been shown to have had a significant impact on reducing the unemployment rate. An empirical study was conducted examine the extent to which the reduction in the unemployment rate can be explained by an increase in job matching efficiency.

Method and material: An autoregressive distributed lag (ARDL) model was employed for the empirical assessment. The daily administrative data on placements, vacancies and LOE from the Employment Insurance System (EIS) Office of the Social Security Organisation (SOCSO) for the period 2 January 2020 to 30 September 2020 were used. The data were split into two different periods, namely, for the pre-MCO (2 January 2020 to 17 March 2020) and the post-MCO (1 July 2020 to 30 September 2020) periods. The workers were categorised into three groups, namely, high-skilled, semi-skilled and low-skilled.

Key findings: Overall, job matching efficiency tended to improve during the post-MCO. The most significant improvement in job matching efficiency was with regard to the semi-skilled category. One of the factors that influenced job matching efficiency was the demand for workers in the semi-skilled group, which was higher compared to the demand for high-skilled and low-skilled workers.

Policy implications: The results showed that the reduction in unemployment could be explained by the improvement in job matching efficiency. Government intervention and hiring incentives had caused the improvement in matching efficiency. Among all the skills categories, the most efficient matching was observed to have brought about the greatest improvement to the semi-skilled category.

JEL Classifications
C22, J28, J63

Keywords:
Job matching efficiency; COVID-19; autoregressive distributed lag (ARDL); administrative data; worker skill level

Job Market Efficiencies During Pre- and Post-Movement Control Order (MCO) in Malaysia

1. INTRODUCTION

Job matching is one of the predominant strands in the fields of macroeconomics and labour economics that is used to measure the efficiency of the labour market. It relates the number of newly-hired workers to the number of unemployed people and job vacancies, and it plays a central role in the theory of labour market equilibrium. The job matching function describes how the flow of job matches is related to the stock of job searchers and the stock of available jobs, much like a standard production function describes the technological relationship between the flow of products and the stocks of production factors. In an empirical assessment, it is the job matching function, which includes the matching efficiency that translates into the productivity of the process of matching jobseekers to available jobs, that provides insights on the turnover in the labour market (Hall & Schulhofer-Wohl, 2018).

In the current economic crisis that has impacted the world due to the unprecedented nature of the COVID-19 pandemic, job matching efficiency has become the primary concern of governments throughout the world, including Malaysia. The fact is that government interventions to reduce the spread of Coronavirus (COVID-19) infections, such as movement control orders (MCOs), have resulted in tremendous disruptions to the labour market. For example, unemployment numbers surged in the first-quarter from 3.5% or 546,600 to 5.1% or 791,800 in the second-quarter of 2020 (Department of Statistics Malaysia, 2020a). Similarly, the loss of employment (LOE) among insured workers increased from 15,602 in the first-quarter to 34,806 in the second-quarter of 2020 (Employment Information and Analysis Services, 2020).

To address the rising unemployment rate caused by labour market disruptions, the Malaysian government initiated key policy responses oriented toward job placement and job creation programs. These included the decision to have a single landing page job portal (MyFutureJobs), and the implementation of support measures under the economic stimulus package such as a hiring incentive program and mobility assistance for new workers. Altogether, these programs have effectively reduced the unemployment rate from 5.3% in May to 4.7% in July 2020 (Department of Statistics Malaysia, 2020b). Does a reduction in the unemployment rate imply that there has been an increase in job matching efficiency? It is claimed that a low unemployment rate means an efficient labour market matching.

The purpose of this study was to empirically assess the magnitude of job matching efficiency during the pre- and post-MCO periods of COVID-19. The major contribution of this paper to the literature on job matching efficiency and economic crises is the empirical application of daily labour market administrative data. The literature review indicated that the existing literature emphasizes mostly on the use of monthly and quarterly labour market data, with limited application of daily administrative data. This also holds true in the case of Malaysia, where studies related to job matching efficiency are scarce. The application of daily administrative labour market data is likely to provide a good leading indicator of reactions in the labour market. For the empirical analysis, a dynamic ARDL model was applied to the daily administrative data on placements, vacancies and loss of employment.

The scope of this paper was limited to assessing job matching efficiency, without providing empirical evidence on potential explanations for changes to the matching efficiency. Several factors determine the level of job matching efficiency, including job competition among workers with different educational achievements, imperfect information on the job market, job specialization and wage differences (Liu, 2013; Mukoyama & Sahin, 2009; Broersma & van Ours, 1999). In the view of researchers, it is highly relevant that potential explanatory variables to matching efficiency be examined during normal economic conditions because some variables involve structural issues that require long-term interventions. As far as economic recovery phases are concerned, it is much more important to increase the efficiency of job matching.

In light of the above, this paper has been structured into five sections, with the empirical literature review being discussed in the next section. Section 3 details the applied econometric model along with the data sources, while Section 4 presents the main findings obtained from the empirical assessment, and Section 5 provides a discussion and the concluding remarks.

2. LITERATURE REVIEW

The literature review indicated that there have been numerous studies on job matching efficiency with specific references to economic crises, with wide applications to quarterly and monthly labour market data (Hornstein & Kudlyak, 2017; Hall & Schulhofer-Wohl, 2018; Lange & Papageorgiou, 2020). Nevertheless, the application of daily labour market administrative data is scarce, thereby justifying the empirical contribution of this paper. The following paragraphs summarize some remarkable findings obtained from related studies on the issue of job matching efficiency in response to economic crises.

Studies measuring the implication of COVID-19 on matching efficiency are limited in the literature. A recent study by Gomme (2020) estimated that the outbreak of COVID-19 in March 2020 caused a reduction of 40% in matching efficiency. Most of the available studies in the literature examined the effects of previous economic crises on matching efficiency, particularly the 2008-2009 global financial crisis. Applying the quarterly and monthly labour market data, all the reviewed studies indicated that the economic crisis led to a reduction in job matching efficiency.

