A Case Study of Unemployment Among Graduates in the Klang Valley

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Cheong Jia Qi
Universiti Malaysia Sabah (UMS)

Jacqueline Fernandez
Universiti Sains Malaysia

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Office of Employment Insurance System (EIS)
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Level 2, No.6 Persiaran Perdana
Precinct 2, 62100 Putrajaya
E-mail: euera@perkeso.gov.my
Website: www.euera.org

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Content

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Heterogenous Effects of Employment on Economic Growth in Malaysia

Muhammad Daaniyall Abd Rahman[a,b*], Muzafar Shah Habibullah[b,c], Clarice Urun Saimon[a], Fakaruddin Kamaruddin[a,b]

Abstract

Motivation and aim: This study examines the relationship between employment and economic growth in Malaysia, with the emphasis on the heterogeneous effects in the labour market. These effects relate to sectoral employment, citizenship, and the skill levels that influence changes in this growth nexus.

Methods and materials: Three main tests are conducted, to deliver empirical evidence on the impact of heterogenous effects in the labour market on economic growth. Time-series econometric approaches are applied to a growth model, involving data ranging from 1971 to 2018.

Key findings: Heterogenous effects in the labour market significantly influence economic growth. On the whole, the findings indicate that labour has a significant positive impact on sectoral economic growth. It is also uncovered that the growth-driven employment of foreign workers, led to the disproportionate displacement of local workers. This in turn can prove to be a negative situation, when it comes to the development of highly-skilled workers.

Policy implication: It is imperative, that the status quo of the current labour market structure be revisited. Considering the current worrying situation, steps need to be taken to reduce the dependency on foreign workers, while implementing re-skilling and up-skilling initiatives, to enhance the performance and contribution of local workers.

Keywords: employment, economic growth, foreign workers, Malaysia

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[a]School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia
[b]EIS-UPMCS Centre for Future Labour Market Studies, Menara PERKESO, Putrajaya, Malaysia
[c]Putra Business School, Serdang, Malaysia
[*]Corresponding author: daaniyall@upm.edu.my

Introduction

According to the growth theory, economic growth expansion is influenced by labour utilisation, alongside other inputs such as capital, raw materials, and technology. As the economy moves towards modern industrialisation, structural shifts have led to advances in technology and innovation, expansion in terms of infrastructure, and reductions of transaction costs. All these mechanisms provide feedback which can be harnessed by the labour market, to implement structural adjustments in compliance to the immediate situation.

The adjustments in the labour market, affect the other factor markets either directly or indirectly, in terms of both supply and demand. In a well-functioning economy, the use of labour is efficient if the labour market mechanism can adjust freely, in response to shocks, thus leading to market correction to restore growth. However, recent evidence in relevant literature suggests an intricate connection between the labour market and economic growth, highlighting the influence of heterogeneous effects.

It has been established that the heterogeneous effects in the labour market that instigate changes in economic growth, can be separated into the sectoral effect, and the composition effect. The sectoral effect has to do with the economic transformation, which is driven by structural changes, particularly in relation to sectoral contribution towards economic growth. In this regard, the use of labour in the economy is adjusted to meet changes in demand, either by increasing labour productivity (Park et al., 2016), or through migrations (Uno & Kobayashi, 2013; Zhao & Li, 2021). The composition effect, however, is less straightforward, and is dependent on the composition of employment in the labour market. Among others, this effect is associated to education level (Razzak & Timmins, 2010), skill types (Hulten & Ramey, 2015), citizenship, (Steinhardt, 2012) and ethnicity (Muange & Kiptoo, 2020).

This paper delves into the impact of heterogeneous effects in the labour market on the Malaysian economic growth. In comparison to other industrialised economies with a similar initial circumstance, Malaysia case is unique as its economic progress is marked by overly extended development periods, which served to render its sluggish transformation into a developed nation. In the context of Malaysia's labour market, our work focuses on uncovering the extent to which Malaysia economic growth is affected in three aspects: (a) the sectoral effect of the labour market (b) foreign labour effects, and (c) the effects of different skills.

The contribution of this paper to the existing literature is two-fold. Firstly, from the knowledge perspective, we provide an empirical assessment on the impact of different labour market structures on the Malaysian economic growth. Aggregate measures are used to gauge a "helicopter view", regarding the extent to which labour market behaviour can influence economic progress, which is then very informative for the development of a macroeconomic policy. Secondly, when it comes to policy decision making, a good understanding of the heterogenous effects in the labour market, on economic performance, is imperative. This information is useful for determining intervention strategies, which can serve to improve labour market conditions, and contribute towards better growth.

This paper is organised as follows. In Section 2, we refer to relevant literature, for a discussion on the evolution of Malaysia's economic development and labour market. In Section 3, we describe the materials and methodology used for conducting the empirical assessment. In Section 4, we discuss the findings. Finally, in Section 5 we draw the conclusion with policy recommendations.

Background and past studies

The past sixty years has seen the transformation of Malaysia from an agriculture-based into a manufacturing-based nation. The rapid pace of industrialisation in Malaysia, which began during the 1980s, contributed towards economic prosperity, which in turn improved the way of life of its citizens. The economic structure transformation (from rural-based agricultural sectors to modern and urban-based industrialisation) has emphasised on the importance of sectoral transformation towards economic growth. Theoretically, the structural changes are driven by resources re-allocation from the agricultural to industrialised sectors, as well as by changes in the patterns of consumption (Kuznet, 1973), involving a complex interaction between demand and supply factors (Chenery & Syrquin, 1989).

As shown in Table 1, for over two decades, the shares of value-added in the five main sectors have been varying, whereby the Agriculture, Forestry and Fishing (herewith Agriculture) sectors, as well as the Mining and Quarrying (herewith Mining) sectors, have exhibited a declining contribution to the gross domestic products

(GDP). While the Manufacturing and Construction sectors have remained stagnant, the services sector has portrayed expanding contribution patterns, which is an indication of the significance of this sector, in terms of economic growth.

Although Malaysia remains a resource dependent nation, due to its natural resource-rich and arable land with large-scale commodity plantations (Gylfason & Zoega, 2006; Olaniyi et al., 2011), the declining contribution of the resource-based sectors to the GDP, has realigned the focus of sectoral development (MITI, 2006). In response to move up the value chain, economic planning has involved the re-direction of economic development towards high value production, and services intensification. Thus, the economic shift has altered the human capital requirement in the economy. Such a development facilitates labour migration to non-agricultural employment, marking a shift in employment from production activities, to services activities. This is made evident by the decline in the share of employment in the Agriculture sector, from 17.87% (1995-2001) to 11.57% (2013-2019), while the share of employment in the Services sector rose from 50.23% to 61.74%, within the same period.

In terms of the structural effect, it is normal for structural change to be associated with the shifting of workforce, between different sectors in the economy. Many studies have uncovered positive correlations, between the aggregate growth and economic transformation, whereby the proliferation of Manufacturing and Services sectors accelerates the demand for employment. This development contributes directly to the country's GDP. Such relationships are directly related to the improvement in economic productivity, creating more opportunities for economic diversifications (Maroto-Sánchez & Cuadrado-Roura, 2009; McMillan & Rodrik, 2011; Lee & McKibbin, 2018).

Table 1 Share of value added and employment by sector (%).

	1995-2001	2001-2007	2007-2013	2013-2019
Agriculture, Forestry & Fishing				
Value added (% of GDP)	11.56	10.46	9.56	7.90
Employment (% of total employment)	17.87	14.70	13.23	11.57
Mining & Quarrying				
Value added (% of GDP)	15.50	14.55	10.62	8.20
Employment (% of total employment)	0.37	0.34	0.55	0.65
Manufacturing				
Value added (% of GDP)	23.09	24.53	23.00	22.32
Employment (% of total employment)	23.00	20.77	17.73	17.12
Construction				
Value added (% of GDP)	4.90	3.64	3.73	4.70
Employment (% of total employment)	8.54	9.06	9.24	8.93
Services				
Value added (% of GDP)	43.38	45.83	52.18	55.68
Employment (% of total employment)	50.23	55.13	59.26	61.74

Source: Authors' computation from the Department of Statistics Malaysia dataset.

Changes in the economic structure have brought about an inevitable labour shortage situation. The employment of foreign workers has become a short-term solution, which could curtail long-term growth without an adequate institutional quality. Though it is widely debated in economic literature, the findings with regards to this composition effect remain inconclusive. Despite a negative public perception towards the presence of foreign workers, there are studies suggest that their contribution do accelerate economic progress. On the other hand, undesirable effects prevail as the issue of substitutability exists between local and foreign workers.

On the positive side, several studies indicate that foreign workers contribute towards Malaysia's economic progress and growth (Tham & Liew, 2014; World Bank, 2015). It is argued that the employment of foreign workers reduces the cost of production, enhances productivity, and increases wages. Kanapathy (2001) observed that during the high growth period of the 1980s and 1990s, the participation of foreign workers led to an elevation in wages. It is notable, that the presence of foreign workers does not cause a dip in the wages of local workers. The positive effects of foreign workers in terms of Malaysia's productivity, are also supported by Jordaan (2017), Noor et al. (2011), and Palel et al. (2016).

On the flip side of the coin, foreign workers have been negatively associated to skill effects that impede labour productivity, suppress wage rates and disincentive technological adoption. Ang et al. (2018) and Rasiah et al. (2015) opined that the employment of foreign workers causes a loss in productivity due to low-skilled labour, while corporations are less inclined to invest in technology, which requires high capital investment. In a similar vein, Ismail (2015, 2014) forwarded that in the context of Malaysia's economic growth, the impact of unskilled foreign workers can be considered negative, while the impact of skilled and semi-skilled foreign workers can be considered positive. Additionally, findings from a study conducted by Nizam et al. (2015) indicate that foreign workers do not contribute towards Malaysia's economic growth.

Other negative consequences of foreign labour dependency include the suppression of the wage rate, as well as an unfavourable skill composition effect in the economic activities. Athukorala and Devadason (2012) indicate that the presence of foreign workers hinders the increase of unskilled-worker wages. On the other hand, Ismail et al. (2014) revealed that foreign workers have a significantly negative effect on the overall wages of a firm. According to the results, among the skilled, semi-skilled and unskilled workers, only the semi-skilled and unskilled foreign workers have negative effects on the overall wages. However, the presence of foreign workers has positive effects on the wages of managers; professionals; and technical and associate professionals. But when it comes to the wages of clerical and general workers, the presence of foreign workers represents a negative effect. Ismail et al. (2014) also uncovered that the effect of foreign workers on wages is greater in the services sector, than in the manufacturing sector. Also, the effect of foreign workers on wages is more evident in large-sized, rather than in small-sized firms.

According to Rasiah et al. (2015), the slow wage growth registered by the manufacturing sector is attributed to the heavy dependence on low-skilled foreign workers, since the late 1990s. It is also apparent that the trade performance of Malaysia's manufacturing sector has declined, while labour productivity has slowed down. Ang et al. (2018) also observed that industries with low productivity have a higher share of low-skilled foreign workers. The firms that employ foreign workers tend to be labour-intensive, with extended working hours. Such firms have been observed to be less efficient, in comparison to firms that employ automation and technologically advanced production methods. Malaysia is currently considered a labour-intensive and low-cost destination country. As a consequence, foreign investors are inclined to relocate their lower value-added processes to Malaysia.

The substitution effect with regards to local workers, due to the influx of foreign workers, is another area of concern. A study conducted by Jajri and Ismail (2006) on the Malaysian manufacturing sector revealed that foreign workers are increasingly the cause of job displacement among local workers. This is made evident by the fact that the wage rate and technological uptakes remain low in the economy (Jegathesan et al., 1997; Ibrahim & Said, 2015). In constrast, studies conducted by Noor et al. (2011) and Tan and Ng (2018), disclosed that foreign labour is neither a substitute, nor a complement for local workers. While these studies have, in one way or another, indicated the effects of the presence of foreign workers on local workers, more comprehensive investigations are required for a more conclusive outcome.

Methodology and research materials

Model specification

Based on the standard growth model specifications, the impact of total employment on economic growth in Malaysia can be estimated by way of the following model:

$$GDP_t = f(EMP_t, Capital_t, Control_t) \quad (1)$$

where GDP_t is measured by the real gross domestic product (GDP), EMP_t is the number of employments, $Capital_t$ is domestic direct investment (proxied by real net capital stock per capita). The control variables are FDI_t (foreign direct investment, proxied by the ratio of FDI inflows to GDP), education level (proxied by educational attainment as defined by Barro and Lee), industrialisation (proxied by CO_2 intensity, measured using carbon dioxide emission per kilogram (kg) of oil equivalent energy use), globalisation (proxied by KOF index of globalisation), fertility is the total fertility rate (measured by the number of births per woman), financial development (measured by ratio of domestic credit to private sector to GDP), and openness (proxied by ratio of total trade to GDP).

With regards to the application of control variables, it is important that the estimation process in this study involve separate regressions. These regression models are distinguished according to the labour market heterogenous effects mentioned above. Namely, these are citizenship (local and foreign), broad sector (Agriculture, Mining & Quarrying, Manufacturing, Construction and Services), and skill levels (9 job categories[1]). Each of these is regressed with the use of different models. Twenty-seven regression models are estimated, with each of them using different control variables, which are selected based on robust estimates.

[1] Nine job categories are defined based on 1-digit level of Malaysia Standard Classification of Occupations (MASCO)

Apart from Equation (1), we also extend our analysis to investigate the displacement of local workers in Malaysia, by foreign workers. This substitution effect can be estimated by way of the following model:

$$Local_t = f\,(Foreign_t, Control_t) \qquad (2)$$

where $Local_t$ is the number of local workers, and $Foreign_t$, is the number of foreign workers. The control variables included in the estimation of Equation (2) are the same selection of variables as mentioned for Equation (1).

In line with Wang (2010), we interpret the substitutability or complementarity of local workers for foreign workers by the indicator of the estimated coefficient of the foreign workers. A negative coefficient for foreign workers suggests that foreign workers are substitutes, while a positive coefficient indicates that foreign workers and local workers are complements. If the estimated coefficient of the foreign workers is negative or positive, but is not statistically significant, then it can be deduced that foreign employment is "neutral".

Table 2 summarises the data sources for all the variables used in the empirical estimations. Data on GDP_t, EMP_t, and $Capital_t$ at the sectoral levels, are gathered from the Department of Statistics, Malaysia, via various publications. Meanwhile, data for the control variables, namely, *financial development*, *openness*, *fertility,* and CO_2 *intensity*, are compiled from the World Development Indicators database. Data on *globalisation* and *FDI inflows* are sourced from the KOF index of globalisation and UNCTAD databases, respectively. Data used in the analysis range from 1971 to 2018.

Generally, the local (*Local*) and foreign worker (*Foreign*) figures are obtained from official statistics, which are based on data collection from formal establishments. As such, some informal activities, which also involve the employment of large workforces, are not included in the data collected. Meanwhile, underestimation in the number of foreign workers could be an issue, due to the existence of undocumented or illegal migrants. However, for this study, this discrepancy in data is not taken into account.

Table 2 Variables for empirical analysis and respective data

Variable	**Data**	**Time series**
GDP	Real GDP	1971-2018
Emp	Number of employments	1971-2018
Capital	Real net capital stock per capita	1971-2018
Local	Number of local workers	1971-2018
Foreign	Number of foreign workers	1971-2018
Control variables		
Education	Educational attainment as defined by Barro and Lee	1971-2018
FDI	FDI inflows to GDP	1971-2018
Industrialisation	Carbon dioxide emission per kilogram (kg) of oil equivalent energy use	1971-2018
Globalisation	KOF index of globalisation	1971-2018
Fertility	Number of births per woman	1971-2018
Financial development	Domestic credit to private sector to GDP	1971-2018
Openness	Total trade to GDP	1971-2018

Results and discussion

As mentioned earlier, the main aim of this study is to examine the impact of employment on economic growth, by considering the heterogeneous effects in the labour market. The discussion on empirical results is separated into four areas. Firstly, we present the impact of total employment on economic growth. Secondly, we elaborate on the comparative impact of local and foreign workers on economic growth. Thirdly, we discuss our results on the substitutability between local and foreign workers. And lastly, we explain the results acquired, regarding the impact of different skill types on economic growth. Sectoral issues are also discussed, depending on the availability of relevant results.

Impact of total employment by sector

Table 3 portrays the impact of employment on economic growth, at the national and the sectoral levels. The first column exhibits the overall results of employment, which affects the national economic growth. Clearly, labour plays a vital role in economic production, besides the use of capital and other control determinants. At the sectoral level (Columns 2-6); the relationship between employment and economic growth appears to vary across sectors, despite it being corroborated with the national level estimation. Again, these results emphasise that the role of labour, with regards to sectoral growth, is significant.

Amongst all broad sectors, the Construction sector is the most likely to be labour-intensive. According to the results, this sector has the highest relationship between employment and sectoral growth. We suggest two compelling explanations to support this view. Firstly, the rapid pace of infrastructure development, in Malaysia, accelerates the growth of the Construction sector. This rapid growth situation calls for a substantial amount of manpower, of which, 69% are made up of foreign workers (Abdul-Rahman et al, 2012). Secondly, in comparison to the Services sector, which employs over 60% of the total workforce, the Construction sector only employs 8% of the total workforce. However, it has been observed that the employment structure of the former sector, is proportionate to its 56% value-added contribution to the GDP (Table 3, Column 4), while the employment structure of the latter, is somewhat disproportionate to its value-added contribution to the GDP. This is an indication that the Construction sector’s overdependence on labour could prove to be a significant obstacle to its growth, should there occur an acute labour shortfall.

Table 3 Impact of employment on economic growth by sectors

Independent Variables	Dependent variable: Real GDP by sectors					
	National (1)	**Agriculture (2)**	**Mining & Quarrying (3)**	**Manufacturing (4)**	**Construction (5)**	**Services (6)**
Constant	-0.0092	3.0174***	1.8843	3.9788***	1.7880**	-0.8882
	(-0.0069)	(3.9235)	(1.0881)	(6.4772)	(2.2712)	(-0.8203)
Employment, by sectors	0.5188***	0.4013***	0.2694***	0.5576***	0.7298***	0.7228***
	(2.8643)	(3.2115)	(4.2731)	(2.9551)	(26.383)	(3.8679)
Capital, by sectors	0.2928***	0.2119**		0.2918*	0.4026***	
	(4.6036)	(2.2833)		(2.0163)	(3.8297)	
Education		2.2209***				
		(17.136)				
FDI						0.0323**
						(2.4606)
Industrialisation	0.1892***			0.4362***	0.8489***	0.4310***
	(4.5834)			(3.3551)	(2.9262)	(3.3663)
Globalisation	1.2924***					1.7035***
	(6.6597)					(3.5211)
Fertility	-0.3847***			-1.5352***		-0.6550***
	(-2.7517)			(-10.895)		(-3.4277)
Financial Development			0.5808***			
			(6.7028)			
Openness			0.5796***	0.2117**		
			(2.9256)	(2.3698)		
$\underline{R}^2$	0.9984	0.9747	0.9033	0.9956	0.9684	0.9957
SER	0.0306	0.0551	0.1340	0.0704	0.1205	0.0603
Diagnostic tests:						
OLS: LMχ^2 (1)	[0.015]**	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
OLS: ARCH χ^2 (1)	[0.391]	[0.013]**	[0.035]**	[0.165]	[0.003]***	[0.018]***
N	44	47	48	44	44	44

Notes: All models have been estimated using OLS with robust standard error following Newey and West (1987) that correct for both autocorrelation and heteroscedasticity. Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% level, respectively. LMχ^2 (1) and ARCHχ^2 (1) denote the Lagrange multiplier test for serial correlation of order one and heteroscedasticity of order one in the OLS equations, respectively. Figures in round brackets (…) are *t*-statistics, while figures in square brackets […] are *p*-values. $\underline{R}^2$ and SER denote adjusted R-squared and standard error of regression, respectively. N is the number of observations. All variables are in logarithm.