For example, Barnichon and Figura (2011) determined the drivers of matching efficiency fluctuations over the past few decades from 1976 to 2009. They concluded that changes in the unemployment composition due to an increase in long-term unemployment and a larger fraction of layoffs during a recession were behind the reduction in matching efficiency. Compared to the previous economic recession in 2001, the 2008-2009 global financial crisis led to a more rapid decline in job matching efficiency.

Furlanetto and Groshenny (2016) it plays a somewhat larger role during the Great Recession when it contributes to raise the actual unemployment rate by around 1.3 percentage points and the natural rate by around 2 percentage points. The matching efficiency due to macroeconomic shocks was interpreted as full-length shocks for structural changes in the labour market, which should emerge as a prominent driver of the surge in the unemployment rate during the recession. The findings indicated that negative matching efficiency shocks played a larger role in slowing down the recovery.

Other studies that showed a decline in job matching efficiency during an economic crisis were Hall & Schulhofer-Wohl (2018), Şahin et al. (2014) and Lange and Papageorgiou (2020). Hall and Schulhofer-Wohl (2018) showed that the decline in job matching efficiency during the 2008-2009 global financial crisis was more pronounced compared to the 2001 global economic slowdown. Şahin et al. (2014) and Lange and Papageorgiou (2020) also concluded that matching efficiency deteriorated during the 2008-2009 global financial crisis, and both studies found that the decline in hiring led to a decline in matching efficiency.

The implication of an economic crisis on job matching efficiency was also examined during the pre- and post-crisis periods. For example, Arpaia et al. (2014) measured the changes in matching efficiency among European Union (EU) countries during the pre- and post-global financial crisis in 2008-2009. The findings indicated that the pre-crisis period implied a reduction in matching efficiency in Hungary, Portugal and Sweden, while the post-crisis period tended to reduce matching efficiency in the Baltics and Nordic countries, Cyprus, Greece, Spain, France, the Netherlands, Slovenia, Slovakia and the United Kingdoms. Conversely, the matching efficiency improved in Germany during the post-crisis period. The variations in the impacts were influenced by several factors such as the degree of discrepancies in the demand and supply of jobs, the role of Active Labour Market Policies (ALMP), and unemployment benefits.

The literature also suggested the importance of detailing the matching efficiency in various labour categories such as in different skill types. The fact is that an economic crisis tends to have a different effect on skilled and unskilled workers (Hall & Schulhofer-Wohl, 2018; Pedraza, 2008; Destefanis & Fonseca, 2007). One of the drivers that explains the variations is the composition of the labour force based on educational attainment. Higher-educated workers are prone to search on the job and move from one job to another without experiencing unemployment. The findings from these studies gave direction to this paper in detailing the job matching efficiency at three skill levels—high-skilled, semi-skilled and low-skilled.

In Malaysia, Said et al. (2021) used the matching function to examine the labour mismatch index and to calculate the contribution of mismatch unemployment to the rise in the unemployment rate. This study employed various source data from the Department of Statistics Malaysia, Ministry of Human Resource Malaysia and Bank Negara Malaysia between 2007 and 2017. It found that the mismatch gradually increased in a decade.

This study was aimed at analysing the job matching efficiency during the COVID-19 pandemic. Furthermore, this study was unique in that it used daily administrative data to measure the matching efficiency during the pre-MCO and post-MCO periods. The next section will show the methodology used in this study.

3. METHODOLOGY AND DATA

In the case of monthly, quarterly and annual data, the vector autoregression model, stochastic frontier analysis and least square dummy variable were the widely applied econometric models in the literature for measuring job matching efficiency (Crawley et al., 2021; Crawley & Welch, 2020; Abid & Drine, 2011; Kano & Ohta, 2005). In the case of daily data, this paper applied an autoregressive distributed lag (ARDL) model because it allows regressors to have a mixed order of integration for each variable, I(0) or I(1), and it is relatively more efficient in cases where small and finite sample data sizes are involved (Sam et al., 2019; Harris & Sollis, 2003). Besides that, all the variables were assumed to be endogenous, and were measured simultaneously for both long-run and short-run estimates through a linear transformation technique (Alam et al., 2020). The ARDL model is capable of taking a sufficient number of lags by capturing the data generation process from a general modelling framework (Laurenceson & Chai, 1998)

3.1 STATIONARITY TEST

Before an empirical model can be estimated, it is common in a time-series estimation to perform a unit root analysis on the data being used to represent the placements, vacancies and LOE. The unit root analysis is performed to determine the degree of integration of each variable. According to the standard procedure, each variable must be I(1), which is a prerequisite for the application of cointegration techniques.

Most of the previous literature used the Augmented Dickey-Fuller test (ADF) (Dickey & Fuller, 1979; 1981) and the Phillips-Perron test (PP) (Phillips & Perron, 1988) to measure the order of integration. However, due to the poor size and power properties, both tests were unreliable in the case of small-coverage sample data, and caused the over-rejection of the null hypothesis when it was true and accepted it when it was false (Dejong et al., 1992; Harris & Sollis, 2003). Thus, to overcome the limitations of the ADF and PP tests, this study applied the Ng-Perron test to measure the order of integration. The Ng and Perron (2001) unit root test has a good size and explaining power. The advantage of this test is that it is suitable for small samples.

The Ng-Perron unit root test is unique in that it is capable of eliminating the limitations of the ADF and PP tests by proposing a set of four test statistics, namely the MZ, MZt, MSB and MPT (Ng & Perron, 2001). The MZ and MZt tests are modified versions of the Phillips-Perron MZ and MZt tests, the MSB test is an improved version of the Bhargava (1986) test, and the MPT test is a modified version of the ADF-GLS (Elliot et al., 1996) test. The null hypotheses for the MZ and MZt tests show that the series have a unit root, while the MSB and MPT tests show the stationarity of the variables. The hypothesis is rejected if the test statistic is smaller than the critical value.

3.2 MODEL SPECIFICATIONS

In this study, the matching function is defined as the flow of new hires to the stocks of vacancies and unemployment. Similar to the production function, the matching function is a convenient device that partially captures a complex reality, with workers looking for the right jobs and firms looking for the right workers. In a continuous-time framework, the flow of hires can be modelled by a standard Cobb-Douglas matching function with constant returns to scale. Specifically, this study adapted the model by Petrongolo and Pissarides (2001), with the matching function being specified as below:

$$P_t = \mu_t V_t^{\alpha} LOE_t^{\beta} \tag{1}$$

where P_t is the number of placements, V_t is the number of vacancies and LOE_t is the loss of employment (LOE) number, and μ_t is a potentially time-varying scaling parameter referred to as matching efficiency. The model by Petrongolo and Pissarides (2001) was adapted based on the consideration that the system can be summarized into two differential equations to represent the flow of employment and the flow of vacancies by allowing for placements (P_t) to be related to LOE and vacancies with a Cobb-Douglas functional form.

For the empirical assessment, Equation (1) was transformed into a logarithmic form, as in Equation (2) below.

$$ln\, P_t = \beta_0 + \beta_1 ln\, V_t + \beta_2 ln\, LOE_t + \varepsilon_t \qquad (2)$$

where ε and t represent the error term and time, respectively. P, V and LOE are as defined earlier. The parameters, β_1 and β_2, are the long-term elasticity of placement for vacancies and LOE.

3.3 ESTIMATIONS METHOD

The ARDL cointegration technique has several advantages. First, this technique is able to deal with the problem of endogeneity. Second, it is capable of estimating the short-run and long-run parameters by using the same model. Third, this technique is superior in detecting the cointegration among variables, which can have different degrees of integration such as I(0) or I(1).

To measure the cointegration among the variables, this study used the estimated bound F-test statistic proposed by Pesaran et al. (2001). The following conditional equation error-correction model (ECM) is specified below:

$$\begin{aligned}\Delta ln\, P_t = \gamma_0 + \gamma_1 ln\, P_{t-1} + \gamma_2 ln\, V_{t-1} + \gamma_3 ln\, LOE_{t-1} \\ + \sum_{i=1}^{m} \theta_{1i} ln\, P_{t-i} + \sum_{i=0}^{n} \theta_{2i} ln\, V_{t-i} \\ + \sum_{i=0}^{o} \theta_3 ln\, LOE_{t-i} + \mu_t\end{aligned} \qquad (3)$$

where Δ represents the first difference, β_0 denotes the drift component, μ_t is the white noise residual, and the variables P, V and LOE are as defined earlier.

To obtain the optimum number of lag lengths for each variable, this study employ the lag selection criteria based on the Schwarz Bayesian Criterion (SBC). The joint F-statistic was used to test the null hypothesis of no cointegration.

Pesaran et al. (2001) and Narayan (2005) reported that there are two sets of critical values for the level of significance namely lower critical bound and upper critical bounds. By using guidelines from Pesaran et al. (2001), if the F-statistic is higher than the upper critical bounds, there is exist a long-run relationship. On the other hand, if the F-statistic is lower than lower critical bounds, there is no long-run relationship. However, if the F-statistic is between the lower critical bounds and upper critical bounds the result are inconclusive.

To determine the outcome of the cointegration test, the value of the F-statistic was based on decision by comparing it with the critical bound values. Following the procedure provided by Pesaran et al. (2001), if the computed value of the F-statistic is greater than the upper bound I(1) critical value, the null hypothesis is rejected, and a cointegration exists between the variables. If the computed F-statistic is less than the lower bound value, then the null hypothesis is accepted, and there is no cointegration between the variables. However, if the F-statistic is greater or equal to the lower bound value and less or equal to the upper bound value, then the decision is inconclusive.

According to Pesaran et al. (2001), Equation (2) can be derived from Equation (3) to obtain the long-run model. Note that in the long run, it is assumed that $\Delta = 0$ and $ln\ P_{t-1} = ln\ P_t$, and so on. Thus, the model was as follows:

$$0 = \gamma_0 + \gamma_1 ln\, P_t + \gamma_2 ln\, V_t + \gamma_3 ln\, LOE_t + \mu_t \tag{4}$$

$$\gamma_1 ln\, P_t = -\gamma_0 - \gamma_2 ln\, V_t - \gamma_3 ln\, LOE_t - \mu_t \tag{5}$$

$$ln\, P_t = -\frac{\gamma_0}{\gamma_1} - -\frac{\gamma_2}{\gamma_1} ln\, V_t - \frac{\gamma_3}{\gamma_1} ln\, LOE_t - \frac{1}{\gamma_1}\mu_t \tag{6}$$

Therefore,

$$ln\, P_t = \beta_0 + \beta_1 ln\, V_t + \beta_2 ln\, LOE_t + \varepsilon_t \tag{7}$$

where $\beta_0 = -\frac{\gamma_0}{\gamma_1}$, $\beta_1 = -\frac{\gamma_2}{\gamma_1}$, $\beta_2 = -\frac{\gamma_3}{\gamma_1}$, and $\varepsilon_t = -\frac{1}{\gamma_1}\mu_t$.