Impact of labour citizenship by sector

Previous empirical results reveal that labour is a key factor for Malaysian economic growth. Given its important role, a deeeper investigation is necessary, to understand the extent to which labour composition affects growth, with the emphasis on the dispersion effects between local and foreign worker employment. Table 4 illustrates the impact of local and foreign workers on economic growth. Generally, according to the results shown in Table 3, the positive and significant impact of employment on economic growth can be considered long-lasting, particularly for the national level estimation. As can be gathered from the first column of Table 4, both local and foreign employment is significant for Malaysia's economic growth, with the former delivering a greater impact.

However, the magnitude, to which local and foreign labour roles diverge, should be the main focus of investigations, especially at the sectoral levels. According to the results, with the exception of the Manufacturing sector, foreign labour in all the other economic sectors has a positive impact on sectoral growth. A greater magnitude of foreign employment effect on growth is observed for the Agriculture and Construction sectors. This is to be expected, as these sectors employ a significant number of foreign workers, to facilitate their growth. A study conducted by Del Carpio et al. (2015) reveals that the Agriculture sector in Malaysia, especially the large plantations, employ a staggering 69% of foreign workers, with about 98% of the workforce comprising unskilled workers. Similarly, the Construction sector is largely dependent on foreign workers, with the majority of them in the unskilled category (Han et al., 2008; Del Carpio et al, 2015).

On the other hand, the local workforce plays a significant role, in the long-term growth of the Manufacturing and Services sectors. This finding is anticipated, as most of the total local workforce is concentrated in these two sectors.

Table 4 Impact of local and foreign workers on economic growth by sectors

Independent Variables	**Dependent variable: Real GDP by sectors**					
	National	**Agriculture**	**Mining & Quarrying**	**Manufacturing**	**Construction**	**Services**
Constant	12.166***	5.6685	11.540***	9.5367***	-48.600***	4.2444***
	(20.133)	(1.1042)	(89.989)	(8.6484)	(-4.2650)	(5.2455)
Local Employment,	0.1861***	0.3623	-0.0428	0.6372***	-0.1236	0.7870***
by sectors	(3.3131)	(0.5773)	(-1.5125)	(5.1467)	(-0.8301)	(10.687)
Foreign Employment,	0.0377***	0.3325*	0.0318***	-0.0061	0.2494***	0.1272***
by sectors	(4.4403)	(2.4311)	(3.4804)	(-0.3179)	(4.0304)	(6.6027)
Education	0.7010***					
	(12.983)					
FDI			0.0374*			
			(1.9716)			
Industrialisation		1.1301				1.0941***
		(1.6710)				(4.0919)
Globalisation					13.375***	
					(5.0118)	
Fertility				-2.6432***		
				(-8.2668)		
$\underline{R}^2$	0.9931	0.2917	0.4036	0.9485	0.9497	0.9066
SER	0.0164	0.0690	0.0393	0.0341	0.0700	0.0607
Diagnostic tests:						
OLS: LMχ^2 (1)	[0.684]	[0.670]	[0.123]	[0.332]	[0.052]*	[0.612]
OLS: ARCHχ^2 (1)	[0.218]	[0.880]	[0.516]	[0.446]	[0.311]	[0.231]
N	14	10	14	13	12	10

Notes: All models have been estimated using OLS with robust standard error following Newey and West (1987) that correct for both autocorrelation and heteroscedasticity. Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% level, respectively. LMχ^2 (1) and ARCHχ^2 (1) denote the Lagrange multiplier test for serial correlation of order one and heteroscedasticity of order one in the OLS equations, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] are p-values. $\underline{R}^2$ and SER denote adjusted R-squared and standard error of regression, respectively. N is the number of observations. All variables are in logarithm.

Substitutability between local and foreign workers

The empirical results attained support the fact that Malaysia's economic growth is dependent on labour, whether in the form of local human capital or foreign immigrants. The impact of both workforces varies according to the type of economic activity under scrutiny. The influx of foreign labour can lead to the displacement of local employment, either through substitution, or the shifting of locals to a higher value-added economic activity. It has been established that most foreign workers are employed to perform low-skilled tasks. While this situation serves to reduce costs, it comes at the expense of local wages suppression.

Table 5 presents the impact of foreign workers on local employment. The main objective here is to estimate the substitutability between both workforces, at the aggregate level, across the main sectors.

Based on Table 5, three important findings are worth discussing. Firstly, at the national level, our results show that the presence of foreign workers may induce a negative impact on local workers (see first column of Table 5). In the context of local employment opportunities, the substitution of local workers for foreign workers can lead to adverse effects (Hassan, 2008). Secondly, the substitution effects are more apparent at the Services and Agriculture sectors, while the complementary effects are presented at the Manufacturing and Construction sectors.

The use of aggregate measures in our analysis makes it difficult to empirically verify that local and foreign workers are substitutes in the Services sector. However, previous studies have revealed that foreign workers are needed to fill the employment gap in certain sectors, which are frequently shunned by locals (Aziz et al., 2017). Furthermore, firms in non-tradable sectors, such as those involved in service-based activities, persistently turn to foreign labour to cushion the effects of rising labour costs (Athukorala, 2006). Also, in order to maintain a steady economic growth, it is essential that a sufficient supply of unskilled and semi-skilled workers be readily available. Otherwise, this circumstance has led to the rising demand for foreign workers (Del Carpio et al., 2015).

Table 5 Impacts of foreign workers on local employment by sectors

Independent Variables	**Dependent variable: Local workers by sectors**					
	National (1)	**Agriculture (2)**	**Mining & Quarrying (3)**	**Manufacturing (4)**	**Construction (5)**	**Services (6)**
Constant	-0.9437*	8.5399***	-5.6746***	1.8842	2.6791***	-3.3449***
	(-1.9614)	(21.724)	(-7.9797)	(1.0988)	(6.1416)	(-4.7165)
Foreign workers	-0.2375***	-0.2445***	-0.0701**	0.0955**	0.4461***	-0.2754***
by sectors	(-12.261)	(-3.5651)	(-3.0511)	(2.8918)	(14.719)	(-23.993)
Capital, by sectors	1.0758***	-0.0028	1.0718***	0.5575**		1.2977***
	(21.289)	(-0.0924)	(14.006)	(2.8432)		(18.655)
Industrialisation					1.7181**	
					(3.4383)	
$\underline{R}^2$	0.9653	0.4583	0.8977	0.6312	0.9532	0.9539
SER	0.0305	0.0668	0.1220	0.0579	0.0793	0.0486
Diagnostic tests:						
OLS: LMχ^2 (1)	[0.705]	[0.159]	[0.266]	[0.013]**	[0.376]	[0.756]
OLS: ARCHχ^2 (1)	[0.554]	[0.772]	[0.368]	[0.806]	[0.634]	[0.769]
N	13	14	13	13	10	13

Notes: All models have been estimated using OLS with robust standard error following Newey and West (1987) that correct for both autocorrelation and heteroscedasticity. Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% level, respectively. LMχ^2 (1) and ARCHχ^2 (1) denote the Lagrange multiplier test for serial correlation of order one and heteroscedasticity of order one in the OLS equations, respectively. Figures in round brackets (…) are *t*-statistics, while figures in square brackets […] are *p*-values. $\underline{R}^2$ and SER denote adjusted R-squared and standard error of regression, respectively. N is the number of observations. All variables are in logarithm.

In the Manufacturing sector scenario, the complementary effect between local and foreign workers is somewhat restrained. According to Awad et al. (2018), complementarity prevails, when the inflow of skilled migrant workers complements the existing domestic human capital in the host country. Such a situation facilitates an increase in innovation activities in the host country.

Devadason (2021) provides an empirical analysis, which suggests the existence of the complementary effect between local and foreign workers in the Manufacturing sector. This effect is apparent for both skilled and unskilled workers in this sector. Meanwhile, there is also a viewpoint that the prevalence of the complement effect between foreign and local workers is due to the fact that they are not in direct competition with each other. While the unskilled jobs are taken up mostly by migrants, the locals tend to gravitate towards jobs that call for more refined skills (Ng & Tan, 2019).

And thirdly, other than in the Construction sector[2], the use of capital seems to complement the local workers. It has been established that the substitution effect exists among local and foreign workers for some sectors. Meanwhile, the impact of capital on local workers appears to be rather promising. This can be attributed to the fact that the magnitude, to which the capitals complement local workers is relatively high. For example, the Services sector portrays the greatest substitution effect of foreign workers, in comparison to other sectors. However, capitals are significantly involved in the diminishing of this effect, which indicates their major contribution towards the complementing of local workers' tasks, in the production activities of the sector.

Skill requirements and economic growth

As previously observed, the capitals represent the core input for complementing the local workforce. As such, we can assume that skill requirements are a significant factor, when it comes to the boosting of economic growth. This is in line with the growth theory, which puts forward that higher capitalisation enhances economic growth, through the improvement of productivity and skills (Deng & Zhao, 2018; Yuhn & Kwon, 2000). Table 6 displays the impact of skill types on economic growth. In a nutshell, the results attained verify that all skill categories, significantly contribute towards economic growth, although the scale of contribution may vary across skill types.

It is our view that the impact of high-skilled workers, on economic growth, is lesser to that of medium-skilled workers. Generally, high-skilled workers are represented by managers, professionals, and technicians, while medium-skilled workers are represented by clerical staff, as well as plant and machine operators. According to the results attained, skilled agricultural workers deliver the greatest impact on economic growth, followed by clerical workers. While it has been established that capital plays an imperative role in economic growth (as shown in Table 5), this does not necessarily commensurate with the need for higher-skilled workers, as what the conventional growth theory may suggest. This serves to explain the lesser impact of a high-skilled workforce on economic growth.

Furthermore, the high dependency on foreign labour ‘dilutes’ the concentration of skill requirement in the economy, which in turn reduces its impact on economic growth. For example, Awad et al. (2018) opine that the long-term effect of a substantial increase in migrant workers could alter the skill components of the labour market, and make it dominated by relatively unskilled workers.

Table 6 Impact of workers on economic growth by skill types

Type of skilled workers:	Constant	Number of workers	Control variable:	$\underline{R}^2$	SER	Diagnostic tests: OLS: $LM\chi^2$ (1)	Diagnostic tests: OLS: ARCH $LM\chi^2$ (1)	N
Managers	4.7692*** (7.6218)	0.1120*** (3.2551)	0.7758*** (13.005)	0.952	0.040	[0.0810]*	[0.541]	13
Professionals	16.564*** (117.20)	0.0660*** (4.6153)	Fertility -4.0706*** (-27.636)	0.983	0.023	[0.699]	[0.865]	13
Technicians	6.9096*** (41.086)	0.1256*** (3.5563)	Education 2.7321*** (19.601)	0.971	0.033	[0.241]	[0.658]	14
Clerical workers	6.7602*** (14.072)	0.1385*** (3.4274)	Capital 0.5951*** (12.609)	0.954	0.039	[0.250]	[0.466]	13
Service & sales workers	13.749*** (80.419)	0.0762** (3.0546)	Education 0.6934*** (12.026)	0.992	0.017	[0.704]	[0.142]	14
Skilled agricultural	0.6508 (0.4722)	0.1474*** (4.5119)	Capital 1.1138*** (9.8875)	0.947	0.042	[0.071]*	[0.377]	13
Craft & trade workers	13.862*** (104.55)	0.0680*** (3.1264)	Education 0.7856*** (24.434)	0.992	0.017	[0.657]	[0.783]	14
Plant & machine operators	9.5431*** (52.125)	0.0926*** (3.1897)	Education 2.2873*** (20.656)	0.964	0.037	[0.044]**	[0.447]	14
Elementary occupations	13.762*** (109.53)	0.0687*** (4.1832)	Education 0.7593*** (20.031)	0.993	0.015	[0.763]	[0.184]	14

Notes: All models have been estimated using OLS with robust standard error following Newey and West (1987) that correct for both autocorrelation and heteroscedasticity. Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% level, respectively. $LM\chi^2$ (1) and $ARCH\chi^2$ (1) denote the Lagrange multiplier test for serial correlation of order one and heteroscedasticity of order one in the OLS equations, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] $\underline{R}^2$ are p-values. and SER denote adjusted R-squared and standard error of regression, respectively. N is the number of observations. All variables are in logarithm.

Linking the labour market long-term effect to the current economic crisis

This investigation focuses on the long-term effect of the labour market on economic growth. The results attained indicate that (a) labour plays a significant role in economic growth at the sectoral level, (b) while growth is driven by local and foreign labour, the resistance to local employment remains, and (c) the growth effect of high-skilled workers remains low.

The occurrence of the novel coronavirus (Covid-19) pandemic has imposed a relook at the labour market structure in the economy, due to serious disruptions in both the supply and demand chains. As a labour-intensive economy, Malaysia is not exempted from this dire situation, which affects the job security and livelihood of its workforce. Moreover, the prolonged and unresolved distribution issues have been exacerbated during the crisis, bringing further tension on the policy-makers to juggle between economic progress and people's welfare.

In the context of the labour market, the realisation of reliable solution to an anticipated dismal post-crisis situation will be difficult. Taking into consideration our empirical findings, two areas urgently call for appropriate policy measures.

First, dependency on foreign labour post a challenge to reverse, especially due to presence of substitutability effect and perpetuated long-term growth-driven foreign employment. We have elaborated earlier that labour is key for economic growth, either they are local or migrant workers. Though it is acceptable to ascertain this positive relationship because the use of labour could bring better return to the economy, yet more alarming concern lies on the substitutability effect of foreign worker for local workers. It seems imperative to look deeper into this effect as it could lead to diverse economic and social implications, including lower technological adoption, scarce innovation, talent brain-drain, wage stagnancy, which then crowding out local talents as well lead to underemployment.

Second, the increase in the number of higher education graduates signifies the presence of sufficient if not over-supply of high-skilled local talent pools in the economy. According to our findings, the growth impact of high-skilled workers is lesser than that of medium-skilled workers. This is an indication that the limited economic gains can be attributed to the underutilisation of high skills. This situation can be linked to the high dependency on foreign workers, which, as mentioned earlier, hinders capital intensive production.

Therefore, in the midst of the current pandemic, the prevalence of skill mismatches and underemployment needs to be addressed, so that local talents can be optimised through active labour market policy interventions. This will serve to ensure market efficiency and rectify imbalances.

Conclusions and policy implications

The heterogeneous effects in the labour market can influence economic growth in several ways. This study approaches these effects from three perspectives.

Firstly, we assess the components of sectoral employment. According to the results, labour is an important factor for growth, at both the national and sectoral levels. Labour-intensive activities characterised the growth of economic sectors, putting the performance of these sectors at risk, should a labour shortage situation emerge. This state of affairs is rendered even direr, if the employees are migrant workers assigned to menial tasks, as this would bring about adverse effects on the country's skill and wage premiums.

Secondly, we investigate the impact of worker citizenship on economic growth. Malaysia's economic growth is highly dependent on both local and foreign workers. Generally, local workers play a greater role in the country's economic growth than foreign workers. However, the role played by foreign workers cannot by any means be considered minimal. For instance, when it comes to sectoral growth, foreign workers play a more significant role than local workers. In terms of the substitutability between local and foreign workers, this is observed to be significant for some sectors. The substitutability between foreign and local workers comes with the potential to displace the local workforce, particularly in the area of low-skilled jobs.

Thirdly, we delve into the role of skill levels in economic growth. It is well-argued that high-skilled jobs, go hand in hand, with the development of a high-income nation. While the findings verify the importance of foreign workers in terms of Malaysia's economic growth, the impact of the high-skilled workforce in this area is deemed marginal in comparison to the medium-skill workforce. This not only indicates a lopsided dependency on low-skilled jobs, but also lack of high-skilled job creation in the economy.

The findings from this study clearly indicate the need for a reassessment on the status quo of the current labour market structure in order to realise a comprehensive reformation. According to these findings, there are two concerns with regards to policy implication. Firstly, in order to achieve the status of a developed nation, the sectoral development should include the availability of a high-skilled workforce, in coexistence with high-quality investment, to support the fast-changing and complex industrialisation processes. Secondly, high-dependency on cheap labour, comprising mostly of migrant workers, is deemed unsustainable for the facilitation of further growth, especially when they disproportionately crowd-out local talents. Given that substantial investments are allocated towards human capital development, particularly towards tertiary education, such effects would serve to devalue the returns on education.

In the current pandemic-led economic crisis, the Malaysian government has undertaken active measures to reduce foreign workers dependency, while at the same time executing upskilling initiatives to empower local human capital. *Malaysianization* (job replacement for local), reskilling and upskilling programmes are among the current initiatives carry by the government to tackle the labour market structural issues. However, bear in mind that, our empirical evidence proves the existence of workforce substitutability in the economic sectors, which to a greater extent, any measures to reduce foreign workers shall be selective and well-targeted. This is to avoid supply shock due to massive labour supply shortage, which could prove to be critically unfavourable for the post-crisis economic recovery.

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Determining the Leading Indicators for the Unemployment Rate in Malaysia

Henny Abigailwillyen Sinjus[ab]*, Heizlyn Amyneina Hamzah[ab], Muhammad Khalid Ahmad Kamal[ab], Estro Dariatno Sihaloho[c]

Abstract

Motivation and Aim: Whilst unemployment rate is one of the key indicators used to monitor the health of the economy, the indicator is usually published with a two-month lag that impedes rapid response for appropriate policy measure. This paper develops a methodology to determine a set of leading indicators for the unemployment rate in Malaysia.

Methods and Materials: Following a composite leading indicators methodology developed by the OECD, 17 candidate variables are selected from diverse aspects of economic activity. Data filtration and evaluation is conducted based on pairwise correlation and Granger causality analyses. A composite index is computed before in-sample and out-of-sample unemployment rate forecast is measured.

Key Finding: The results show that the Kuala Lumpur composite index (KLCI), total loans (LOAN) and money supply (M2) satisfy all the leading indicators criteria for the unemployment rates in Malaysia. Hence, the composite leading index constructed from these variables provides accurate tracking of the unemployment rate in Malaysia.

Policy Implications: Leading indicators of unemployment rate can be a useful short-term tool for the government to formulate a responsive labour market policy. Their function is to provide an early signal system to the Active Labour Market Policy (ALMP) for attenuating cyclical and structural unemployment.

Keywords: Leading indicators, unemployment rate, labour market, Malaysia

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[a] School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia
[b]EIS-UPMCS Centre for Future Labour Market Studies, Menara PERKESO, Putrajaya, Malaysia
[c]Department of Economics, Faculty of Economics and Business, Padjadjaran University Bandung, Indonesia.
*Corresponding author: hennyabigailwillyen@gmail.com

Introduction

A leading indicator is economic data that corresponds with a future movement or change in some phenomenon of interest. The indicator was initially used as an early signal for turning points in business cycles, but due to its significant influence, it is now applied in predicting aggregate economic activity. An indicator helps by detecting the direction of the economy earlier, enabling the government to make and launch policies at the right time. Given that output and unemployment are inter-related—the higher the growth in output, the greater the demand for labour and vice-versa—the development of timely, reasonably accurate and reliable leading indicators to predict the labour market movements are necessary.