Then, this study also estimated the short-run model as follows:

$$\begin{aligned}\Delta ln\, P_t = \phi_0 + \sum_{i=1}^{m} \phi_{1i} \Delta ln\, P_{t-i} + \sum_{i=0}^{n} \phi_{2i} \Delta ln\, V_{t-i} \\ + \sum_{i=0}^{o} \phi_{3i} \Delta ln\, LOE_{t-i} + \lambda ECM_{t-1} + e_t\end{aligned} \tag{8}$$

where, $ECM_{t-1} = \varepsilon_{t-1} = ln\, P_{t-1} - [\beta_0 + \beta_1 ln\, V_{t-1} + \beta_2 ln\, LOE_{t-1}]$. It showed that any disequilibrium in the short-run between the dependent and independent variables would converge back to the long-run equilibrium relationship. Parameter λ is the speed of adjustment, and has a negative sign. It would also indicate a cointegration, where the parameter would lie between 0 and -2. Diagnostic tests, which included serial correlation and heteroscedasticity tests, were used to determine the validity of the model.

3.4 DATA REQUIREMENT

This study employed daily administrative data on placements, vacancies and LOE obtained from the Employment Insurance System (EIS) Office of the Social Security Organisation (SOCSO). A placement is defined as the successful allocation of a person to a job that is either permanent, fixed term or temporary, with an employer. Placements include job seekers both with and without employment insurance coverage. LOE is defined as insured workers who have been terminated from their jobs due to reasons such as business closure, business downsizing, mutual separation and voluntary separation schemes. Vacancies refer to active job vacancies advertised in the MYFutureJobs portal. Data on vacancies and placements were extracted from the MYFutureJobs portal, while data on placements and LOE were obtained from the EIS portal of SOCSO.

The daily data were extracted from 2 January 2020 to 30 September 2020. To examine the job matching efficiency pre- and post-MCO of COVID-19, the data had to be split for analysis into two different periods: 2 January 2020 to 17 March 2020 for the pre-MCO period, and 1 July 2020 to 30 September 2020 for the post-MCO period. It should be noted that these data are not available to the public. Workers were split according to three categories—high-skilled, semi-skilled and low-skilled. The skill categorization for these three groups was made based on the educational attainment of the workers. Following the standard, workers with tertiary education (i.e., diploma, degree and above) were classified as high-skilled, those with upper secondary education (i.e., STPM, SPM, SKM or equivalent) were defined as semi-skilled, and those with lower secondary education and below (i.e., PMR, SRP, LCE, UPSR or equivalent) were grouped as low-skilled.

4. RESULTS OF THE ESTIMATION

4.1 Stationarity test

This study applied the Ng-Perron unit root test to determine the stationarity of the variables. The hypothesis for the MZ and MZt tests were set as the unit root, while the MSB and MPT tests were set for the stationarity. The hypothesis would be rejected if the test statistic was smaller than the critical value. The condition for the bound test for cointegration did not require all the variables to be integrated in the order of I(1), but it was important to ensure that all the variables were not integrated in the order of I(2). The results of the unit root tests are presented in tables 1, 2, 3 and 4. The results showed that all the variables were I(1), except for the vacancies for semi-skilled and low-skilled workers which were I(0). Then this study proceed to the cointegration test.

Table 1: Ng-Perron Unit root Tests on level and first difference intercept

Variable	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
Level								
A. Aggregate								
	-2.42	1.05	0.43	9.82	-1.42	-0.70	0.49	14.07
Placement	(6)	(6)	(6)	(6)	(7)	(7)	(7)	(7)
	-0.41	-0.31	0.76	32.22	-0.50	-0.49	0.98	47.16
Vacancies	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
	-0.58	-0.50	0.87	37.83	-0.59	-0.49	0.83	34.92
LOE	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
B. High-skilled								
	-2.43	-1.06	0.44	9.82	-1.92	-0.88	0.46	11.66
Placement	(5)	(5)	(5)	(5)	(7)	(7)	(7)	(7)
	-1.14	-0.66	0.58	18.18	-0.49	-0.43	0.86	38.33
Vacancies	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
	-1.11	-0.71	0.64	20.64	-0.56	-0.50	0.89	39.33
LOE	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
C. Semi-skilled								
	-7.25*	-1.89*	0.26*	3.44*	-0.78	-0.46	-0.59	20.39
Placement	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
	-1.55	-0.83	0.54	14.80	-0.73	-0.60	0.82	32.83
Vacancies	(9)	(9)	(9)	(9)	(6)	(6)	(6)	(6)
	-1.36	-0.79	0.58	17.17	-0.71	-0.49	0.70	26.06
LOE	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
D. Low-skilled								
	-6.06*	-1.71*	0.28*	4.13*	-0.71	-0.44	0.61	21.63
Placement	(3)	(3)	(3)	(3)	(6)	(6)	(6)	(6)
	-16.44***	-2.84***	0.17***	1.60***	0.62	-0.51	0.82	33.94
Vacancies	(1)	(1)	(1)	(1)	(6)	(6)	(6)	(6)
	-2.33	-1.08	0.46	10.49	-0.98	-0.64	0.65	21.80
LOE	(3)	(3)	(3)	(3)	(6)	(6)	(6)	(6)
First Difference								
E. Aggregate								
	-30.20***	-3.88***	0.13***	0.82***	-68.71***	-5.85***	0.09***	0.38***
Placement	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
	-30.85***	-3.90***	0.13***	0.88***	-69.54***	-5.89***	0.08***	0.36***
Vacancies	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
	-17.38***	-2.95***	0.17***	1.41***	-53.57***	-5.17***	0.10***	0.47***
LOE	(6)	(6)	(6)	(6)	(0)	(0)	(0)	(0)
F. High-skilled								
	-28.51***	-3.77***	0.13***	0.86***	-78.85***	-6.27***	0.08***	0.34***
Placement	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
	-27.26***	-3.69***	0.14***	0.90***	-76.88***	-6.19***	0.08***	0.35***
Vacancies	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
	-27.11***	-3.68***	0.14***	0.91***	-72.87***	-6.03***	0.08***	0.36***
LOE	(0)	(0)	(0)	(0)	(1)	(1)	(1)	(1)
G. Semi-skilled								
	-42.30***	-4.58***	0.11***	0.62***	-111.13***	-7.45***	0.07***	0.23***
Placement	(1)	(1)	(1)	(1)	(6)	(6)	(6)	(6)
	-51.75***	-5.06***	0.10***	0.53***	-62.33***	-5.58***	0.09***	0.39***
Vacancies	(1)	(1)	(1)	(1)	(0)	(0)	(0)	(0)
	-8.39*	-2.05**	0.24*	2.92**	-107.69***	-7.34***	0.07***	0.23***
LOE	(4)	(4)	(4)	(4)	(3)	(3)	(3)	(3)