This paper seeks to identify the potential leading indicators for the labour market in Malaysia with specific application to the unemployment rate. Managing labour market conditions during crisis and post-crisis periods is challenging because of dynamic economic movements. It has been observed that economic activities and the labour market have been responsive to the various movement control restrictions implemented by the government to prevent the COVID-19 infection. For example, unemployment rates reduced from 5.3% in May 2020 to 4.9% in June 2020 when the government relaxed the movement control restrictions. Policy monitoring is restricted as the unemployment rate data is reported with a two-month lag in relation to the current real-time. With the unprecedented global pandemic and world economic downturn, it is crucial to conduct a timely assessment of the labour market conditions in Malaysia by utilising the leading indicators.

In identifying the potential leading indicators for unemployment in Malaysia, this paper evaluates diverse sets of data, including financial and monetary policies, international trade, the Kuala Lumpur Composite Index (KLCI) and credit conditions to provide a total of 17 potential indicators. The potential leading indicators selected significantly affect the movement of the unemployment rate and are reliable sources of data. Following the OECD approach (Gyomai & Guidetti, 2012), the selection of indicators was determined according to three major steps: (i) the choice of the target and candidate leading variable, (ii) data filtering and (iii) data evaluation. Next, the leading indicators were aggregated into a composite leading index and their forecast performance of the unemployment rate was measured.

The major contribution of this study is its development of leading indicators for the labour market in Malaysia with specific application to the unemployment rate. Research related to the development of leading indicators for the labour market in Malaysia has been the subject of long-standing debate. However, to the best of the authors' knowledge, studies solely focusing on developing leading indicators for the unemployment rate in Malaysia remain scarce. In this regard, the development of the leading indicators would assist policy-makers in determining effective policy responses to labour market issues. This study contributes to the labour market literature by offering empirical evidence on developing the leading indicators for the unemployment rate in Malaysia.

Although this paper determines the leading indicators for the unemployment rate, the methodologies developed in this paper can deal with various candidates for the leading indicators and different targeted variables, such as loss of employment (LOE) and employment generation. The unemployment rate was applied as the targeted variable and the 17 candidates for the potential leading indicators were chosen because of the data availability that would enable sufficiently robust observations. It is extremely important to measure fiscal policy variables, in particular, public expenditure and disbursement, as they directly and indirectly influence employment, but they were not available for inclusion in this assessment model.

This paper is structured into five sections. Section 2 provides a review of the related literature, with specific attention given to the leading indicators for the labour market. Section 3 explains the research methodology along with the data sources applied in this study. Section 4 provides the estimation results and Section 5 concludes by providing several policy implications of the study.

Review of Related Studies

In this section, the literature review summarises the importance of developing leading indicators and the research gaps in determining these indicators for the labour market in Malaysia.

Leading indicators studies in economics

Leading indicators have been considered an informative set of tools that reflect future economic conditions since the pioneering work of Mitchell and Burns (1938) and Burns and Mitchell (1946). Their studies combined several selected variables into a composite index to give an overall assessment of the economy. Afterwards, Koopmans (1947) revised the Burns-Mitchell study, focusing on different features of the components and the evaluation and methods needed to find the best indicators. The field has attracted many researchers and practitioners to apply leading indicators in predicting economic directions Puah et al., 2016; Handoko, 2017; Plakandaras et al., 2017; Stundziene et al., 2017

Puah et al. (2016) constructed a composite leading index based on a non-parametric approach to track the macroeconomic environment in Cambodia. The study displays two notable leading variables with an average lead time of several months, namely money supply (M1) and total exportation. Handoko (2017) analysed 24 variables with monthly data from 2010 to 2016 to compile a composite leading index for the Gross Regional Domestic Product of Eastern Indonesia. Plakandaras et al. (2017) utilised dynamic probit and Support Vector Machine (SVM) models to analyse how accurately the leading indicators can forecast United States recessions. Stundziene et al. (2017) examined various candidate leading indicators taken from different categories, such as economics, industry, finance, the real estate market and business expectations, to predict the economic cycles of Lithuania. Iyetomi et al. (2020) studied 62 time series to determine the best-performing leading indicators for analysing business cycles of the United States.

In the Malaysian context, the Department of Statistics Malaysia (DOSM) computes and reports periodically the leading indicators to reflect the economic conditions of the country (Department of Statistics Malaysia, 2020). The DOSM currently suggests seven indicators for constructing a composite leading index: real money supply (M1), the Bursa Malaysia industrial index, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, the number of housing units approved, the expected manufacturing sales value and the number of new companies registered.

Various studies in the Malaysian literature apply leading economic indicators in their research. For example, Izani and Raflis (2004) examined the behaviour of nine leading economic indicators of Malaysia and showed that the indicators provide important information about the economic conditions at state levels. Wong et al. (2012) demonstrated that the performance of the composite leading index in forecasting the real Gross Domestic Product (GDP) is relatively adequate. Lau and Lee

(2015) compared the ability of the equity style index and stock market index to predict the future movement of the composite leading economic index in a multivariate Granger causality framework. They found that the equity style index is more sensitive and performs better in detecting turning points of business cycles.

Recently, several studies have examined the indicator-based forecasting tool from different perspectives in Malaysia. For example, Abu Mansor et al. (2015) developed an early warning indicator to forecast economic vulnerability and monitor macroeconomic risk. Wong et al. (2016) constructed a factor-based business cycle indicator capable of generating the early signals of economic crises, on average up to 4.4 months in advance. Recently, Voon et al. (2020) examined monthly data from 2000 to 2015 to build a composite leading indicator for housing affordability. The study also employed a time-varying Markov switching model to assess the indicator and found that it has a leading period of 9.5 months on average.

Significance of leading indicators in the labour market

The aforementioned leading indicator studies only focus on forecasting economic activity, but recent literature has emphasised the use of the leading index approach in assessing future labour market conditions. This is possible because production output and unemployment are inter-related—the higher the growth in output, the greater the demand for labour and vice-versa. For instance, Atabek et al. (2015) included variables related to the labour market in constructing a composite leading index for economic activity. Among the variables are the number of employees, payments to workers in the manufacturing industry and business tendency survey results regarding expected employment. Guerard et al. (2020) used several leading economic indicators to forecast the unemployment rate of the United States. Given the linkages between the labour market and economic activity indicators, a composite leading index for unemployment can be developed to reveal early signal changes that can be used as a reference resource for policy-making.

The literature survey found that studies of leading indicators for the unemployment rate in Malaysia are scarce, although similar studies in other countries are abundant. One recent study applied leading indicators to predict the state of the labour market in Turkey (Yunculer et al., 2014). The authors analysed 72 series related to the Turkish non-agricultural unemployment rate, searching for composite leading indicators that would reflect future labour market conditions. Later, Tule et al. (2016)

computed a composite leading index for the unemployment rate in Nigeria. The study investigated 16 variables from six categories of indicators: aggregate economic activity, foreign trade, financial and monetary policies, foreign activity, consumer and business confidence and credit. Moreover, Claus (2011) examined 95 variables to construct seven leading indexes for quarterly employment in New Zealand. The study revealed no leading index model that dominates at all forecast horizons, although the indexes show a smaller root mean square error.

Over recent years, several attempts have been made to use internet search data as a leading indicator in predicting the unemployment rate. Chadwick and Sengul (2012) applied Google Trends data to nowcast the monthly non-agricultural unemployment rate for Turkey. D'Amuri and Marcucci (2017) revealed that the Google-based model outperforms other models, improving the forecast horizon in predicting the monthly United States unemployment rate. Nagao et al. (2019) also showed that Google search data performs better in nowcasting the unemployment rate.

Although research on composite leading indicators for the labour market has been undertaken, it is limited to only certain countries. This gap motivated the authors to identify the leading indicators for predicting the unemployment rate in Malaysia and, furthermore, to evaluate the composite leading index performance.

Methodology and Data Sources

In identifying the leading indicators for the unemployment rate, this study applied the approach of the OECD (see Gyomai et al., 2012) that was widely adopted for selecting empirical leading indicators (see, for example, Yunculer et al., 2014; Tule et al., 2016; Handoko, 2017). Methodologically, it involved three major steps: (i) the choice of the target and candidate leading variables, (ii) data filtering and (iii) data evaluation. The first step was to select the target variables and choose the appropriate indicators that could serve the target series. The second step was to filter all the targeted variables with proper filtering methods, such as TRAMO/SEATS and Hodrick-Prescott. The third step assessed each candidate leading series against the target variables using both pairwise correlation and Granger causality techniques, as suggested by Gyomai et al. (2012) and Marcellino (2006), respectively. After the leading indicators had been identified, the indicators were aggregated into a composite index and the forecast performance of the index was measured.

Candidates for leading variable

The first step involved the identification of the target variables and potential leading indicators. In general, the potential leading indicators comprised various short-term indicators that could be informative in inferring the movements of the unemployment rate in Malaysia. Table 1 presents a description of the leading indicator candidates for the unemployment rate in Malaysia. All the listed variables used monthly frequency data, spanning January 2014 to December 2020 (84 observations).

Choice of targeted variable

The targeted variable is the goal variable that the authors wanted to observe and consider as a lagging component. In this study, the focus is on the unemployment rate as the targeted variable. By definition, the unemployment rate is the proportion of the unemployed population compared to the total population of the labour force. Essentially, it includes the unemployed workers in all employment categories and includes employees, employers, the self-employed and unpaid family workers.

Conventionally, the unemployment rate is often used as a key indicator to explain the inter-linkages between labour market outcomes and economic conditions at any point in time. This is due to the high sensitivity between unemployment rates and economic fluctuations. For example, a downturn in the economy would trigger a reduction in job demand, leading to an increase in unemployment. Hence, unemployed people cannot pay taxes and less money would be spent on the economy, resulting in negative economic consequences.

It is important to note that the choice of the targeted variable for the labour market is not limited to the unemployment rate. Other indicators such as loss of employment (LOE), the size of the informal sector, employment generation and the participation rate could also be utilised as variables for monitoring labour market conditions. Nevertheless, these variables could not be considered in this paper because insufficient data observations were available to allow effective modelling.

LOE is a unique variable that can be considered in the future development of leading indicators for the labour market. From the labour market perspective, LOE is a sub-set of the unemployment rate. These indicators are distinct as they are compiled based on different methodologies and coverage. LOE is real-time administrative data maintained by the Office of Employment Insurance System (EIS) and the Social Security Organisation (SOCSO). It captures information about insured people from among the private-sector employees in the formal sector who had lost their jobs (excluding voluntary resignation, expiry of a fixed-term contract and retrenchment due to misconduct). Meanwhile, the unemployment rate is estimated based on survey-based data (i.e., a Labour Force Survey) by the Department of Statistics Malaysia (DOSM) and captures data on the labour force, including employers, employees, own-account workers and unpaid family worker who did not work during the reference week, regardless of whether they are actively or inactively unemployed. Although LOE is a sub-set of unemployment, it provides a good approximation for labour market monitoring purposes

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Candidates for leading indicator variables

A leading indicator is a series of economic data that corresponds to a future movement or change in the targeted variable. It helps to build a broad understanding of the future performance and forecast any change in the targeted variable before it occurs; in this case, the variable is the unemployment rate. The candidate leading variables were selected from a wide range of indicators that can intuitively allow the movement of the unemployment rate to be inferred. As shown in Table 1, the authors identified 17 different candidate leading series that can be grouped under the following six categories:

i. Macroeconomic indicators

Indications of future unemployment trends could be observed through fluctuations in aggregate demand or its components, where employment growth is often expected to precede output growth. This study uses the industrial production index (IPI) as a proxy of aggregate demand conditions.

ii. Foreign trade indicators

In an open economy, foreign trade measures the production growth from the perspective of the exchange of goods, services and capital across countries. Foreign trade in Malaysia is strongly developed due to globalisation and economic liberalisation and comprises a significant proportion of total output and employer growth. The real effective exchange rate (REER), exports (X), imports (M), total trade (XM), real imports of semiconductors (RMSC) and real imports of other basic precious and other non-ferrous metals (RMPM) are among the established indicators employed. REER influences the competitive position of countries, while imports and exports indicate the effects of trade activities on unemployment.

iii. Monetary and financial variables

Monetary and fiscal policies are essential in shaping the direction of economic activity, which accelerates the labour absorption in the economy. Candidate variables that could capture the effects of monetary policy on economic activities are the Kuala Lumpur composite index (KLCI) and money supply (M1[1], M2[2], M3[3]).

iv. Consumer and business confidence indicators

Consumer and business confidence indicators are valuable sources of information that influence the magnitude of the production of output and labour demand. The study uses the consumer price index (CPI) to reflect the expenditure information of individuals, households and businesses. The sales value of manufacturing (MAN) is also employed as another potential indicator.

v. Credit conditions

The availability and cost of credit are drivers of the growth in domestic demand. An increase in domestic demand will ultimately be reflected in a rise in employment, particularly in the labour-intensive small and medium enterprises sub-sector. For example, total loans (LOAN) and the number of housing units approved (HA) could be considered variables that illustrate credit conditions.

vi. Labour market indicators

The labour market indicator is directly related to the supply and demand of labour in the job market. In this regard, the study uses average salaries and wages per employee in the manufacturing sector (SW) and companies on the register at the end of the period (NCR).

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[1] M1, or narrow money, is money supply that is composed of currency in circulation (notes and coins), demand deposits, traveller's cheques and other checkable deposits, which can be immediately converted into currency.

[2] M2, or intermediate money, includes M1 plus savings deposits, short-term time deposits, 24-hour money market funds, certificates of deposit and other time deposits.

[3] M3, or broad money, is defined as M2 plus large time deposits in banks.

Filtering

The second step in finding the most significant empirical leading indicators was filtering the data. Data filtering is needed to eliminate seasonal patterns, outliers and trends that could potentially hinder the true underlying cyclical patterns in the candidate series. The filter process involved the following procedures: seasonal adjustment, outlier detection, de-trending and smoothening and normalisation.

The seasonality of a time series can be considered stochastic or deterministic, depending on how seasonal patterns evolve through times. Stochastic seasonality assumes that seasonality can be represented by a stochastic process, while deterministic seasonality assumes that the seasonal pattern is constant. In this stochastic analysis, constant seasonality is removed because fixed seasonal patterns might obscure the underlying trend of the series.

Table 1 List of target variables and candidates for leading indicators.

No	Description	Variable	Type	Unit	Period (monthly)	Source
1	Unemployment rate	UR	Target	%	2014-2020	DOSM
2	Industrial production index	IPI	Candidate	Index	2014-2020	DOSM
3	Consumer price index	CPI	Candidate	Index	2014-2020	DOSM
4	Total export	X	Candidate	RM million	2014-2020	DOSM
5	Total import	M	Candidate	RM million	2014-2020	DOSM
6	Total trade (X+M)	XM	Candidate	RM million	2014-2020	DOSM
7	Real imports of semiconductors	RMSC	Candidate	RM million	2014-2020	DOSM
8	Real imports of other basic precious & other non-ferrous metals	RMPM	Candidate	RM million	2014-2020	DOSM
9	Sales value of manufacturing	MAN	Candidate	RM million	2014-2020	DOSM
10	Companies on register at end of period	NCR	Candidate	In number	2014-2020	DOSM
11	Total loans	LOAN	Candidate	RM million	2014-2020	BNM
12	No. of housing units approved	HA	Candidate	In number	2014-2020	BNM
13	Average salaries and wages per employee in manufacturing sector	SW	Candidate	RM	2014-2020	DOSM
14	Kuala Lumpur composite index	KLCI	Candidate	Index	2014-2020	DOSM
15	Money supply, M1	M1	Candidate	RM million	2014-2020	BNM
16	Money supply, M2	M2	Candidate	RM million	2014-2020	BNM
17	Money supply, M3	M3	Candidate	RM million	2014-2020	BNM
18	Real effective exchange rates	REER	Candidate	Index	2014-2020	IMF

Note: DOSM, BNM and IMF refer to the Department of Statistics Malaysia, Bank Negara Malaysia and International Monetary Fund, respectively.

As mentioned in sub-section 3.1, this study applied monthly data series, so seasonal adjustment had to be performed. Seasonal adjustment is a procedure that removes the seasonal and calendar variations from a time series that may harm its cyclical movements. This process is essential to standardise the time series as seasonality affects them with different timing and levels of intensity. Hence, the seasonally adjusted data highlighted the remaining components: the irregular, trend and cyclical components.

This study utilised TRAMO/SEAT methods via EViews10 software as the programme is a fully automatic procedure that is flexible yet robust and can handle routine applications to a large number of series. TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) and SEATS (Signal Extraction in ARIMA Time Series) are linked programmes initially developed by Gómez and Maravall (1997) at the Bank of Spain. This method is divided into two main parts, which TRAMO and SEATS will run, respectively. The first part is the pre-adjustment and removal of deterministic effects (i.e., outlier and calendar variations) from the series through a regression model with ARIMA noise. The second part is the decomposition of the time series to estimate and remove seasonal components from the time series. Hence, TRAMO pre-adjusts the series, which is then adjusted by SEATS.

Outlier detection

Outliers are observations in the component series that lie outside the normal range of observations. It is important to identify and remove outliers from the series because they potentially skew statistical measurements and data distributions, leading to a misleading representation of the underlying data. Thus, removing the outliers gives results with a better fit of data and, in turn, more skilful predictions. Through the TRAMO/SEATS seasonal adjustment method, the TRAMO programme incorporates algorithms to automatically detect the location and nature of potential outliers in each series and then correct them.

De-trending and smoothening

De-trending involves removing long-term trends in the data while smoothening keeps the cyclical pattern of the series. For this purpose, the Hodrick-Prescott filter (Hodrick & Prescott, 1997) was applied, which remains one of the most widely used de-trending methods to obtain a smooth estimate of the long-term trend component of a series. For monthly data, the smoothing parameter, λ = 14,400 was used in order to obtain the optimal results.

Normalisation

Data normalisation is the process of rescaling the data to a specific range when the series is associated with large differences in units and scales. This process is essential in comparing phenomena of different size but with the same origin. Hence, all the potential leading indicators must be normalised as they differ in size. The normalisation method developed by Gyomai et al. (2012) was used in this study, where the filtered observation (x) is subtracted from the mean of the filtered series (μ), then divided by the standard deviation (σ) of the filtered series; a value of 100 is added to each observation. Data normalisation (x'), based on the Gyomai and Guidetti method, can be written as follows:

$$x' = \frac{x' - \mu}{\sigma} + 100 \qquad (1)$$

Evaluation of the conformity of selected indicators with the targeted variable

The last step involved evaluating the candidate leading series for their behaviour related to the targeted variable using a set of statistical methods. Two analyses were adopted in this study, the pairwise correlation and Granger causality approaches. Pairwise correlation estimates the cross-correlation structure and correlation coefficient between the candidate variable and the targeted variable, while Granger causality identifies the series that Granger-cause the targeted variable. Then, the candidate series that passed both evaluations were considered the leading indicators for the unemployment rate.

Pairwise correlation

Leading indicators can be determined by investigating the leads and lags of the candidate variables and the correlation between the candidate and targeted variables. This pairwise correlation provides valuable information on the cyclical relationship between the candidate series and the targeted variable. The goal is to find candidate variables that lead the targeted variable and have a highly significant correlation.

Cross-correlation, or lead-lag correlation structure, is an analysis that determines whether there is a causal relationship between two data series (i.e., the targeted variable and the leading indicator). Given two time series: X_t and Y_t, the cross-correlation function can be defined as:

$$Corr\,(\tau) = Corr\,(X_t, Y_{t-\tau}),\ \tau = 0, \pm 1, \pm 2, \ldots, \pm \ell \qquad (2)$$

where Y_t shifted by the time τ, and ℓ is the number of lags included in the estimation. Asymmetry of the cross-correlation function around the zero lag suggests that one time series (X_t) predicts or leads the other time series

(Y_t). *If Corr* (τ) > *Corr* ($-\tau$), this means $X_{t'}$ leads $Y_{t'}$; *Corr* (τ) < *Corr* ($-\tau$) , this means $Y_{t'}$, leads $X_{t'}$.

Furthermore, a correlation coefficient is used to measure the direction and strength of the linear relationship between two data series. It is a measure related to covariance and can be expressed as:

$$Corr\,(X,\,Y) = \frac{Cov\,(X,Y)}{Std\,(x)\;std\,(Y)} \qquad (3)$$

where the covariance of two variables is divided by their standard deviations. In addition, the result coefficients must range between −1 and +1 . A coefficient of −1 implies a perfect negative relationship or weak correlation, while +1 indicates a perfect positive relationship or strong correlation.

Granger causality

The next step in the evaluation process was to evaluate the causality between the targeted variable and the leading variable. Causality is the relationship between cause and effect, whereby independent (candidate) variables are the factors that cause changes in the dependent (target) variable but not the other way around.

Granger causality is a statistical concept of causality or influence in terms of predictability (Granger, 1969). If X_t Granger-causes Y_t then past values of X_t contain information that helps in the prediction of Y_t. A simple Granger causality test involving two stationary series (X_t and Y_t) can be written as:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \qquad (4)$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \mu_t \qquad (5)$$

where ε_t and μ_t are the uncorrelated white-noise series. can equal infinity but, in practice, it is assumed to be finite due to the limited length of the available data.

By assuming that only stationary series are involved, the definition of the simple Granger causality test above indicates that X_t do not Granger-cause Y_t if c_j is zero, as shown in Equation (5); similarly, Y_t do not Granger-cause X_t if b_j is zero, as shown in Equation (4). This means that each variable is independent of the other. If both events occur or b_j and c_j is not zero, this means that there is a feedback or bi-directional causality between X_t and Y_t. Otherwise, there would be one-way or unidirectional Granger causality running from X_t to Y_t or Y_t to Y_t.

Aggregation of leading series into a composite index

Once the leading indicators had been empirically determined, the series was aggregated into a composite leading index and the forecast performance of the index was measured. The leading indicators were aggregated using a simple averaging technique due to its simplicity and practicability. Aggregation of the leading indicators was performed to improve the predictive capacity of the overall index.

Results and discussion

This section discusses the result of each stage of developing the leading indicators for the unemployment rate in Malaysia. The authors used the autoregressive integrated moving average (ARIMA) method for benchmark model regression and the ordinary least square (OLS) method for the composite leading index model regression to compare both forecast performances.

Data filtering

To identify the leading indicators, each pre-selected component series was filtered by sequence—seasonally adjusted, outliers corrected, de-trended, smoothed, turning points detected and normalisation—to reveal the true underlying cyclical pattern of the series.

Any seasonal patterns of the target and each candidate series were removed and the presence of outliers was corrected by performing the TRAMO/SEATS method in EViews10. Afterwards, an internal trend of the series was extracted via the Hodrick-Prescott filter technique and each series was finally normalised, as explained in section 3.2. The results of data filtering are displayed in Figure 1, in which the filtered series provides a seasonally smoother version of the original series. The blue line in Figure 1 represents raw variables; meanwhile, the red line represents filtered variables.

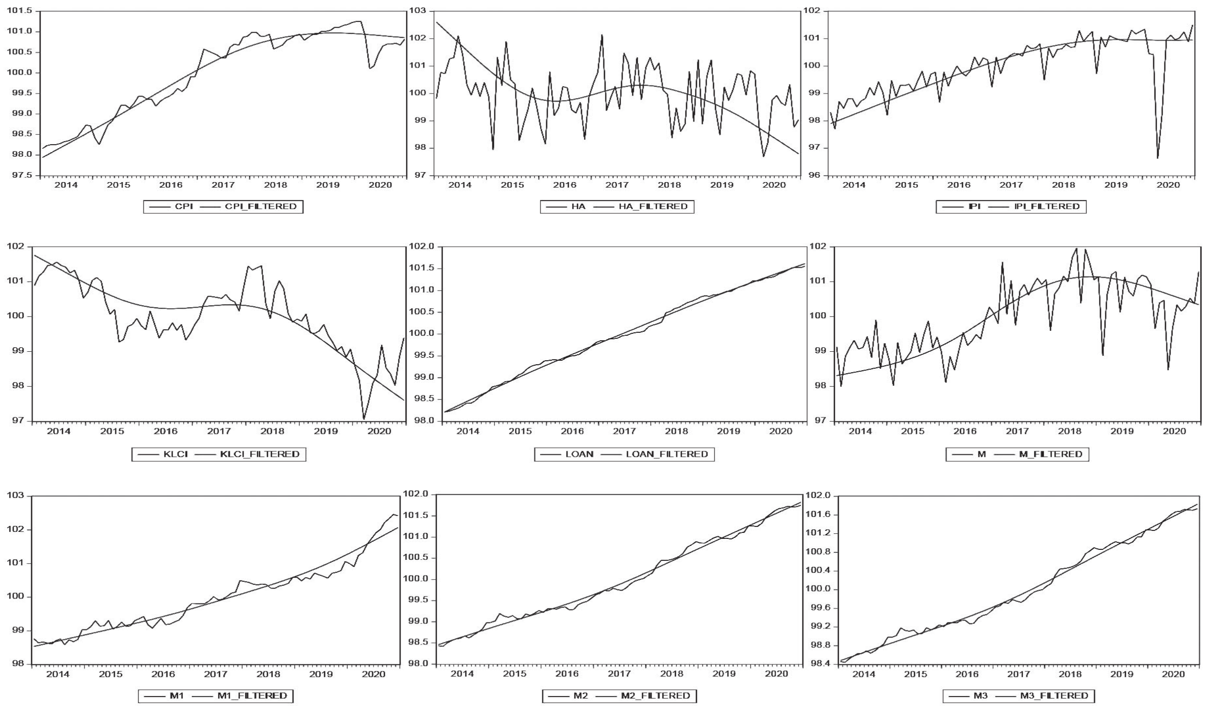


Figure 1 Plots of raw and filtered variables.

Note: Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.

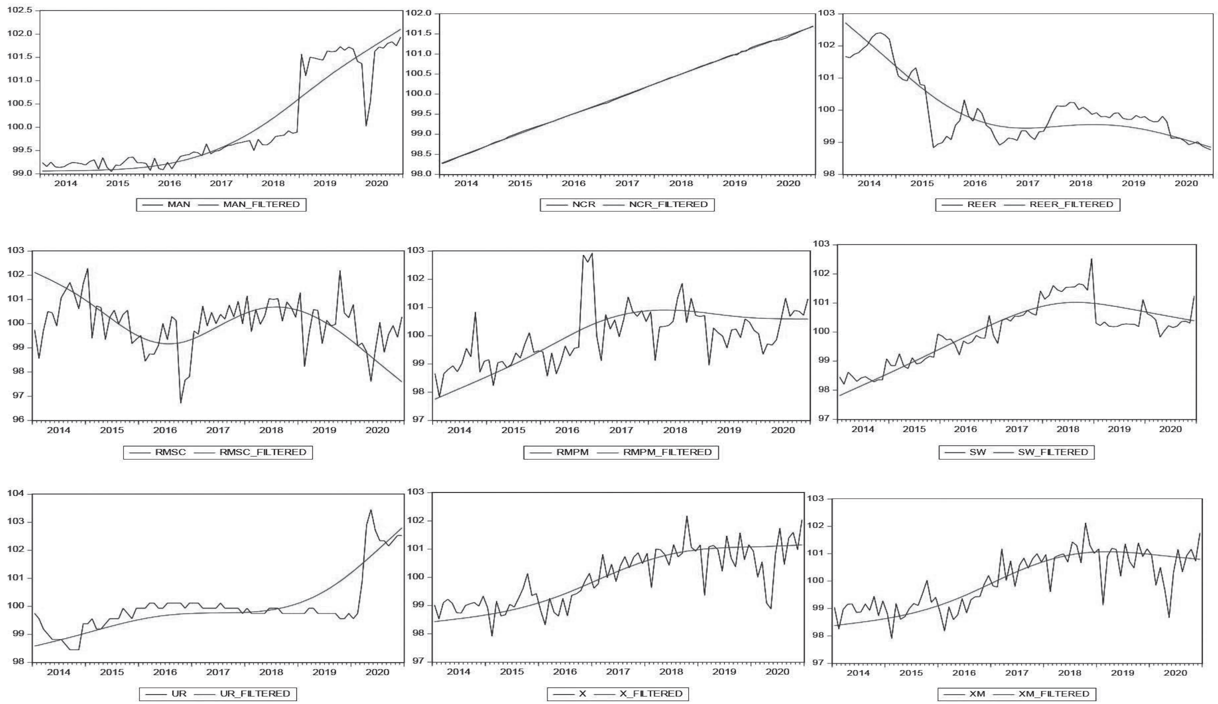


Figure 1 (*cont'd*).

Note: Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.

Data evaluation

Next, the candidate component series was evaluated for its cyclical performance using two statistical analyses, as described in section 3.3. The first evaluation was based on pairwise correlation analyses, which was used to determine the relationship between the candidate leading indicator and the target variable. Secondly, Granger causality was used, which identifies potential leading series that Granger-cause the unemployment rate.

Pairwise correlation analyses

A cross-correlation function was utilised to check whether the pre-selected component series leads or lags the unemployment rate, which follows the condition of $Corr\ (\beta) < Corr\ (-\beta)$. As monthly data frequency was available, the cross-correlation between the series analysed up to 12 lag lengths. In addition, the candidate series was also expected to have a correlation value of not less than 0.55 with the unemployment rate and positive intervals in terms of the correlation structure. Table 2 presents the results of the pairwise correlation between the candidate leading series and the unemployment rate.

Among the given indicators in Table 2, the variables that have significant correlation values and lead the unemployment rate include the sales value of manufacturing (MAN), companies on the register at the end of the period (NCR), total loans (LOAN), the Kuala Lumpur composite index (KLCI), the money supply (M1, M2, M3) and real effective exchange rate (REER). The negative correlation value of the KLCI and REER shows a negative relationship with the unemployment rate.

Table 2 also shows that the consumer price index (CPI), real imports of semiconductors (RMSC), number of housing units approved (HA), and average salaries and wages per employee in the manufacturing sector (SW) lead the unemployment rate. However, due to weak correlation (less than 0.55), these variables could not be considered leading indicators.

Table 2 Pairwise correlation between the unemployment rate and candidate leading indicators.

No	Candidate Leading Indicators	Correlation Value	Correlation Structure
1	IPI	0.3946***	Lag (-7)
2	CPI	0.4887***	Lead (+12)
3	X	0.4112***	Lag (-12)
4	M	0.1874	Lag (-7)
5	XM	0.3243**	Lag (-12)
6	RMSC	-0.4231***	Lead (+7)
7	RMPM	0.3893***	Lag (-12)
8	MAN	0.5546***	Lead (+12)
9	NCR	0.6847***	Lead (+12)
10	LOAN	0.6730***	Lead (+12)
11	HA	-0.3885***	Lead (+8)
12	SW	0.4473***	Lead (+10)
13	KLCI	-0.7387***	Lead (+12)
14	M1	0.7681***	Lead (+12)
15	M2	0.6857***	Lead (+12)
16	M3	0.6809***	Lead (+12)
17	REER	-0.7463***	Lead (+12)

Notes: ***, ** and * refer to the rejection level of the null hypothesis at a significance level of 1%, 5% and 10%, respectively. Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.

Source: Authors' computations.

Granger causality analysis

Before executing the Granger causality analysis, two important steps were undertaken: (1) stationarity and (2) selection of optimal lags. Stationarity is required in a series to remove the risk of spurious regression. Thus, each series was first tested using the Augmented Dickey-Fuller, ADF (Dickey & Fuller, 1981) and Phillips-Perron, PP (Phillips & Perron, 1988) unit root tests, where the presence of the unit root is rejected at a 5% significance level (see Appendix A). The selection of optimal lags for the series was also essential as excessive long lags would decrease the degree of freedom and over-parametrisation; meanwhile, short lags would lead to omitted variables and produce serially correlated errors. In this study, the lag length was selected using the Akaike Information Criterion (AIC), considering 1 to 12 lags for each specification.

The results, as presented in Table 3, show three causalities. The first was a unidirectional causality to the unemployment rate from the total loans (LOAN), Kuala Lumpur composite index (KLCI) and money supply (M1, M2, M3). As these variables were also confirmed as leading the unemployment rate, as shown in Table 3, these candidate series were chosen as the final choice of leading indicators for the unemployment rate in Malaysia. Second, bi-directional causal nexus relationships were found between the unemployment rate and the sales value of manufacturing (MAN), real imports of other basic precious and other non-ferrous metals (RMPM) and companies on the register at the end of the period (NCR). Third, a unidirectional causality was identified from the unemployment rate to the industrial price index (IPI), consumer price index (CPI), total exports (X), total imports (M), total trade (XM), total loans (LOAN) and number of housing units approved (HA). The second and third causalities were exempted from the selection of final leading indicators as they were irrelevant.

Only a causality that runs from the candidate leading series to the unemployment rate was considered a leading indicator. Variables with bi-directional and unidirectional causality from the unemployment rate were excluded because they were unsuitable as leading indicators. The existence of bi-directional causality results in a biased composite leading index, while causality running from the unemployment rate indicates the leading indicator is a lag variable.

Table 3 Granger causality between the target unemployment rate and candidate leading indicators.

No	Granger Causal Relations	Optimal Lag (Criteria: AIC)	Chi-Sq. Stat	P-values
1	IPI does not Granger cause UR	12	9.724	0.6402
	UR does not Granger cause IPI		40.6397	0.0001
2	CPI does not Granger cause UR	2	3.849	0.1460
	UR does not Granger cause CPI		7.5682	0.0227
3	X does not Granger cause UR	3	1.1196	0.7723
	UR does not Granger cause X		22.6703	0.000
4	M does not Granger cause UR	3	2.8873	0.4093
	UR does not Granger cause M		16.4694	0.0009
5	XM does not Granger cause UR	3	1.6285	0.6529
	UR does not Granger cause XM		21.8706	0.0001
6	RMSC does not Granger cause UR	2	0.2941	0.8633
	UR does not Granger cause RMSC		3.6447	0.1616
7	RMPM does not Granger cause UR	2	4.7158	0.0946
	UR does not Granger cause RMPM		6.6618	0.0358
8	MAN does not Granger cause UR	2	5.6415	0.0596
	UR does not Granger cause MAN		5.3126	0.0702
9	NCR does not Granger cause UR	2	6.0793	0.0479
	UR does not Granger cause NCR		13.4612	0.0012
10	LOAN does not Granger cause UR	2	5.7991	0.055
	UR does not Granger cause LOAN		1.4673	0.4802
11	HA does not Granger cause UR	3	3.0002	0.3916
	UR does not Granger cause HA		15.3353	0.0016
12	SW does not Granger cause UR	3	2.2871	0.515
	UR does not Granger cause SW		2.3971	0.4942
13	KLCI does not Granger cause UR	2	28.3369	0.000
	UR does not Granger cause KLCI		3.1788	0.2041
14	M1 does not Granger cause UR	2	6.647	0.036
	UR does not Granger cause M1		1.5449	0.4619
15	M2 does not Granger cause UR	2	6.8405	0.0327
	UR does not Granger cause M2		0.3033	0.8593
16	M3 does not Granger cause UR	2	7.1844	0.0275
	UR does not Granger cause M3		0.251	0.8820
17	REER does not Granger cause UR	2	4.1273	0.1270
	UR does not Granger cause REER		1.8127	0.4040

Note: ***, ** and * refer to the rejection level of the null hypothesis at a significance level of 1%, 5% and 10%, respectively. Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total exports, total imports, total trade, real imports of semiconductors, real imports of other basic precious and other non-ferrous metals, sales value of manufacturing, companies on the register at the end of the period, total loans, no. of housing units approved, average salaries and wages per employee in the manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3 and real effective exchange rates, respectively.

Source: Authors' computations.

Measuring the forecast performance of composite leading indicators

Finally, the study investigated the forecast performance of the leading indicators, KLCI, LOAN and M21[1], by constructing a composite leading index. These leading variables were aggregated into the index using simple averaging following the OECD approach (Gyomai et al., 2012). However, simple average aggregation implicitly implies that an index is weighted by its standard deviations since the series are normalised by their standard deviations (see section 3.2).

Table 4 summarises the estimation results from the benchmark and composite leading index model of the unemployment rate for in-sample and out-of-sample forecasting. The unemployment rate was modelled as an AR(3) autoregressive process and a constant term as a benchmark, while for the leading index model, a 1-period lag of the UR and CLI was included. In forecasting the unemployment rate, both in-sample and out-of-sample forecasting was implemented, based on the parameters estimated over 2014:1 to 2020:12 and 2014:1 to 2020:6, respectively.

[1] M2 can be replaced by M1 and M3 as the variables also included as leading indicators.

Table 4 Benchmark and composite leading index model estimation for in-sample and out-of-sample forecasting.

Sample	**In-sample forecasting**			**Out-of-sample forecasting**		
	2014:1 to 2020:12			**2014:1 to 2020:6**		
Variable	**Coefficient**	**t-Statistic**	**P-value**	**Coefficient**	**t-Statistic**	**P-value**
Panel A. Benchmark Model.						
C	100.5917	89.4056	0.0000	100.1779	109.7297	0.0000
AR(3)	0.9946	25.0930	0.0000	0.9937	21.7457	0.0000
R-squared	0.9595			0.9497		
Adjusted R-squared	0.9585			0.9484		
Panel B. Composite Leading Index Model.						
C	-0.7873	-0.5775	0.5653	-0.4476	-0.3334	0.7398
NUR(-1)	1.0503	178.6978	0.0000	1.0600	115.4983	0.0000
CLI	-0.0419	-2.5529	0.0126	-0.0550	-3.1708	0.0022
R-squared	0.9994			0.9989		
Adjusted R-squared	0.9994			0.9989		

Note: AR, NUR and CLI refer to the autoregressive, normalised unemployment rate and composite leading index, respectively.

Source: Authors' computations.

The forecast performance can be measured by the root mean square (RMSE), mean absolute error (MAE), mean absolute per cent error (MAPE) and Theil inequality (Theil) of the forecasts relative to the unemployment rate. Comparing the forecast performance measurements for the in-sample and out-of-sample, the forecasting model results, as shown in Table 5, reveals that the composite leading index forecasting model performed better than the benchmark forecasting model. This shows that the CLI is reliable in predicting future cycles of the unemployment rate. The evaluation graphs of the benchmark forecasting model and composite leading index forecasting model for the in-sample and out-of-sample scores can be referred to in Appendix B.