Variable	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
H. Low-skilled								
Placement	-129.83*** (2)	-8.07*** (2)	0.06*** (2)	0.19*** (2)	-15.35*** (5)	-2.77*** (5)	0.18*** (5)	1.61*** (5)
Vacancies	-12.87** (0)	-2.48** (0)	0.19** (0)	2.11** (0)	-22.35*** (3)	-3.34*** (3)	0.15*** (3)	1.12*** (3)
LOE	-12.47** (0)	-2.27** (0)	0.18** (0)	2.80** (0)	-24.19*** (4)	-3.48*** (4)	0.14*** (4)	1.01*** (4)
Critical Value								
1%	-13.80	-2.58	0.17	1.78	-13.80	-2.58	0.17	1.78
5%	-8.10	-1.98	0.23	3.17	-8.10	-1.98	0.23	3.17
10%	-5.70	-1.62	0.28	4.45	-5.70	-1.62	0.28	4.45

Note:
1. *Critical values is based on table Ng and Perron (2001).*
2. **,**,*** represent the 10%, 5% and 1% levels of significance.*
3. *Parenthesis […] shows optimal lags for Ng-Perron unit root test.*

Table 2:Ng-Perron Unit root Tests on level and first difference intercept and trend

Variable	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
A. Aggregate								
Placement	-6.29 (5)	-1.77 (5)	0.28 (5)	14.50 (5)	-2.35 (6)	-0.95 (6)	0.40 (6)	33.13 (6)
Vacancies	-1.26 (9)	-0.75 (9)	0.60 (9)	66.33 (9)	-0.64 (6)	-0.37 (6)	0.59 (6)	70.94 (6)
LOE	-0.44 (6)	-0.27 (6)	0.62 (6)	79.83 (6)	-2.50 (6)	-1.03 (6)	0.41 (6)	33.05 (6)
B. High-skilled								
Placement	-6.55 (5)	1.80 (5)	0.27 (5)	13.92 (5)	-2.88 (6)	-1.05 (6)	0.36 (6)	27.62 (6)
Vacancies	-2.71 (8)	-1.15 (8)	0.42 (8)	33.10 (8)	-0.47 (6)	-0.29 (6)	0.61 (6)	77.86 (6)
LOE	-1.54 (5)	-0.69 (5)	0.45 (5)	41.91 (5)	-2.31 (6)	-0.94 (6)	0.41 (6)	33.59 (6)
C. Semi-skilled								
Placement	-12.01 (5)	-2.45 (5)	0.20 (5)	7.59 (5)	-6.31 (8)	-1.71 (8)	0.27 (8)	14.44 (8)
Vacancies	-18.21** (2)	-3.02** (2)	0.17** (2)	5.01** (2)	-1.99 (6)	-0.89 (6)	0.45 (6)	39.37 (6)
LOE	-9.44 (5)	-2.10 (5)	0.22 (5)	9.94 (5)	-3.29 (6)	-1.25 (6)	0.38 (6)	27.16 (6)
D. Low-skilled								
Placement	-4.12 (8)	-1.43 (8)	0.35 (8)	22.09 (8)	-2.17 (6)	-0.92 (6)	0.43 (6)	36.10 (6)
Vacancies	-16.26* (1)	-2.83* (1)	0.17* (1)	5.71* (1)	-0.99 (6)	-0.51 (6)	0.52 (6)	55.30 (6)
LOE	-3.50 (3)	-1.31 (3)	0.37 (3)	25.79 (3)	-6.39 (7)	-1.77 (7)	0.28 (7)	14.27 (7)
First Difference								
E. Aggregate								
Placement	27.41*** (0)	-3.68*** (0)	0.13*** (0)	3.43*** (0)	-51.54*** (0)	-5.07*** (0)	0.10*** (0)	1.80*** (0)
Vacancies	-30.21*** (0)	-3.88*** (0)	0.13*** (0)	3.03*** (0)	-53.81*** (0)	-5.18*** (0)	0.10*** (0)	1.71*** (0)
LOE	-30.19*** (0)	-3.88*** (0)	0.13*** (0)	3.03*** (0)	-44.71*** (4)	-4.73*** (4)	0.11*** (4)	2.04*** (4)
F. High-skilled								
Placement	-25.07*** (0)	-3.52*** (0)	0.14*** (0)	3.77*** (0)	-26.65*** (2)	-3.64*** (2)	0.14*** (2)	3.50*** (2)
Vacancies	26.68*** (0)	-3.65*** (0)	0.14*** (0)	3.44*** (0)	-70.94*** (1)	-5.95*** (1)	0.08*** (1)	1.32*** (1)
LOE	-26.57*** (0)	-3.64*** (0)	0.14*** (0)	3.45*** (0)	-48.71*** (1)	-4.94*** (1)	0.10*** (1)	1.87*** (1)