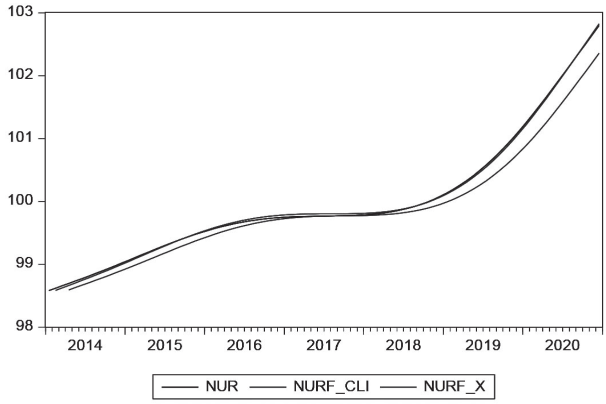
Table 4 Evaluation of in-sample and out-of-sample forecasting.

Models	In-Sample forecasting				Out-of-sample forecasting			
	RMSE	MAE	MAPE	Theil	RMSE	MAE	MAPE	Theil
UR_X	0.1998	0.1458	0.1447	0.0010	0.2106	0.1478	0.1466	0.0010
UR_CLI	0.0246	0.0220	0.0220	0.0001	0.0256	0.0227	0.0227	0.0001

Note: RMSE, MAE, MAPE and Theil refer to the root mean square error, mean absolute error, mean absolute per cent error and Theil inequality, respectively.

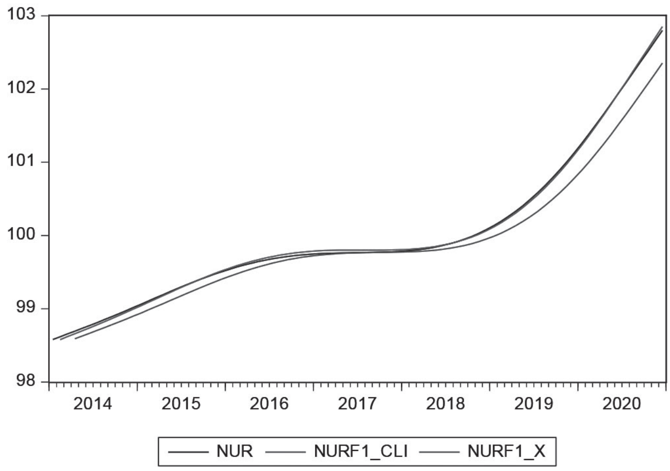
Source: Authors' computations.

Figure 2 and Figure 3 compare the track of the normalised actual unemployment rate with the normalised benchmark forecasted unemployment rate, as well as the normalised forecasted unemployment rate with the composite leading index for the in-sample and out-of-sample forecasts. The blue, red and green lines represent the normalised actual unemployment rate, normalised benchmark forecasted unemployment rate and normalised forecasted unemployment rate with composite leading index, respectively. In Figure 2, it can be observed that the cyclical of NURF_CLI tracks the NUR more closely and accurately compared to the NURF_X. Similarly, Figure 2 also shows that NURF1_CLI tracks the NUR better than NURF1_X. Both results indicate that the leading indicators contain adequate information with which to anticipate the turning points of the unemployment rate cycles in Malaysia. The collected normalised and forecasted data are given in Appendix C.



Source: Authors' computations.

Figure 2 Evolution of the actual unemployment rate (NUR), in-sample normalised forecasted unemployment rate with composite leading index (NURF_CLI) and in-sample normalised benchmark forecasted unemployment rate (NURF_X).



Source: Authors' computations.

Figure 3 Evolution of the actual unemployment rate (NUR), out-of-sample normalised forecasted unemployment rate with composite leading index (NURF1_CLI) and out-of-sample normalised benchmark forecasted unemployment rate (NURF1_X).

Conclusion and policy implications

This study aimed to develop reasonable accurate, reliable and timely signals related to the set of leading indicators for the unemployment rate in Malaysia. By following the standard methodology in the literature, the identification of leading indicators involved three main phases, namely the choice of target and candidate leading variable, data filtering and data evaluation. Among the 16 leading indicator candidates, the study findings indicate that the Kuala Lumpur composite index (KLCI), total loans (LOAN) and money supply (M1, M2, M3) are the leading indicators for the unemployment rate in Malaysia. It was also found that the composite leading index significantly outperformed the benchmark forecasting model for both in-sample and out-of-sample forecasting.

In relation to the labour market, this paper offers three policy implications. Firstly, leading indicators are a convenient and quick set of tools that can help develop responsive policy-making. The existence of leading indicators can remove at least one month of lag in the unemployment rate due to its lead nature, as it provides faster information about the labour market movement. Hence, the timely signal offers valuable input for the government to allocate resources and funding at the right time to mitigate labour market issues.

Secondly, the leading indicators can provide an early signal system to the Active Labour Market Policy (ALMP) for attenuating unemployment. ALMP approaches can be described as public interventions in the labour market that aim to facilitate its efficient functioning and correct disequilibria, and which can be distinguished from other general employment policy interventions in that they act selectively to favour particular groups in the labour market. Interventions are divided into *measures*, *services* and *supports*. Leading indicators support the information that is useful for the *measures* approach to combating cyclical and structural unemployment and promoting employment.

Thirdly, monetary policy is highly sensitive to labour market movements. The monetary leading indicators provide valuable inputs for the authorities to use in making policy interventions. They influence the commodities and alleviate financial pressures that affect businesses. Monetary policy instruments, such as the overnight policy rate (OPR), can influence the liquidity in the market. A reduction in the OPR means lower borrowing costs and greater money to spend, hence more investment and aggregate domestic demand. This can help in attenuating unemployment and thus boosting economic growth in Malaysia.

Although the findings on leading indicators are most relevant to monetary-policy variables, this does not imply that fiscal-policy variables are insensitive to the movement of unemployment rates. The fact that this study was unable to include fiscal-policy variables in the models was due to data unavailability. It is extremely important to measure fiscal-policy variables, in particular, public expenditure and disbursement, as they directly and indirectly influence employment. The methodologies and approaches provided in this paper can easily be updated once monthly fiscal data is available.

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All remaining errors are the sole responsibility of the authors.

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Appendix A Unit Root Test Results.

Variable	Level		First Difference	
	Intercept	**Trend and Intercept**	**Intercept**	**Trend and Intercept**
Panel A. Augmented-Dickey Fuller Test.				
UR	-1.0451	-2.7696	-6.3104***	-6.3272***
IPI	-2.3007	1.0943	-3.3268**	-4.0025**
CPI	-1.7256	-1.2725	-7.0705***	-7.2199***
X	-0.7121	-3.1992*	-2.9994**	-2.9689
M	-1.9631	-2.5122	-2.9118**	-3.1079
XM	-0.9423	-2.7442	-3.0128**	-3.0767
RMSC	-5.3747***	-5.3880***	-5.9597***	-5.9133***
RMPM	-1.4395	-5.1343***	-3.4782**	-3.4797**
MAN	-0.4175	-3.0415	-11.4346***	-11.4273***
NCR	-2.9151**	-2.2118	-4.9809***	-12.2876***
LOAN	-2.6971*	-1.2622	-8.1242***	-8.7779***
HA	-6.7177***	-6.8962***	-6.8242***	-6.7897***
SW	-1.4792	-1.7344	-1.9562	-2.1228
KLCI	-1.89	-2.4511	-6.6902***	-6.6241***
M1	0.8416	-1.9327	-1.3287	-1.6137
M2	0.0129	-1.944	-5.3497***	-5.3201***
M3	0.1331	-1.8384	-5.4244***	-5.4036***
REER	-1.7596	-2.1527	-6.9406***	-6.9024***
Panel B. Phillips-Perron Test.				
UR	-0.8772	-2.2862	-6.1145***	-6.1429***
IPI	-3.7874***	-5.7417***	-20.2493***	-21.1733***
CPI	-1.7583	-1.3314	-6.4371***	-6.5161***
X	-2.9691**	-6.3380***	-14.846***	-16.0327***
M	-3.8565***	-6.1535***	-19.1851***	-19.142***
XM	-3.1343**	-6.1655***	-15.9559***	-15.8543***
RMSC	-5.5066***	-5.5113***	-15.0027***	-14.9202***
RMPM	-3.9107***	-5.1009***	-17.709***	-18.838***
MAN	-0.4176	-2.8316	-11.7151***	-11.9418***
NCR	-3.3783**	-1.888	-10.6492***	-12.0148***
LOAN	-2.5309	-1.3835	-8.2647***	-8.7857***
HA	-6.7131***	-6.9137***	-35.1396***	-35.0081***
SW	-1.6359	-2.5686	-13.2005***	-13.1961***

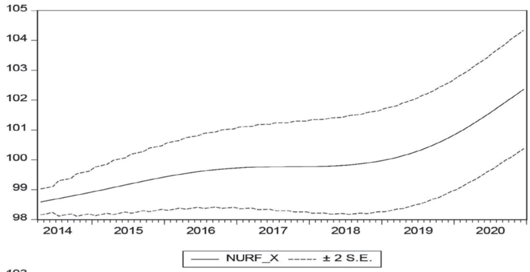
Appendix A (*cont'd*)

Variable	Level		First Difference	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
KLCI	-1.8322	-2.3981	-8.4186***	-8.3358***
M1	1.0766	-2.1726	-9.8428***	-9.9717***
M2	-0.2518	-2.3459	-8.9867***	-8.9322***
M3	-0.1684	-2.2583	-9.0676***	-9.0091***
REER	-1.6412	-1.9986	-6.9483***	-6.9101***

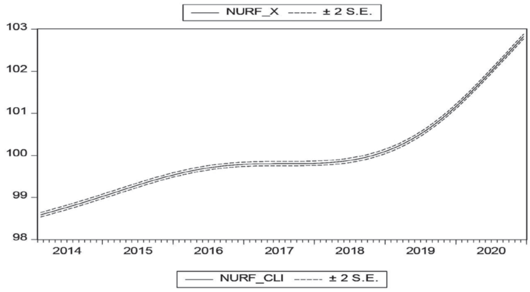
Note: ***, ** and * refer to the rejection level of the null hypothesis at a significance level of 1%, 5% and 10%, respectively. Variables UR, IPI, CPI, X, M, XM, RMSC, RMPM, MAN, NCR, LOAN, HA, SW, KLCI, M1, M2, M3, and REER denote unemployment rate, industrial production index, consumer price index, total export, total import, total trade, real imports on semi-conductor, real imports of other basic precious & other non-ferrous metals, sales value of manufacturing, companies on register at end of period, total loans, no. of housing units approved, average salaries and wages per employee in manufacturing sector, Kuala Lumpur composite index, money supply M1, money supply M2, money supply M3, and real effective exchange rates, respectively.

Source: Authors' computations.

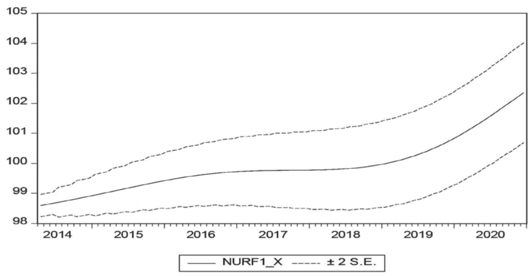
Appendix B. Evaluation Graphs of in-Sample and Out-of-Sample Benchmark Forecasting Model and Composite Leading Index Forecasting Model



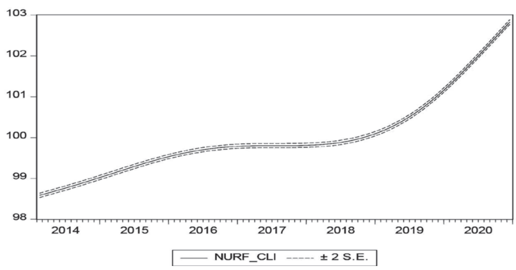
Forecast: NURF_X	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M04 2020M12	
Included observations: 81	
Root Mean Squared Error	0.199767
Mean Absolute Error	0.145830
Mean Abs. Percent Error	0.144663
Theil Inequality Coefficient	0.000999
Bias Proportion	0.532801
Variance Proportion	0.314540
Covariance Proportion	0.152659
Theil U2 Coefficient	2.915531
Symmetric MAPE	0.144857



Forecast: NURF_CLI	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M02 2020M12	
Included observations: 83	
Root Mean Squared Error	0.024642
Mean Absolute Error	0.022036
Mean Abs. Percent Error	0.022042
Theil Inequality Coefficient	0.000123
Bias Proportion	0.000000
Variance Proportion	0.000156
Covariance Proportion	0.999917
Theil U2 Coefficient	0.363759
Symmetric MAPE	0.022042



Forecast: NURF1_X	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M04 2020M12	
Included observations: 81	
Root Mean Squared Error	0.201637
Mean Absolute Error	0.147798
Mean Abs. Percent Error	0.146623
Theil Inequality Coefficient	0.001008
Bias Proportion	0.537277
Variance Proportion	0.313017
Covariance Proportion	0.149704
Theil U2 Coefficient	2.942910
Symmetric MAPE	0.146821



Forecast: NURF_CLI	
Actual: NUR	
Forecast sample: 2014M01 2020M12	
Adjusted sample: 2014M02 2020M12	
Included observations: 83	
Root Mean Squared Error	0.024642
Mean Absolute Error	0.022036
Mean Abs. Percent Error	0.022042
Theil Inequality Coefficient	0.000123
Bias Proportion	0.000000
Variance Proportion	0.000156
Covariance Proportion	0.999917
Theil U2 Coefficient	0.363759
Symmetric MAPE	0.022042

Note: Variables NURF_X, NURF_CLI, NURF1_X, and NURF1_CLI denote in-sample normalised benchmark forecasted unemployment rate, in-sample normalised forecasted unemployment rate with composite leading index, out-of-sample normalised benchmark forecasted unemployment rate, and out-of-sample normalised forecasted unemployment rate with composite leading index, respectively.

Source: Authors' computations.

Appendix C Normalised and Forecasted Data, January 2014 - December 2020.

Year	Month	Normalised Data					Forecasted Data			
		NUR	NKLCI	NLOAN	NM2	CLI	NURF _X	NURF _CLI	NURF1 _X	NURF1 _CLI
2014	January	98.58	101.76	98.21	98.46	99.48	-	-	-	-
2014	February	98.62	101.69	98.26	98.49	99.48	-	98.58	-	98.58
2014	March	98.66	101.62	98.31	98.53	99.48	-	98.62	-	98.62
2014	April	98.69	101.55	98.35	98.56	99.49	98.59	98.66	98.59	98.66
2014	May	98.73	101.48	98.40	98.59	99.49	98.63	98.70	98.63	98.70
2014	Jun	98.77	101.41	98.45	98.63	99.49	98.67	98.74	98.67	98.74
2014	July	98.81	101.34	98.49	98.66	99.50	98.70	98.78	98.70	98.78
2014	August	98.85	101.27	98.54	98.69	99.50	98.74	98.82	98.74	98.82
2014	September	98.89	101.20	98.59	98.73	99.50	98.78	98.87	98.78	98.86
2014	October	98.93	101.13	98.64	98.76	99.51	98.82	98.91	98.82	98.91
2014	November	98.98	101.06	98.68	98.79	99.51	98.86	98.95	98.86	98.95
2014	December	99.02	100.99	98.73	98.82	99.52	98.90	99.00	98.90	99.00
2015	January	99.06	100.93	98.78	98.86	99.52	98.94	99.04	98.94	99.04
2015	February	99.11	100.86	98.82	98.89	99.52	98.98	99.09	98.98	99.09
2015	March	99.15	100.80	98.87	98.92	99.53	99.03	99.13	99.03	99.13
2015	April	99.19	100.73	98.91	98.95	99.53	99.07	99.18	99.07	99.18
2015	May	99.24	100.67	98.96	98.98	99.54	99.11	99.22	99.11	99.22
2015	Jun	99.28	100.62	99.00	99.02	99.55	99.16	99.27	99.16	99.27
2015	July	99.32	100.56	99.05	99.05	99.55	99.20	99.31	99.20	99.31
2015	August	99.36	100.51	99.09	99.08	99.56	99.24	99.36	99.24	99.36
2015	September	99.40	100.46	99.14	99.11	99.57	99.28	99.40	99.28	99.40
2015	October	99.44	100.42	99.18	99.14	99.58	99.33	99.44	99.32	99.44
2015	November	99.47	100.38	99.23	99.17	99.59	99.37	99.48	99.36	99.48
2015	December	99.51	100.35	99.27	99.21	99.61	99.40	99.51	99.40	99.52
2016	January	99.54	100.32	99.31	99.24	99.62	99.44	99.55	99.44	99.55
2016	February	99.57	100.29	99.35	99.27	99.64	99.48	99.58	99.48	99.58
2016	March	99.60	100.27	99.40	99.30	99.66	99.51	99.61	99.51	99.62
2016	April	99.62	100.26	99.44	99.34	99.68	99.54	99.64	99.54	99.64
2016	May	99.64	100.24	99.48	99.37	99.70	99.57	99.67	99.57	99.67
2016	Jun	99.67	100.23	99.52	99.40	99.72	99.60	99.69	99.60	99.69
2016	July	99.68	100.23	99.56	99.44	99.74	99.63	99.71	99.62	99.71
2016	August	99.70	100.23	99.60	99.47	99.77	99.65	99.73	99.65	99.73
2016	September	99.71	100.23	99.64	99.51	99.79	99.67	99.75	99.67	99.75
2016	October	99.73	100.24	99.68	99.55	99.82	99.69	99.76	99.69	99.76

Appendix C (*cont'd*)

Year	Month	Normalised Data					Forecasted Data		
		NUR	NKLCI	NLOAN	NM2	CLI	NURF _X	NURF _CLI	NURF1 _X
2016	November	99.74	100.24	99.72	99.58	99.85	99.70	99.77	99.70
2016	December	99.74	100.25	99.77	99.62	99.88	99.72	99.78	99.72
2016	November	99.74	100.24	99.72	99.58	99.85	99.70	99.77	99.70
2016	December	99.74	100.25	99.77	99.62	99.88	99.72	99.78	99.72
2017	March	99.76	100.29	99.89	99.74	99.97	99.75	99.80	99.75
2017	April	99.76	100.30	99.93	99.78	100.00	99.76	99.80	99.75
2017	May	99.76	100.31	99.97	99.82	100.04	99.76	99.80	99.76
2017	Jun	99.77	100.32	100.01	99.86	100.07	99.76	99.80	99.76
2017	July	99.77	100.33	100.05	99.91	100.10	99.77	99.80	99.76
2017	August	99.77	100.34	100.09	99.95	100.13	99.77	99.80	99.77
2017	September	99.77	100.34	100.13	100.00	100.16	99.77	99.80	99.77
2017	October	99.77	100.34	100.17	100.04	100.18	99.77	99.80	99.77
2017	November	99.78	100.33	100.21	100.09	100.21	99.77	99.80	99.77
2017	December	99.78	100.33	100.26	100.13	100.24	99.77	99.81	99.77
2018	January	99.79	100.31	100.30	100.18	100.26	99.78	99.81	99.77
2018	February	99.80	100.29	100.34	100.22	100.28	99.78	99.82	99.78
2018	March	99.81	100.27	100.38	100.27	100.31	99.79	99.83	99.78
2018	April	99.82	100.24	100.42	100.32	100.33	99.79	99.84	99.79
2018	May	99.84	100.20	100.46	100.37	100.34	99.80	99.85	99.80
2018	Jun	99.86	100.16	100.50	100.41	100.36	99.81	99.87	99.81
2018	July	99.89	100.11	100.54	100.46	100.37	99.83	99.89	99.82
2018	August	99.91	100.06	100.58	100.51	100.38	99.84	99.92	99.84
2018	September	99.95	100.00	100.62	100.56	100.39	99.86	99.95	99.86
2018	October	99.99	99.94	100.66	100.61	100.40	99.89	99.98	99.89
2018	November	100.03	99.87	100.70	100.65	100.41	99.92	100.02	99.92
2018	December	100.08	99.80	100.74	100.70	100.41	99.95	100.07	99.95
2019	January	100.13	99.72	100.78	100.75	100.42	99.99	100.12	99.99
2019	February	100.19	99.64	100.82	100.80	100.42	100.03	100.17	100.03
2019	March	100.26	99.56	100.86	100.84	100.42	100.08	100.24	100.08
2019	April	100.33	99.47	100.90	100.89	100.42	100.13	100.31	100.13
2019	May	100.41	99.38	100.93	100.94	100.42	100.19	100.38	100.19
2019	Jun	100.49	99.29	100.97	100.98	100.42	100.26	100.46	100.26
2019	July	100.58	99.20	101.01	101.03	100.41	100.33	100.55	100.33

Appendix C (*cont'd*)

Year	Month	Normalised Data							
		NUR	NKLCI	NLOAN	NM2	CLI	NURF _CLI	NURF1 _X	NURF1 _CLI
2019	August	100.68	99.11	101.05	101.08	100.41	100.65	100.41	100.65
2019	September	100.78	99.01	101.08	101.12	100.41	100.75	100.49	100.75
2019	October	100.89	98.91	101.12	101.17	100.40	100.86	100.58	100.86
2019	November	101.01	98.82	101.16	101.22	100.40	100.97	100.68	100.98
2019	December	101.13	98.72	101.19	101.26	100.39	101.10	100.78	101.10
2020	January	101.26	98.62	101.23	101.31	100.39	101.22	100.89	101.23
2020	February	101.39	98.53	101.26	101.36	100.38	101.36	101.00	101.37
2020	March	101.52	98.43	101.30	101.40	100.38	101.49	101.12	101.50
2020	April	101.66	98.34	101.33	101.45	100.37	101.63	101.25	101.65
2020	May	101.80	98.24	101.37	101.50	100.37	101.78	101.38	101.79
2020	Jun	101.94	98.15	101.40	101.54	100.37	101.93	101.51	101.94
2020	July	102.08	98.06	101.44	101.59	100.36	102.07	101.65	102.09
2020	August	102.22	97.97	101.48	101.64	100.36	102.22	101.79	102.24
2020	September	102.37	97.88	101.51	101.68	100.36	102.37	101.93	102.39
2020	October	102.51	97.79	101.55	101.73	100.35	102.52	102.07	102.55
2020	November	102.66	97.70	101.58	101.78	100.35	102.68	102.21	102.70
2020	December	102.80	97.61	101.62	101.82	100.35	102.83	102.35	102.85
2020	October	102.51	97.79	101.55	101.73	100.35	102.52	102.07	102.55
2020	November	102.66	97.70	101.58	101.78	100.35	102.68	102.21	102.70
2020	December	102.80	97.61	101.62	101.82	100.35	102.83	102.35	102.85

Note: Variables NUR, NKLCI, NLOAN, NM2, CLI, NURF_X, NURF_CLI, NURF1_X, and NURF1_CLI denote normalised unemployment rate, normalised Kuala Lumpur composite index, normalised total loans, normalised money supply M2, composite leading index, in-sample normalised benchmark forecasted unemployment rate, in-sample normalised forecasted unemployment rate with composite leading index, out-of-sample normalised benchmark forecasted unemployment rate, and out-of-sample normalised forecasted unemployment rate with composite leading index, respectively.

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Measuring the Impact of Ending the Wage Subsidy Programme on Employment

Muhamad Zharif Luqman Hashim[a,b*], Zahira Adila Zahuri[a,b], Mazzatul Raudah Abdul Halim[a,c], Nur Azreen Mokhyi[a,b], and Ahmad Hakiim Jamaluddin[d]

Abstract

Motivation and Aims: The coronavirus pandemic (COVID-19) has undeniably had an enormous impact on the production sectors and labour market worldwide, and Malaysia is no exception. In response to this issue, the Malaysian government has introduced several economic rescue programmes, including a temporary Wage Subsidy Programme (WSP) to help firms retain their employees. WSP has contributed significantly to workforce recovery but only providing short-term assistance. The ending of the WSP leads to a critical policy debate on how it affects employees and unemployment rates. This paper aims to examine the potential impacts of ending the WSP on employment in Malaysia.

Methods and Materials: Descriptive and inferential statistics were carried out on 469 firms selected throughout the country still receiving WSP benefits. An online survey was undertaken using a questionnaire for about one month, consisting of 12 questions covering the firm's background information, employability of future employees, and business situation.

Key Finding: The findings showed that ending the WSP would unlikely increase unemployment rates and the net effects of the WSP on employment are positive.

Policy Implication: This study provides a "prima-facie" case towards implementing a targeted WSP for 2021 as the results indirectly indicate the positive signs of labour market recovery.

Keywords: COVID-19; Temporary wage subsidy program; Employment; Labor market

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[a]EIS-UPMCS Centre for Future Labour Market Studies, Menara PERKESO, Putrajaya, Malaysia
[b]School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia
[c]Putra Business School, Universiti Putra Malaysia, Serdang, Malaysia
[d]School of Mathematics and Statistics, University of New South Wales
*Corresponding author:zharifluqman@gmail.com

Introduction

The unprecedented nature of the Coronavirus 2019-nCoV (COVID-19) pandemic has brought a sudden disruption to the production sectors of all infected countries and labour markets. In response to the pandemic, the governments of almost all infected countries have restricted economic activities and people movements to protect the population from this life-threatening disease. As a result of the restriction control measures in place, the International Monetary Fund (2020) has declared that this pandemic has contributed to a stagnation of the global economy, predicted to be greater than the subprime economic crisis in 2008 and the Asian financial crisis of 1997. In addition, this crisis has impacted a total of 3.3 billion employees globally (International Labour Organisation, 2020a). Likewise, the spread of the virus across Asia and the Pacific region is anticipated to significantly impact employment losses.

Malaysia is not an exception, given that this pandemic has sparked the most prominent employment crisis experienced in decades. Statistics reveal that the amount of unemployed in Malaysia has risen significantly from the normal unemployment rate of 3.5% or 546.6 thousand in the first quarter to 5.1% or 791.8 thousand in the second quarter of 2020 (Department of Statistics Malaysia, 2020). Loss of employment numbers for those covered under the Office of Employment Insurance System has also increased remarkably from 15,602 in the first quarter to 34,806 in the second quarter of 2020 (Social Security Organisation, 2020a). Thousands of businesses have also been significantly impacted since they needed to pause their business operations indefinitely and retrench and decrease their employee numbers. Due to the reality that some individuals have briefly been cut off and others indefinitely shut-off, certain people cannot gain employment, leading to the lack of a primary source of income.

In response to the labour market disruption, specific temporary programmes have been designed to mitigate unemployment in sustaining jobs and aiding companies to retain a significant number of employees (International Labour Organisation, 2020b). Under the Economic Stimulus Package of PRIHATIN, the government of Malaysia has implemented several remedial measures, including the temporary Wage Subsidy Programme (WSP), Employment Retention Programme (ERP), and Hiring Incentive Programme (HIP). Among these programmes, the WSP is the most extensive financial assistance programme offered to employers for local employees earning RM4,000 or less, which commenced on 1st April 2020 (see Social Security Organisation, 2020b). It is important to note that a temporary WSP has also been adopted in many outbreak-affected countries with different terminologies used to represent it, such as *Job Support Scheme* in Singapore, *Temporary Emergency Bridging Measure* in the Netherlands and *Emergency Wage Subsidy* in Canada.

The WSP ended in September 2020 and benefiting 2.7 million employees (Social Security Organisation, 2020c). Under this WSP, the government provided employers with six months of assistance to retain employees. The WSP was further extended for three months under the WSP 2.0 scheme, ending by 31st December 2020. As of 13th November 2020, WSP and WSP 2.0 contributed to retaining 3.4 million employees and benefited 400,350 employers. Altogether, these two programmes involved RM 17.7 billion of direct disbursement from the government. In addition, these programmes have contributed to a positive change in Malaysia's labour market as the unemployment rate decreased to 4.7% in the third quarter of 2020 relative to the second quarter of 2020 (Department of Statistics Malaysia, 2020).

However, ending the WSP leads to a critical policy question: "How does it affect the employees and unemployment rates?". This paper documents the findings obtained from a snap employer survey, examining the potential impacts of ending the WSP on employees and unemployment rates. In the snap survey, 1,700 samples of targeted firms are extracted from the firm "population" currently receiving the WSP in the Social Security Organisation (SOCSO) data system. The survey is performed employing an online survey, commencing for about a month from 30th October 2020 to 22nd November 2020. Our contribution to the scientific knowledge in this field is essentially an empirical assessment of ending the WSP, which is limited in the current literature. This paper is also expected to provide policy responses to the decision of ending the WSP. For example, the results provide a "prima-facie" case to implementing a targeted WSP in 2021 because ending the current WSP is unlikely to increase the unemployment rates.

In light of the above, the paper is structured into five sections, with the empirical literature review is discussed in the next section. Section 3 focuses on the methodologies for data collection and data analyses. Section 4 presents the most important findings obtained from the descriptive statistics and econometric model. Finally, section 5 provides a summary and concluding remarks.

Literature Review and Design of a Temporary Wage Subsidy

This section reviews the related literature on a temporary wage subsidy, aiming to provide justification for the novelty of our study. Our review indicates that there is limited evidence on the impacts of ending a temporary wage subsidy with the particular application during the COVID-19 crisis (Cassells & Duncan, 2020; Hubbard & Strain, 2020; Faulkender et al., 2020), although there are many countries that have implemented it. Therefore, in this paper, we empirically contribute to examining the impact of ending a temporary wage subsidy on employment.

The literature indicates that the temporary wage subsidy is not new or unique under the employment retention programme. For example, a temporary wage subsidy was implemented during the Global Financial Crisis of 2007-2008, using different terminologies such as *Kurzarbeit* scheme in Germany and *Productive Recovery Programme* (REPRO) in Argentina. It sought to provide temporary financial support to relieve a temporary shock to the labour market and a reduction in labour demand (Verick & Islam, 2010; Hijzen & Martin, 2012). The case of COVID-19 shows the broad applications of temporary wage subsidy compared to other economic and health-related crises. Table 1 summarises several temporary wage subsidy schemes implemented in several selected countries in response to the COVID-19 crisis.

There are several differences between Malaysia and other countries in designing the temporary wage subsidy, depending on each country's circumstances and ability. Differences can be observed concerning eligibility, duration and amount of the subsidy. In relation to eligibility, the coverage of some schemes depends on the level of employees' wages or the business size, while others cover a broad range of employees or businesses. In the case of Malaysia, all registered businesses and employees earning RM4,000 or less are eligible to apply under this scheme. This is in contrast to Singapore and the United Kingdom (UK), where the temporary wage subsidy schemes cover all registered business and employees' regardless of the business size.

Our review shows that the duration of a temporary wage subsidy is different from one country to another. Usually, the temporary wage subsidy schemes tend to occur between three months to one year, with possible extensions based on the country's economic situation. In Malaysia, the temporary wage subsidy was initially enabled for six months before extending to a further three months. In Brunei and Indonesia, the temporary wage subsidy scheme is available for up to three and four months, respectively.

The variation is also applied for the monthly allocation, where some countries prefer lump sum assistance while others are rated based on the share of wage loss to the total wage. For example, in Malaysia, firms with more than 200 employees, between 75 and 200 employees and less than 75 employees are eligible for a wage subsidy of RM600, RM800 and RM1,200 per month, respectively. In the UK, Thailand and the United States (US), the temporary wage subsidy is allocated between 50% and 80% of employees' monthly wages.

Nevertheless, there are also similarities between Malaysia and other countries concerning the disbursement mechanism and implementing agencies. Most of the temporary wage subsidy schemes are disbursed to enterprises in some countries such as Malaysia, the UK, the US and Singapore, which transfer directly to employees. In relation to implementing agencies, Malaysia and other countries like the Philippines, Thailand and Indonesia are administered through the Social Security Contributions.

Regarding the modelling techniques, computable general equilibrium (CGE) and statistical modelling are the most common techniques used to measure the impacts of the temporary wage subsidy. For example, Go et al. (2010) applied a CGE model to the case of South Africa, showing that the temporary wage subsidy is likely to benefit the overall employment with the elasticity of substitution ranges from 1.9% to 7.2%. Using statistical modelling, a synthetic control method, Kim and Lee (2019) conducted secondary data analysis, discovering that the geographically targeted temporary wage subsidy initially had little impact in retaining employment due to the temporary wage subsidy scheme underutilised.

Table 1 List of temporary wage subsidies across countries

No	Country	Programme	Eligibility	Duration	Allocation	Implementing Agencies
1	United States (Internal Revenue Service, 2020; International Labour Organisation, 2020b; International Labour Organisation, 2020c; US Small Business Administration, 2020)	Employment Retention Credit (ERC) and Pay cheque Protection Programme (PPP) Loans	**ERC** (1) All employers, regardless of size (2) Business is fully or partially suspended by government order due to COVID-19 during the calendar quarter. (3) Gross receipts below 50% of the comparable quarter in 2019. **PPP** (1) SMEs with 500 or fewer employees (2) Employers must show that 60% of loans were used for payroll (initially is 75%)	10 months	**ERC** 50% of the qualifying wages (based on the firm size in 2019) paid up to $10,000 in total per employee **PPP** Average monthly payroll expense multiplied by 2.5 (up to $10 million) "wages" includes cash payments and a portion of the healthcare benefit allowance.	**ERC** Internal Revenue Service (IRS) **PPP** Small Business Administration (SBA)
2	United Kingdom (Government of the United Kingdom, 2020a; Government of the United Kingdom, 2020b)	Coronavirus Job Retention Scheme	• All organisation with employees (businesses, charities, recruitment agencies or public authorities are included). • Employees must have: (1) PAYE payroll scheme on or before 30th October 2020. (2) Enrolled for PAYE online (3) UK bank account	May - October 2020 (extended until 30th April 2021)	(1) June to August • 80% of wages up to £2,500 • Includes Employer National Insurance Contributions (ER NICS) and pension except for August (2) September • 70% of wages up to £2,187.50 (3) October • 60% of wages up to £1,875	
3	Singapore (Inland Revenue Authority of Singapore, n.d)	Jobs support scheme	• All employers who have made mandatory CPF contributions for their local employees (Singapore Citizens and Permanent Residents).	10 months (up to Aug 2020) and 7 months (Sep 2020 to Mar 2021)	(1) **Initially 10-month** 25% to 75% of the first S$ 4,600 of gross monthly wages per employee (2) **Extended 7-month** 10% to 50% of wages, adjusted based on sectors	Inland Revenue Authority of Singapore
4	Brunei-Darussalam (International Labour Organisation, 2020b; International Labour Organisation, 2020c)		• MSMEs with less than 100 employees • Registered employees that receive less than BND 1,500 • Worked at least 1-month with current employer	3 months	Providing 25% payroll subsidy to local employees of MSMEs	Tabung Amanah Pekerja (TAP)

Table 1 (*Cont'd*)

No	Country	Programme	Eligibility	Duration	Allocation	Implementing Agencies
5	Thailand (EABC Thailand, 2020)	Thailand Stimulus Packages	**Payment of wages** (1) Employees without wages during the temporary closure of business up to 2 months due to government order **Tax Deduction of the wages paid** (1) Business income from last 12 months not exceeding 500 million baht (2) No more than 200 employees with earnings 15,000 baht per month per employee (3) The number of insured employees from 1st April 2020 to 31st July 2020 must not be less than the number of insured employees as of 31st March 2020	Payment of wages: 4 months (April – July 2020) Tax Deduction of wages paid: 6 months	**Payment of wages** 62% of daily wages, up to 90 days **Tax deduction of the wages paid** SMEs can deduct the wage expenses three times	Social Security Fund (SSF) and The Revenue Department
6	Indonesia (Sumarto & Ferdian-syah, 2021)	Wage Subsidy Programme	• Registered local employees • Employees with earnings Rp 5 million or less per month	4 months	Rp 1.2 million per employee every two months	BPJS Ketenagakerjaan
7	Philippines (RSM Philippines, 2020)	Small Business Wage Subsidy (SBWS)	• An employee of an eligible small business • Unpaid for at least two weeks during the temporary closure of work in accordance with Labour Advisory No. 1, Series of 2020	2 months, (depending on the extent of the ECQ)	5,000 to 8,000 pesos per month (depending on their region of work) for up to two months (depending on the extent of the ECQ)	Social Security System (SSS)
8	Malaysia (Social Security Organ-isation, 2020b; Social Security Organisation, 2020c)	Wage Subsidy Programme (WSP) and Wage Subsidy Programme 2.0 (WSP 2.0)	**WSP** (1) Firm loss of 50% or more revenues by March 2020. (2) Employers must be registered with the Companies Commission of Malaysia (SSM) **WSP 2.0** (1) Firm loss of 30% or more revenues (from 2019 to 2020) after the implementation of the Recovery Movement Control Order (RMCO) (2) Registered employers and employees (3) Employees earning RM4000 or less (4) Employers are forbidden from retrenching employees but allowed to reduce working hours or wages if their employees agree after negotiation	3 - 6 months	**WSP 1.0** Based on firm size: (1) 75 or fewer employees • RM1,200 per employee per month (2) Between 75 and 200 employees • RM800 per employee per month (3) 200 or more employees • RM600 per employee per month **WSP 2.0** (1) Current WSP Recipients • RM600 per employee per month for 3 months (2) New Applicants • RM600 per employee per month for 6 months	Social Security Organi-sation (SOSCO)

Methodologies

Empirical analyses in this paper are performed based on primary data collection. Section 3.1 describes the data collection methods, detailing the scope and sampling technique. Section 3.2 presents the methodologies for data analysis, focusing on descriptive statistics and econometric model

Data Collection Method

This study collected data by using an online survey approach where emails were sent to randomly targeted firms. The online survey is the most appropriate approach used for data collection given the restricted mobility for conducting a face-to-face data collection implied under the Conditional Movement Control Order (partially lockdown). In addition, the online survey is cost-effective (Heiervang & Goodman, 2011; Baker et al., 2010; Smith et al., 2007) and time-efficient in gaining a quick response (Heiervang & Goodman, 2011).

The samples of targeted firms were extracted from the "population" of firms that are incumbent recipients of WSP and WSP 2.0 assistance in the SOSCO data system. The online survey was conducted for about one month, starting from 30th October to 22nd November 2020. The survey questions contained a total of 12 questions covering the domains of the firm's background information (3 questions), future employees' welfare (4 questions), and business situation (5 questions). The survey was refined and amended based on the International Labour Organisation (ILO) survey questionnaire for assessing the needs of enterprises resulting from COVID-19 (International Labour Organisation, 2020d). The survey questions are detailed in Appendix 1.