Variable	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
G. Semi-skilled								
Placement	-42.87*** (1)	-4.63*** (1)	0.11*** (1)	2.15*** (1)	-45.00*** (0)	-4.74*** (0)	0.11*** (0)	2.03*** (0)
Vacancies	-52.21*** (1)	-5.10*** (1)	0.10*** (1)	1.78*** (1)	-76.06*** (1)	-6.17*** (1)	0.08*** (1)	1.20*** (1)
LOE	-57.86*** (1)	-5.38*** (1)	0.09*** (1)	1.58*** (1)	-72.05*** (1)	-6.00*** (1)	0.08*** (1)	1.27*** (1)
H. Low-skilled								
Placement	-15.20* (0)	-2.76* (0)	0.18* (0)	6.00* (0)	-17.48** (4)	-2.94** (4)	0.17** (4)	5.30** (4)
Vacancies	-17.18* (3)	-2.91** (3)	0.17** (3)	5.42** (3)	-22.49*** (3)	-3.35** (3)	0.15** (3)	4.06** (3)
LOE	-24.71*** (1)	-3.37** (1)	0.14*** (1)	4.52** (1)	-82.90*** (1)	-6.44*** (1)	0.08*** (1)	1.10*** (1)
Placement	-15.20* (0)	-2.76* (0)	0.18* (0)	6.00* (0)	-17.48** (4)	-2.94** (4)	0.17** (4)	5.30** (4)
Critical Value								
1%	-23.80	-3.42	0.14	4.03	-23.80	-3.42	0.14	4.03
5%	-17.30	-2.91	0.17	5.48	-17.30	-2.91	0.17	5.48
10%	-14.20	-2.62	0.19	6.67	-14.20	-2.62	0.19	6.67

Note:
1. *Critical values is based on table Ng and Perron (2001).*
2. *,**,*** represent the 10%, 5% and 1% levels of significance.*
3. *Parenthesis […] shows optimal lags for Ng-Perron unit root test.*

4.2. Cointegration Test

The results of the cointegration test are provided in Panel A of Table 3. It shows that all the variables were cointegrated for both the pre- and post-crisis periods of COVID-19. The *F*-statistic for both models was statistically significant at the 1% and 5% levels. When all the variables were cointegrated, the estimated long-run coefficients for both models are given in Panel B. For a robust and reliable empirical estimation and policy relevance, a sensitivity test (diagnostic test) was conducted on the data series, as reported in Panel C. The diagnostic test showed that the coefficients for both the pre- and post-crisis periods of the COVID-19 models were “free” from serial correlation and heteroscedasticity problems.

Table 3: Summary results ARDL and diagnostic test

		Pre-MCO COVID-19				Post-MCO COVID-19			
		Aggregate	High-skilled	Semi-skilled	Low-skilled	Aggregate	High-skilled	Semi-skilled	Low-skilled
A. ARDL bounds tests									
F-statistics		8.49***	9.16***	5.48**	7.35***	21.42***	12.39***	11.35***	15.18***
Critical Value									
1%	I(0)	4.56	4.56	4.61	4.95	4.36	4.36	4.36	4.36
	I(1)	5.59	5.59	5.56	6.03	5.39	5.39	5.39	5.39
5%	I(0)	3.29	3.29	3.30	3.48	3.24	3.24	3.24	3.24
	I(1)	4.07	4.07	4.10	4.34	4.05	4.05	4.05	4.05
B. Long-run coefficient									
ARDL model		(1,0,1)	(1,0,1)	(1,1,2)	(1,0,0)	(1,0,4)	(2,1,2)	(1,1,4)	(1,0,4)
Constant		1.91**	1.27	0.58	0.66	4.02***	1.64*	4.89***	3.58***
Vacancies		0.03	-0.02	-0.04	0.09	0.89***	1.12***	0.40**	0.45***
LOE		0.49***	0.60***	0.75***	0.38*	-0.79***	-0.69*	-0.48**	-0.67***
$ECM_{(t-1)}$		-0.68***	-0.72***	-0.58***	-0.86***	-0.64***	-0.63***	-0.61***	-0.69***
C. Diagnostic Test									
Serial correlation		0.05 (0.81)	0.20 (0.64)	0.19 (0.64)	0.79 (0.34)	0.38 (0.52)	0.15 (0.69)	0.33 (0.54)	1.72 (0.15)
Heteroscedasticity		0.18 (0.67)	0.54 (0.64)	0.01 (0.92)	2.36 (0.08)	0.24 (0.62)	0.19 (0.66)	1.54 (0.21)	1.24 (0.26)

Note: 1. **,**,*** represent the 10%, 5% and 1% levels of significance.*
2. *Parenthesis [...] shows the probability of the diagnostic test.*

4.3 Sensitivity Analysis

This study carried out a sensitivity analysis to check the robustness of the model. The results of the sensitivity analysis are shown in Table 4. From the table, it can be interpreted that the ARDL, OLS, FMOLS and DOLS estimation approaches showed the same pattern in the estimation results. For example, the impact of vacancies for low-skilled workers in the post-MCO period was consistently higher in all the four methods. Furthermore, the LOE for the semi-skilled group in the post-MCO period remained between -0.30 and -0.55. Lastly, the LOE coefficient for the high-skilled group in the pre-MCO period ranged between 0.60 and 0.89. Overall, the sensitivity analysis confirmed the robustness of all the models.