The survey samples included small and medium enterprises (SMEs) and large firms throughout Malaysia still receiving WSP benefits. As of 23rd October 2020, 378,557 firms received benefits from the WSP during the COVID-19 outbreak (Social Security Organisation, 2020a). The samples of 46,670 were obtained from the SOCSO database representing firms that still receive the assistance. For sample selection, the nonprobability purposive sampling technique was used to determine the desired information for the study (Dattalo, 2008). The minimum number of respondents required for this study was 382 firms with a margin-of-error at 5% and 95% confidence level according to Cochran's sample size determination (Kotrlik & Higgins, 2001). In turn, a total of 469 responses were successfully collected, with a response rate of 27.6% from 1,700 samples. This data collection exceeded the minimum sample size required for this study in representing the WSP recipients.

The key characteristics of 469 firms are summarised in Figure 1. The results show that 57.6% of the firms represent the Manufacturing sector, followed by 20.5% for Services, 17.3% for Construction, 4.3% for Agriculture, Forestry & Fishing sectors and 0.4% for Mining & Quarrying. Geographically, firms in the state of Selangor represent the highest response rate with 31.6%, followed by Johor with 21.3% and Penang with 10.2%. Regarding the size of establishments[1], small enterprises constitute the highest response rate at 54.8%, while microenterprises denote the lowest with 0.4%. Medium and large enterprises represent 25.6% and 19.2%, respectively, of total responses.

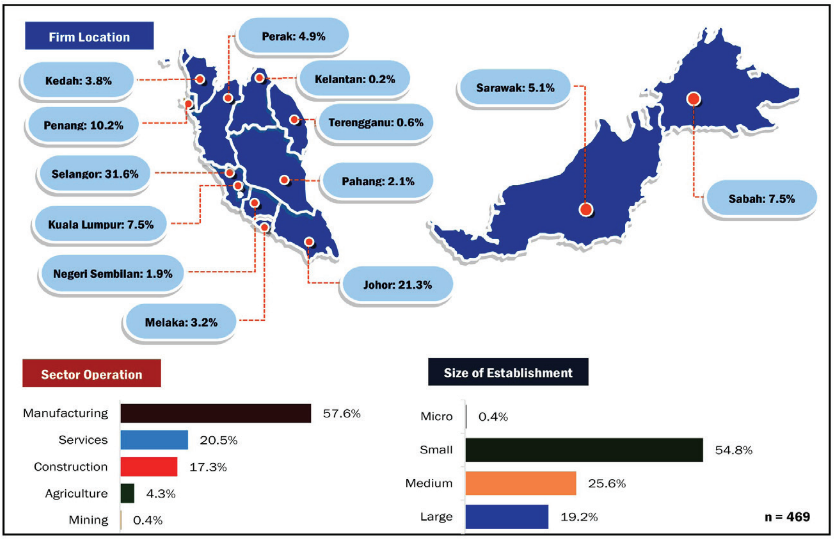

Figure 1 Firm's background information

[1] Size of establishment refers to the micro, small, medium and large enterprises in Malaysia. According to SME Corp. Malaysia (2013), a common definition for SMEs endorsed by the National SME Development Council (NSDC) are based on the number of full-time employees or sales turnover. The definition is as follows:

- Microenterprises: All sectors that have less than 5 full-time employees.
- Small: For Manufacturing (including agro-based) and Manufacturing-related Services required to have full-time employees from 5 to less than 75 while Services and other sector have full-time employees from 5 to less than 30.
- Medium: Manufacturing sector have full-time employees from 75 to not exceeding 200 while Services and other sectors have full-time employees from 30 to not exceeding 75.
- Large: Manufacturing sector have full-time employees more than 200 while Services and other sectors have full-time employees more than 75.

Data Analysis and Modelling

Data collected from this survey was analysed using descriptive and inferential statistics. Descriptive statistics are typically used to summarise and describe the initial findings from the data by percentage and cross-tabulation between variables. Inferential statistics are used to establish some empirical relationships observed from the descriptive statistics (Byrne, 2007). We provided inferential statistics on the relationship between a firm's business situation and employment plans (whether hiring or dismissal). The objective of this analysis was to examine the empirical factors that determine employment plans.

For inferential statistics, we used the Probit model to analyse dichotomous or binary outcome variables. In the Probit model, the inverse standard normal distribution of the probability was modelled as a linear combination of the predictors. Since our main objective was to estimate the probability of unemployment concerning the WSP, the application of the Probit model was deemed the most appropriate approach. As a matter of fact, the application of the Probit model is widely used in labour market studies literature (see, for example, Brown & Sessions, 1997; Cirillo et al., 2020; Cowling et al., 2020).

The Probit model that fits our goal can be written as follows:

$$PR\ (Employment\ plans_i = 1) = \Phi\ (\beta_0 + \beta_1\ Impact_i + \beta_2\ Recovery + \beta_3\ Continue)$$

Employment plans are the dependent variables that represent two cases: the dismissal or hiring of employees. The dependent variable takes the value of 1 for the case of dismissal employees and 0 if otherwise. A similar approach was used for the case of hiring employees. *Impact* refers to the magnitude of impact on firms' performance due to COVID-19. *Recovery* is a dummy variable where the value of 1 indicates the firm business recovery, only 1 to 25% compared to before COVID-19 occurred, and 0 otherwise. *Continue* represents an indication of firms to the continuation of business operations in 2021. It is described by using dummy variables where the value 1 is for the continuity of business operations as usual in 2021 and 0 is otherwise.

Result and Discussion

Overall, the results show that ending the WSP is unlikely to increase the unemployment rates as the percentage of firms that plan to dismiss employees was relatively smaller than the firms planning to increase employee numbers. Specifically, the survey indicates that more than half (55.9%) of the firms plan to retain employees, 29.2% scheduled to increase, and only

14.9% were likely to dismiss their employees despite the discontinuation of the WSP. Thus, altogether, the net effects of the WSP on employees were positive.

The results in Table 2 detail the employment plans by firm size. It can be observed that the majority of the firms that intended to hire employees is dominated by firms with 31-75 employees, which contributes 12.2%. For the case of dismissal, the pattern shows that the decision is closely associated with the number of employees in the firms. That is, the higher (lower) the number of employees in a firm, the lower (higher) the number of firms expected to dismiss their employees. For example, firms with 5-30 employees have a high dismissal rate at 4.7% compared to firms with more than 200 employees, which recorded the lowest dismissal rate at only 2.6%. Meanwhile, firms with an existing size of employees between 5-30 and 31-75 are more likely to retain their employees, accounting for 19.6% and 20.3%, respectively.

Table 2 Employment plans by establishment size (%)

Number of Employees[a]	**Retaining**[b]	**Hiring**[b]	**Dismissc**
Less than 5 employees	0.4	0.0	0.0
5 - 30 employees	19.6	7.5	4.7
31 - 75 employees	20.3	12.2	4.3
76 - 200 employees	10.4	6.0	3.4
More than 200 employees	5.1	3.6	2.6
Total	**55.9**	**29.2**	**14.9**

Note: [a]Refer to question 3; [b]Refer to question 7; [c]Refer to question 5 in Appendix 1

Retaining Employees. While most firms that plan to retain employees were concentrated in the manufacturing sector, most were small enterprises, as indicated in Table 3. The manufacturing sector accounted for the largest firms to retain employees contributing 58.0% of the overall sectors. This was followed by the construction sector with 21.4% and the services sector with 17.2%. Unexpectedly, small enterprises across all sectors were more likely to retain their employees, accounting for 58.8%. Small enterprises could survive during the pandemic by maintaining the flow of goods and services and restoring public confidence of other business owners and the community at large (Doern et al., 2019). Additionally, Irvine and Anderson (2006) and Muñoz et al. (2019) found that small firms with proper crisis planning survive and recover better from crises events. Empirical studies can support this, showing that smaller firms contribute more to job creation than larger firms in the EU country as a whole (De Wit & De Kok, 2014).

Table 3 Percentage of retaining employees by sector and size of establishment

Sector	Size of Establishment (%)				
	Micro	**Small**	**Medium**	**Large**	**Total**
Manufacturing	0.0	38.9	12.6	6.5	58.0
Services	0.8	9.2	3.8	3.4	17.2
Construction	0.0	9.2	7.3	5.0	21.4
Agriculture, Forestry & Fishing	0.0	1.1	1.5	0.4	3.1
Mining & Quarrying	0.0	0.4	0.0	0.0	0.4
Total	0.8	58.8	25.2	15.3	100.0

Hiring Employees. The manufacturing sector not only shows the highest percentage of retaining employees but is also the largest contributor to the potential expansion of employment, accounting for 64.0%, as indicated in Table 4. On the other hand, the mining and quarrying sector is expected to contribute to the lowest expansion of employees at 0.7%.

Concerning the magnitude of potential expansion, most of the firms were planning to increase employment by around 1 to 10% (67.9%), followed by 11 to 20% (19.0%) and 21 to 30% (9.5%). Among the firms planning to increase employment from 1 to 10%, 59.0% were contributed by the manufacturing sector, with most sourced from small enterprises with 50.5%. The results indicate that employers are planning to hire new employees only on a small scale in 2021. Indeed, the government order to close all non-essential services and business premises has led to a cash flow imbalance. However, employers are still obligated to make compulsory expenses such as business loans, rental fees, and employee salaries (Omar et al., 2020). This circumstance has led the firms to hire a low number of employees as an alternative to reduce the cost of business operations.

Dismissal of Employees. The potential employment reduction is mainly sourced from the manufacturing and services sectors. Detailing by sizes, it was found that small (44.3%), medium (22.9%) and large enterprises (32.9%) contribute largely to the reduction of employment, with the small enterprises dominating the most, as illustrated in Table 4. The magnitude of reduction is observed to occur between 1 to 10% and 11 to 20%.

The manufacturing sector was the hardest hit; the sector recorded the highest number of dismissed employees (44.3%) if the WSP ends. Small enterprises are the most affected at 24.3%, while medium enterprises are likely to experience a smaller effect at 7.1%. Despite the highest percentage of dismissed employees in the manufacturing sector, this sector also dominates the percentage of hiring employees in 2021.

The magnitude of employment reduction in the services sector is comparable to the manufacturing sector, which contributes 40.0% to the total potential reduction. The COVID-19 pandemic had affected the services sector since the beginning of the lockdown in March 2020. The most impacted industries in the services sector included accommodation, motor vehicles, and transportation and storage, which recorded the highest decline in GDP at 77.1%, 45.0% and 41.4%, respectively, in the third quarter of 2020 (Department of Statistics Malaysia, 2020). Contrary to the findings for the manufacturing sector, large firms in the services sector were most affected by the outbreak of COVID-19, with 17.1% of dismissed employees.

Together, the main implication that can be drawn from this survey is that ending the WSP does not significantly impact firms since the magnitude of employee dismissals is less inclined by the majority of firms. Regarding the establishment sizes, small enterprises tended to be more strongly affected by COVID-19 than other establishment sizes, as indicated by the high percentage of dismissals. Concerning the economic sectors, manufacturing is the key sector that contributes to employee increase and dismissals. This implies that some manufacturing firms are less affected and are recovering, and some firms are severely affected and taking longer to recover.

Table 4 Percentage of dismiss and increase number of employees by sectors and size of establishment

Sector	Establishment Size	Percentage of Dismiss of Employees[c]						Percentage of Increase of Employees[d]					
		1-10	11-20	21-30	31-40	>41	Total	1-10	11-20	21-30	31-40	>41	Total
Agriculture, Forestry & Fishing	Small	0.0	0.0	0.0	0.0	0.0	0.0	1.6	0.8	0.0	0.0	0.0	2.4
	Medium	0.0	2.9	0.0	0.0	0.0	2.9	1.6	0.0	0.0	0.0	0.0	1.6
	Large	0.0	0.0	1.4	0.0	0.0	1.4	3.2	0.0	0.0	0.0	0.0	3.2
	Total	0.0	2.9	1.4	0.0	0.0	4.3	6.3	0.8	0.0	0.0	0.0	7.1
Manufacturing	Small	17.1	4.3	1.4	1.4	0.0	24.3	28.6	8.7	3.2	0.8	0.8	42.1
	Medium	4.3	0.0	0.0	0.0	2.9	7.1	6.3	4.0	1.6	0.0	0.8	12.7
	Large	2.9	4.3	2.9	1.4	1.4	12.9	4.8	1.6	0.8	0.0	0.8	7.9
	Total	24.3	8.6	4.3	2.9	4.3	44.3	39.7	14.3	5.6	0.8	2.4	62.7
Construction	Small	4.3	1.4	0.0	0.0	0.0	5.7	3.2	0.0	0.0	0.0	0.0	3.2
	Medium	0.0	2.9	1.4	0.0	0.0	4.3	5.6	0.8	0.0	0.0	0.0	6.3
	Large	0.0	0.0	1.4	0.0	0.0	1.4	0.8	0.0	0.8	0.0	0.0	1.6
	Total	4.3	4.3	2.9	0.0	0.0	11.4	9.5	0.8	0.8	0.0	0.0	11.1
Services	Small	2.9	5.7	1.4	1.4	2.9	14.3	0.8	2.4	0.8	0.0	0.0	4.0
	Medium	4.3	2.9	0.0	1.4	0.0	8.6	5.6	0.0	0.8	0.0	0.0	6.3
	Large	8.6	4.3	2.9	1.4	0.0	17.1	5.6	0.0	1.6	0.8	0.0	7.9
	Total	15.7	12.9	4.3	4.3	2.9	40.0	11.9	2.4	3.2	0.8	0.0	18.3
Total	Small	24.3	11.4	2.9	2.9	2.9	44.3	34.1	11.9	4.0	0.8	0.8	51.6
	Medium	8.6	8.6	1.4	1.4	2.9	22.9	19.0	4.8	2.4	0.0	0.8	27.0
	Large	11.4	8.6	8.6	2.9	1.4	32.9	15.1	1.6	3.2	0.8	0.8	21.4
	Total	44.3	28.6	12.9	7.1	7.1	100.0	68.3	18.3	9.5	1.6	2.4	100.0

Note: [c]Refer to question 1, 3 and 5; [d]Refer to question 1, 3 and 6

Next, we link the employment plans with the firms' business situation. Figures 2a and 2b show that the COVID-19 pandemic has seriously disrupted firm sales, explaining 98.7% of the business performances. The magnitude of impact is sizeable, with 45.1% of firms largely impacted, 38.4% mediumly impacted, and 12.1% severely impacted.

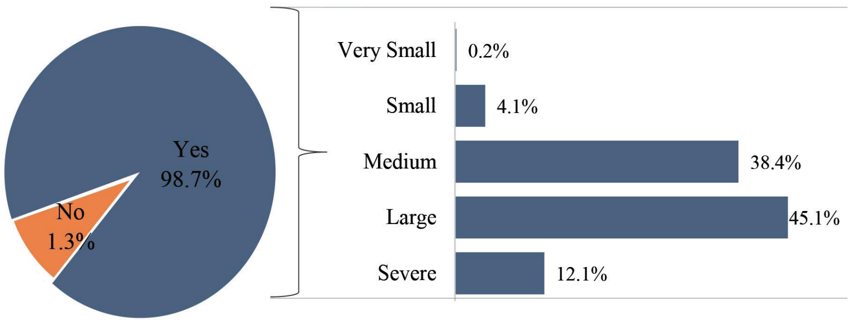

Figure 2a COVID-19 impact on firm's performance in terms of salef

Note: ᶠrefer to question 8 and 9

Figure 2b Level of impact from impacted firms' performances in terms of salef

Several key business indicators determine the decision of firms to dismiss and hire employees. Table 5 provides an in-depth comparison between the key indicators which affect the firm's decision. The magnitude of the impact due to the COVID-19 pandemic clearly influences the decision of firms to dismiss or hire employees. For example, firms that plan to dismiss employees because most are severely impacted reflects 30.0% compared to only 8.0% for firms hiring employees.

Table 5 Key business indicators for firms with hiring and dismissing employees

Variables	Hiring	Dismissal
Severity of impacts[g]		
Minor	1.5	1.4
Moderate	44.5	25.7
Major	46.0	42.9
Severe	8.0	30.0
Business recovery[h]		
1-25%	29.2	38.6
25-50%	43.1	32.9
50-75%	23.4	21.4
75-100%	4.4	7.1
Full recovery period[i]		
6 months	5.8	1.4
6 to 12 months	46.7	41.4
More than 12 months	47.4	57.1
Business continuity[j]		
Yes	87.6	60.0
Not sure	12.4	38.6
No	-	1.4

Note: [d]Refer to question 9; [h]Refer to question 10; [i]Refer to question 11; [j]Refer to question 12 in Appendix 1.

Furthermore, the magnitude of recovery also determines the firm decision in dismissing and hiring employees. The results show that for all business recovery scales, the recovery phases for the firms with hiring employees are relatively higher than firms dismissing employees. Moreover, the tendency of firms to reduce employment is higher when more extended recovery periods are required. For example, the score of firms dismissing employees take more than 12 months to recover fully is higher than firms hiring employees, 57% vs 47%. Finally, it is common that business prospects determine the demand for employment. More than 87.6% of firms hiring employees plan to continue their business operations in 2021, compared to 60.0% of firms dismissing employees.

The results shown in Table 5 provide descriptive statistics without confirming the relationship between key business indicators and employment plans. The results in Table 6 provide the empirical relationship between the key business indicators and employment plans, estimated by using the Probit model.

Both the estimated coefficients that are statistically significant and the marginal effects are shown in the table. The marginal effects are used to determine the magnitude of the effect of the independent variables (key business indicators) towards the dependent variables (employment plans).

Table 6 The case of firms with hiring employees

	Panel A		Panel B	
Dependent variable	**Hiring employees**		**Dismissal employees**	
Independent variables	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Impact	-0.014	-0.005	0.382***	0.082***
Recovery	0.127	0.043	0.290*	0.061*
Continue	0.537***	0.180***	-0.450***	-0.096***
Pseudo R2	0.021		0.081	
No. of Observation	469			

Note: z-statistic correspond to the test of the following underlying coefficient being zero ***p<0.01; **p<0.05; *p<0.10

The results in Panel A of Table 6 show that the coefficient for *Continue* is positive and with a statistically significant sign indicating the firms with a plan to continue business operations in 2021 have a higher likelihood of increasing their employee numbers. The marginal effects show that as the firms plan to continue business in 2021, there is a 17.8% chance for firms to increase their employee numbers.

For the dismissal of employees, the coefficient for the level of *Impact* shows a positive relationship and is statistically significant. The firms face a higher impact by COVID-19; there is an 8.2% chance for the firms to dismiss their employees. Firms with a large impact are associated with high financial constraints since most firms need to cease or pause their operations due to government intervention in curbing the spread of COVID-19. Here permanent employment layoffs have a close association with financial constraints (see Chundakkadan et al., 2020).

The estimation shows *Recovery* of firms compared to before the COVID-19 virus hit, having a positive relationship and is statistically significant at 10%. This indicates that a low recovery rate tends to be associated with a higher likelihood of employee dismissals. Results find a negative and significant coefficient for *Continue*. It implies that firms planning to continue business operations in 2021 are less likely to dismiss their employees. The observation shows that firms that plan to continue business have 9.6% fewer chances to dismiss their employees next year.

Summary & Conclusion

This study documents the findings gathered from a snap employer survey, aiming to examine the impacts of ending the WSP on employment. The findings confirmed our expectation that ending the WSP is unlikely to increase unemployment rates. Out of all respondents who participated in this survey, 15% plan to reduce the employment size, 29% scheduled to increase employment, and 56% are likely to retain the current employment numbers. Altogether, the net effects of the WSP on employment are positive. This provides a "prima-facie" case to implementing a targeted WSP for 2021, given the results indirectly indicate positive signs about labour market recovery.