Table 4: Robustness test General

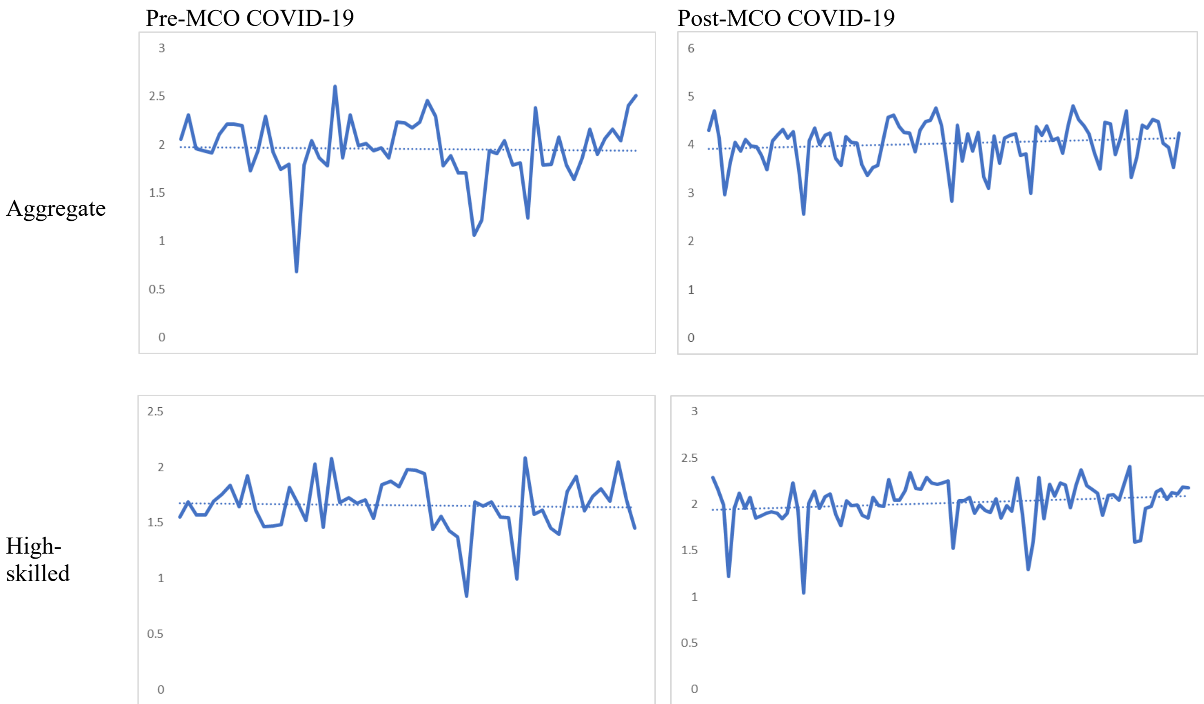
	Pre-MCO				Post-MCO			
	ARDL	OLS	FMOLS	DOLS	ARDL	OLS	FMOLS	DOLS
A. General-Skilled								
Constant	1.91***	0.84	0.64	1.25***	4.02***	2.54***	4.06***	3.82***
Vacancies	0.03	0.02	0.03	0.02	0.89***	0.85***	0.97***	1.01***
LOE	0.49***	0.71***	0.73***	0.62**	-0.79***	-0.47***	-0.91***	-0.91***
B. High-Skilled								
Constant	1.27	0.02	-0.24	0.39	1.64*	1.81***	3.06***	2.76***
Vacancies	-0.02	-0.01	0.04	0.04	1.12***	0.69***	0.77***	0.97***
LOE	0.60***	0.87***	0.89***	0.75**	-0.69***	-0.20	-0.54***	-0.73***
C. Semi-Skilled								
Constant	0.58	1.02	0.865	0.77	4.90***	2.67***	3.79***	4.07***
Vacancies	-0.04	0.01	-0.003	-0.04	0.40**	0.61***	0.73***	0.57**
LOE	0.75***	0.60***	0.650***	0.71***	-0.48**	-0.30*	-0.72***	-0.55***
D. Low-skilled								
Constant	0.66	0.80*	0.42	1.87	3.58***	1.65***	2.58***	2.81**
Vacancies	0.10	0.09**	0.12	0.17	0.45***	0.48***	0.59***	0.55*
LOE	0.38*	0.35***	0.45**	-0.12	-0.67***	-0.07	-0.61***	-0.61**

Note: **,**,*** represent the 10%, 5% and 1% levels of significance*

4.4 ADRL Estimation Test Results

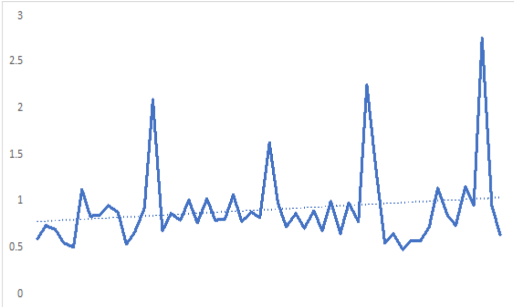
Two remarkable findings could be summarized from the empirical results in Panel B of Table 3. First, the empirical results indicated that the economic crisis due to the COVID-19 pandemic tended to improve the job matching efficiency. As mentioned, the coefficient for the matching efficiency in the econometric model was represented by the constant variable. It could be observed that the coefficients for the post-crisis period were larger and statistically significant compared to those of the pre-crisis period. The most significant improvement in job matching efficiency was found to be for the semi-skilled category, where the coefficient improved from 1.27 to 4.89. The lowest improvement was observed to be for the high-skilled category, where the matching efficiency coefficient increased from 1.27 to 1.64. To illustrate the improvement in the matching efficiency, the so-called matching rate, which is defined as $\mu_t = \frac{P_t}{V_t^{\alpha} U_t^{\beta}}$, was calculated and tabulated. The results, as presented in Figure 1, showed a clear upward trend in the matching efficiency during the post-MCO period at the aggregate and skill levels, with the most significant increase being observed for the semi-skilled category.

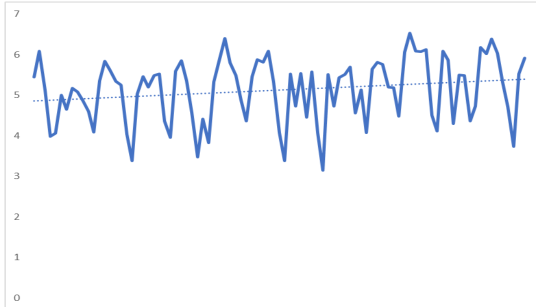
Figure 1: Matching efficiency between pre-MCO COVID-19 and post-MCO COVID-19 by skills



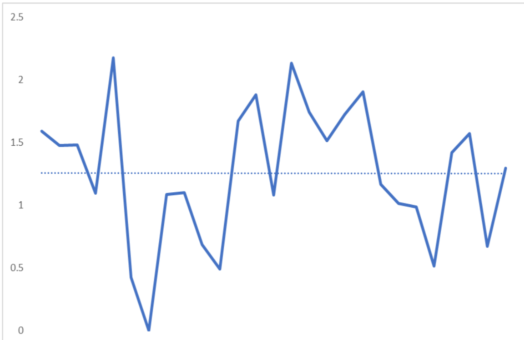
Pre-MCO COVID-19 | Post-MCO COVID-19

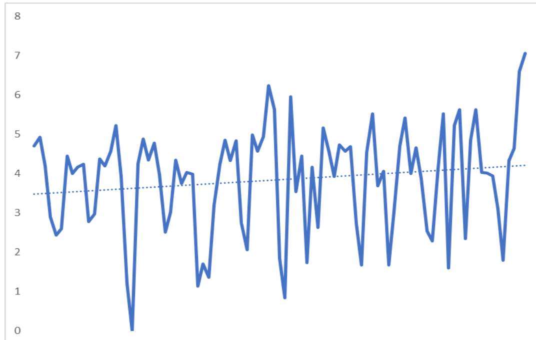
Semi-Skilled





Low-Skilled





Several factors were expected to have a great influence on the magnitude of the matching efficiency coefficients. The matching efficiency for the semi-skilled group improved largely because most of the job demands in the economy were available for this group compared to jobs for high-skilled workers. The database in MyFutureJobs indicated that 45% of the total job demands were dominated by semi-skilled workers, while 37% of the jobs were available for the high-skilled workers. From the perspective of the supply side, 54% of the jobseekers had a tertiary education, which was more relevant for high-skilled jobs. These situations explain why the speed of improvement in the matching efficiency was larger for the semi-skilled than the high-skilled categories. In addition to the nature of the job demand and supply, wage level, specific location and type of industry are among the drivers that are also expected to influence the speed of matching (Wu & Yao, 2006; Fu et al., 2010; Xie, 2008; Cahuc & Zylberberg, 2014). In the case of this study, it was unable to measure such drivers due to data limitations.

The estimated ECM at the bottom of Panel B measured the speed of adjustment from a short-run disequilibrium towards a long-run equilibrium, and demonstrated the speed of adjustment to the long-run equilibrium in the models. The coefficients for ECM in all the models were negative and significant. These results showed that the coefficients of disequilibrium would converge towards the long-run equilibrium. For example, for the post-MCO period of COVID-19, the ECM value for the high-skilled category was -0.63, which means that the model would be adjusted at a speed of 63% back to equilibrium.

Second, although job matching efficiency improved in the post-crisis period of COVID-19, not all the estimated coefficients were in line with the expectation of the theory. Theoretically, the estimated coefficients for vacancies and LOE should have been positive to influence placements. The more vacancies and LOE there are, the more placements will take place. However, the post-crisis model only indicated a positive coefficient for vacancies and not for LOE (negative coefficient). This observation held for all the individual skill categories. For example, the aggregate model indicated that an increase of 1% in vacancies was likely to increase placements by 0.89%, and an increase of 1% in LOE would potentially reduce placements by 0.79%. The results for the pre-crisis period of COVID-19 showed a slight difference, where a negative coefficient applied for vacancies only for the models with high-skilled and semi-skilled workers.

The negative coefficient that was observed for LOE in the post-MCO model was mainly driven by the comparability of the data. As mentioned, the data for placements included both new job market entrants and those insured workers who had lost their jobs. Thus, the variation in the LOE only explained part of the placements, while the other components were not factored in the estimation. LOE could have been replaced by the unemployment rate to examine the sensitivity of the estimation, but this could not be done for the daily estimation because the daily unemployment rate was not available.

5. CONCLUSION

This paper assessed the extent to which the reduction in the unemployment rate during the post-MCO period of COVID-19 could be explained by the improvement in job matching efficiency. When an ARDL econometric model was applied to the unique administrative labour data on a daily basis, the results showed that there was a significant improvement in job matching efficiency, which, in turn, explained the reduction in the unemployment rate. The improvement applied for all skill categories, with the most efficient matching being observed for the semi-skilled category.

From a policy perspective, the improvement in the job matching efficiency can be explained by the several interventions that were put forward. First, an integrated job market platform was formed to reduce job hunting costs incurred in fragmented portals. In June 2020, the government decided to establish a single landing job portal, namely MyFutureJobs. The MyFutureJobs portal is an interactive and integrated platform that guides employers step-by-step in screening candidates. At the same time, it helps job seekers to find employment, without neglecting the vulnerable groups, in facilitating their access to the labour market. Second, a hiring incentive program was implemented to offer financial incentives to employers with the aim of expanding hiring. This program was designed specifically under the PENJANA economic stimulus package, and had benefitted 128,779 workers by end of December 2020. Third, SOCSO held 234 career fairs to mitigate the growing number of unemployed Malaysians who were struggling during the COVID-19 pandemic and to help fresh graduates find suitable employment and match their skill-sets and qualifications. These initiatives focused on matching efficiency and supporting workers at risk of becoming unemployed rather than on their jobs. This study can also provide information to policymakers and the government in improving job matching efficiency, which affects the unemployment rate, especially during the economic recovery phase.

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