Some sectors have shown significant recovery after the government re-opened the economy since June 2020 and complemented massive economic stimulus packages. However, some firms in some sectors, such as the tourism industry, may require an extended recovery period, thus needing WSP assistance from the government. These findings support the main reasoning behind the implementation of the targeted WSP. Therefore, from an economic perspective, a targeted WSP is considered a productive policy decision that could promote economic recovery in sustainable ways.

The findings in this report should be considered as "first hand" information on the employment consequences of ending the temporary WSP. This study has several inherent limitations as it does not consider other significant factors expected to influence the findings. It is worth mentioning two main limitations. First, the survey does not consider the impacts of Conditional Movement Control Order (CMCO) periods. Opening up all economic activities are preconditions for economic recovery, and implementation of the CMCO is likely to influence production and employment recovery speed. Second, the survey questionnaire is limited and could not be used to deep-dive or drill down into the micro-view of the affected employment conditions. For example, information on occupation, qualification and age of employees is important in determining appropriate actions to be taken.

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Appendix 1: Perkeso Snap Employer Survey

PERKESO is conducting a snap employer survey to understand your forward-looking business situation and challenges during the recovery periods of COVID-19 pandemic crisis. We will use the survey response to channel your concerns to government authorities and relevant stakeholders. The information you provide will be kept confidential. The survey will take 10 minutes to complete. We thank you for your support during these difficult times – we are fully operational during the pandemic and we will continue to provide the services you depend on.

No.	Question	Measurement	Categories
1.	Sector of operation:	Nominal Categorical	• Agriculture • Forestry & Fishing • Mining & Quarrying • Manufacturing • Construction • Services
2.	Location of your firm (if you braches, please indicate location of the main branch):	Open-ended	-
3.	Total number of full-time employees before COVID-19 hit (including permanent and contract employees):	Interval scale	• Less than 5 employees • 5 – 30 employees • 30 – 75 employees • 75 – 200 employees • More than 201 employees
4.	Have your firm planned to dismiss any employees after ending the wage subsidy program?	Nominal Categorical	• Yes • No
5.	If Yes, what is percentage of employees released next year? (percentage over your total current employees)	Interval scale	• 1 – 10% • 11 – 20% • 21 – 30% • 31 – 40% • More than 41%
6.	If No for question 4, does your firm plan to increase the number of the employees in the next year?	Nominal Categorical	• Yes • No
7.	If Yes for question 6, what is the percentage of the increase in the number of employees (percentage over your total current employees?	Interval scale	• 1 – 10% • 11 – 20% • 21 – 30% • 31 – 40% • More than 41%

No.	Question	Measurement	Categories
8.	Does COVID-19 still gives an impact to your firm's performance in terms of sales?	Nominal Categorical	• Yes • No
9.	If Yes for question 8, what is the level of the impact?	Interval scale	• Very small • Small • Medium • Large • Severe
10.	Please provide percentage of your business recovery compared to before COVID-19 hit	Interval scale	• 1 -25% • 26 – 50% • 51 – 75 • 76 – 100%
11.	Given the current situation, how long would it takes your firm to fully recover?	Interval scale	• 6 months • 6 – 12 months • More than 12 months
12.	Does your firm have plan to continue your business operations as usual by 2021 onwards?	Nominal Categorical	• Yes • Not sure • No

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Evaluating Labour Market Efficiency During Pre- and Post-Movement Control Order (MCO) During COVID-19 Pandemic

Muhammad Khalid Ahmad Kamal[a,b*], Heizlyn Amyneina Hamzah[a,b], and Mazzatul Raudah Abdul Halim[b,c]

Abstract

Motivation and Aim: The Malaysian government has undertaken job retention incentive in response to labour market disruption caused by the COVID-19 pandemic. It is found to have a significant impact on reducing the unemployment rate. This study examines the extent to which the reduction in the unemployment rate can be explained by an increase in job matching efficiency.

Methods and Materials: An autoregressive distributed lag (ARDL) model was employed on daily administrative data consisting of placements, vacancies and loss of employment obtained from the Employment Insurance System (EIS) Office of the Social Security Organisation (SOCSO). The data were split into pre-MCO and the post-MCO periods and three main skill-based job categories.

Key Findings: The results suggest that job matching efficiency tended to improve during the post-MCO. The most significant improvement in job matching efficiency was experienced by the semi-skilled workers. This is because the demand for workers in the semi-skilled category was higher compared to the demand for high-skilled and low-skilled workers.

Policy Implication: Government intervention through hiring incentives had caused the improvement in the job matching efficiency. It means that, in the midst of economic crisis, corrective measure is highly needed to cushion adverse effect on the labour market.

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

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[a]School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia
[b]EIS-UPMCS Centre for Future Labour Market Studies, Menara PERKESO, Putrajaya, Malaysia
[c]Putra Business School, Universiti Putra Malaysia, Serdang, Malaysia
*Corresponding author: muhd.khalid99@gmail.com

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.

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 and 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 namely 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.

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)

Stationarity

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.

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:

$$P_t = \mu_t V_t^{\beta_1} LOE_t^{\beta_2} \quad (1)$$

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.

$$In\ P_t = \beta_0 + \beta_1 In\ V_t + \beta_2 In\ LOE_t + \mathcal{E}_t \quad (2)$$

where $\mathcal{E}$ 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*, respectively.

Estimation 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:

$$\begin{aligned}\Delta\ In\ P_t = {} & \gamma_0 + \gamma_1 In\ P_{t-1} + \gamma_2 In\ V_{t-1} + \\ & \gamma_3\ In\ LOE_{t-1} + \sum_{i=1}^{m} \theta_{l1}\ \Delta In\ P_{t-i} \\ & + \sum_{i=0}^{n} \theta_{2i}\ \Delta In\ V_{t-i} + \sum_{i=0}^{0} \theta_{3i}\ \Delta In\ LOE_{t-i} \\ & + \mu_t\end{aligned} \quad (3)$$

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 were based on the Schwarz Bayesian Criterion (SBC). The joint F-statistic was used to test the null hypothesis of no cointegration.

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 Δ = 0 and $In\ P_t = In\ P_{t-1}$, and so on. Thus, the model is as follows:

$$0 = \gamma_0 + \gamma_1 In\ P_t + \gamma_2 In\ V_t + \gamma_3 In\ LOE_t + \mu_t \quad (4)$$

$$\gamma_1 In\ P_t = -\gamma_0 - \gamma_2 In\ V_t - \gamma_3 In\ LOE_t - \mu_t \quad (5)$$

$$In\ P_t = -\frac{\gamma_0}{\gamma_1} - \frac{\gamma_2}{\gamma_1} In\ V_t - \frac{\gamma_3}{\gamma_1} In\ LOE_t - \frac{1}{\gamma_1}\mu_t \quad (6)$$

Therefore,

$$In\ P_t = \beta_0 + \beta_1 In\ V_t + \beta_2 In\ LOE_t + \varepsilon_t \quad (7)$$

$$Where\ \beta_0 = -\frac{\gamma_0}{\gamma_1},\ \beta_1 = -\frac{\gamma_2}{\gamma_1},\ \beta_2 = -\frac{\gamma_3}{\gamma_1}$$

$$and\ \varepsilon_t = -\frac{1}{\gamma_1}\mu_t.$$

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

$$\Delta In\ P_t = \phi_0 + \sum_{i=1}^{m} \phi_{1-i} \Delta In\ P_{t-i} + \sum_{i=0}^{n} \phi_{2i} \Delta In\ V_{t-i} + \sum_{i=0}^{0} \phi_{3i} \Delta In\ LOE_{t-i} + \lambda ECM_{t-1} + e_t \quad (8)$$

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.

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.

Results and Discussion

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								
Placement	-2.42	1.05	0.43	9.82	-1.42	-0.70	0.49	14.07
	(6)	(6)	(6)	(6)	(7)	(7)	(7)	(7)
Vacancies	-0.41	-0.31	0.76	32.22	-0.50	-0.49	0.98	47.16
	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
LOE	-0.58	-0.50	0.87	37.83	-0.59	-0.49	0.83	34.92
	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
B. High-skilled								
Placement	-2.43	-1.06	0.44	9.82	-1.92	-0.88	0.46	11.66
	(5)	(5)	(5)	(5)	(7)	(7)	(7)	(7)
Vacancies	-1.14	-0.66	0.58	18.18	-0.49	-0.43	0.86	38.33
	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
LOE	-1.11	-0.71	0.64	20.64	-0.56	-0.50	0.89	39.33
	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
C. Semi-skilled								
Placement	-7.25*	-1.89*	0.26*	3.44*	-0.78	-0.46	-0.59	20.39
	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
Vacancies	-1.55	-0.83	0.54	14.80	-0.73	-0.60	0.82	32.83
	(9)	(9)	(9)	(9)	(6)	(6)	(6)	(6)
LOE	-1.36	-0.79	0.58	17.17	-0.71	-0.49	0.70	26.06
	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)

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 1 (*cont'd*)

Variable	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
D. Low-skilled								
Placement	-6.06*	-1.71*	0.28*	4.13*	-0.71	-0.44	0.61	21.63
	(3)	(3)	(3)	(3)	(6)	(6)	(6)	(6)
Vacancies	-16.44***	-2.84***	0.17***	1.60***	0.62	-0.51	0.82	33.94
	(1)	(1)	(1)	(1)	(6)	(6)	(6)	(6)
LOE	-2.33	-1.08	0.46	10.49	-0.98	-0.64	0.65	21.80
	(3)	(3)	(3)	(3)	(6)	(6)	(6)	(6)
First Difference								
E. Aggregate								
Placement	-30.20***	-3.88***	0.13***	0.82***	-68.71***	-5.85***	0.09***	0.38***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Vacancies	-30.85***	-3.90***	0.13***	0.88***	-69.54***	-5.89***	0.08***	0.36***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
LOE	-17.38***	-2.95***	0.17***	1.41***	-53.57***	-5.17***	0.10***	0.47***
	(6)	(6)	(6)	(6)	(0)	(0)	(0)	(0)
F. High-skilled								
Placement	-28.51***	-3.77***	0.13***	0.86***	-78.85***	-6.27***	0.08***	0.34***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Vacancies	-27.26***	-3.69***	0.14***	0.90***	-76.88***	-6.19***	0.08***	0.35***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
LOE	-27.11***	-3.68***	0.14***	0.91***	-72.87***	-6.03***	0.08***	0.36***
	(0)	(0)	(0)	(0)	(1)	(1)	(1)	(1)

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 1 (*cont'd*)

Variable	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
G. Semi-skilled								
Placement	-42.30***	-4.58***	0.11***	0.62***	-111.13***	-7.45***	0.07***	0.23***
	(1)	(1)	(1)	(1)	(6)	(6)	(6)	(6)
Vacancies	-51.75***	-5.06***	0.10***	0.53***	-62.33***	-5.58***	0.09***	0.39***
	(1)	(1)	(1)	(1)	(0)	(0)	(0)	(0)
LOE	-8.39*	-2.05**	0.24*	2.92**	-107.69***	-7.34***	0.07***	0.23***
	(4)	(4)	(4)	(4)	(3)	(3)	(3)	(3)
H. Low-skilled								
Placement	-129.83***	-8.07***	0.06***	0.19***	-15.35***	-2.77***	0.18***	1.61***
	(2)	(2)	(2)	(2)	(5)	(5)	(5)	(5)
Vacancies	-12.87**	-2.48**	0.19**	2.11**	-22.35***	-3.34***	0.15***	1.12***
	(0)	(0)	(0)	(0)	(3)	(3)	(3)	(3)
LOE	-12.47**	-2.27**	0.18**	2.80**	-24.19***	-3.48***	0.14***	1.01***
	(0)	(0)	(0)	(0)	(4)	(4)	(4)	(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 MZ	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
A. Aggregate								
Placement	-6.29	-1.77	0.28	14.50	-2.35	-0.95	0.40	33.13
	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
Vacancies	-1.26	-0.75	0.60	66.33	-0.64	-0.37	0.59	70.94
	(9)	(9)	(9)	(9)	(6)	(6)	(6)	(6)
LOE	-0.44	-0.27	0.62	79.83	-2.50	-1.03	0.41	33.05
	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
B. High-skilled								
Placement	-6.55	1.80	0.27	13.92	-2.88	-1.05	0.36	27.62
	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
Vacancies	-2.71	-1.15	0.42	33.10	-0.47	-0.29	0.61	77.86
	(8)	(8)	(8)	(8)	(6)	(6)	(6)	(6)
LOE	-1.54	-0.69	0.45	41.91	-2.31	-0.94	0.41	33.59
	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)
C. Semi-skilled								
Placement	-12.01	-2.45	0.20	7.59	-6.31	-1.71	0.27	14.44
	(5)	(5)	(5)	(5)	(8)	(8)	(8)	(8)
Vacancies	-18.21**	-3.02**	0.17**	5.01**	-1.99	-0.89	0.45	39.37
	(2)	(2)	(2)	(2)	(6)	(6)	(6)	(6)
LOE	-9.44	-2.10	0.22	9.94	-3.29	-1.25	0.38	27.16
	(5)	(5)	(5)	(5)	(6)	(6)	(6)	(6)

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 (*cont'd*)

Variable MZ	Pre-MCO COVID-19				Post-MCO COVID-19			
	MZ	MZt	MSB	MPT	MZ	MZt	MSB	MPT
D. Low-skilled								
Placement	-4.12	-1.43	0.35	22.09	-2.17	-0.92	0.43	36.10
	(8)	(8)	(8)	(8)	(6)	(6)	(6)	(6)
Vacancies	-16.26*	-2.83*	0.17*	5.71*	-0.99	-0.51	0.52	55.30
	(1)	(1)	(1)	(1)	(6)	(6)	(6)	(6)
LOE	-3.50	-1.31	0.37	25.79	-6.39	-1.77	0.28	14.27
	(3)	(3)	(3)	(3)	(7)	(7)	(7)	(7)
First Difference								
E. Aggregate								
Placement	27.41***	-3.68***	0.13***	3.43***	-51.54***	-5.07***	0.10***	1.80***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Vacancies	-30.21***	-3.88***	0.13***	3.03***	-53.81***	-5.18***	0.10***	1.71***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
LOE	-30.19***	-3.88***	0.13***	3.03***	-44.71***	-4.73***	0.11***	2.04***
	(0)	(0)	(0)	(0)	(4)	(4)	(4)	(4)
F. High-skilled								
Placement	-25.07***	-3.52***	0.14***	3.77***	-26.65***	-3.64***	0.14***	3.50***
	(0)	(0)	(0)	(0)	(2)	(2)	(2)	(2)
Vacancies	26.68***	-3.65***	0.14***	3.44***	-70.94***	-5.95***	0.08***	1.32***
	(0)	(0)	(0)	(0)	(1)	(1)	(1)	(1)
LOE	-26.57***	-3.64***	0.14***	3.45***	-48.71***	-4.94***	0.10***	1.87***
	(0)	(0)	(0)	(0)	(1)	(1)	(1)	(1)

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 (*cont'd*)

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

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

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.

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 $\mu_t = \frac{P_t}{V_t^{\beta_1} \, LOE_t^{\beta_2}}$, 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.

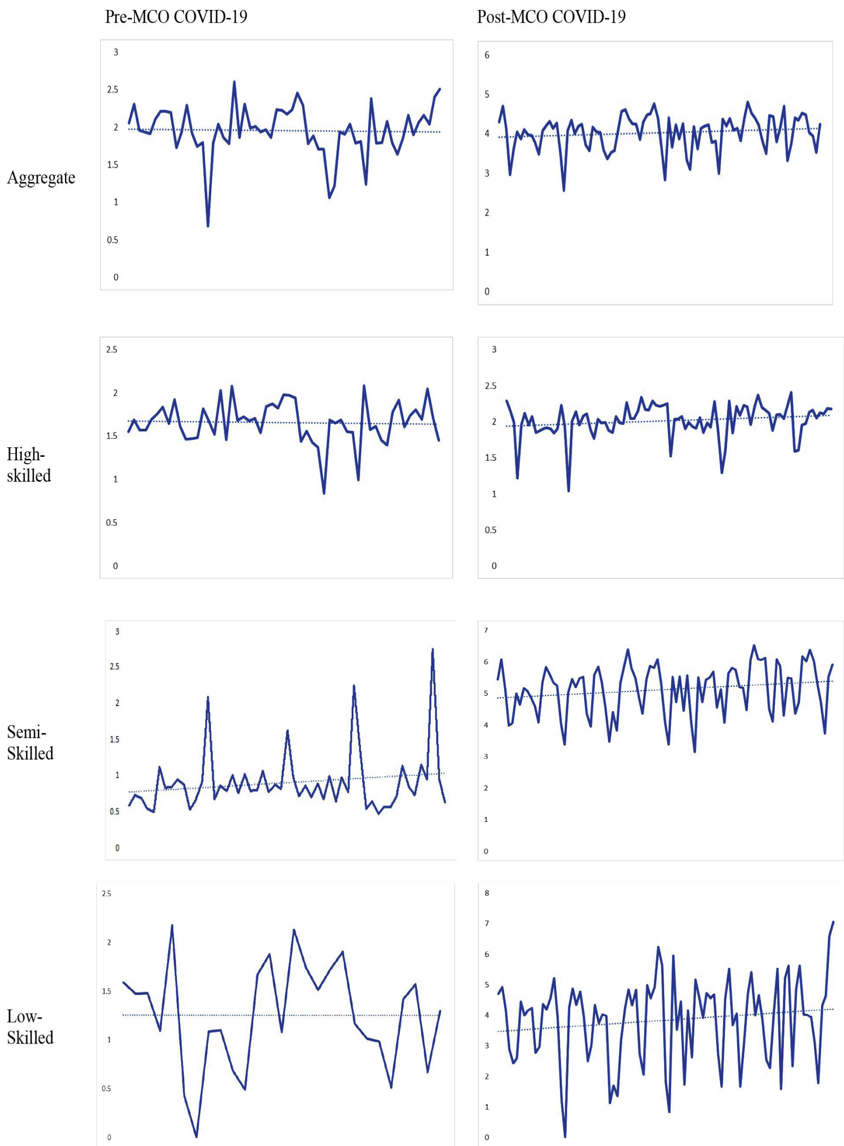

Figure 1 Matching efficiency between pre-MCO COVID-19 and post-MCO COVID-19 by skills

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; 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.

Concluding Remarks

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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A Case Study of Unemployment Among Graduates in the Klang Valley

Cheong Jia Qi[a*], Jacqueline Liza Fernandez[b], Shyue Chuan Chong[c]

Abstract

Motivation and Aims: Malaysia has made progress in improving access to higher education for Malaysians. However, graduate unemployment in the country is a serious and growing issue that concerns not only graduates who are seeking employment, but policy makers and employers as well.

Method and Materials: This paper explored the underlying factors contributing to graduate unemployment in the country and presents the research findings based on a survey that was done in 2019.

Key Findings: This study specifically investigated the factors contributing to graduate unemployment based on the perceptions of graduates from both public and private tertiary institutions in the Klang Valley.

Policy Implications: Several recommendations are provided in an effort to address the issue of unemployment among graduates.

Keywords: graduates; unemployment; universities; Malaysia

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Introduction

The issue of graduate unemployment is a growing concern in numerous countries around the world (Barkan, 1994; Owusu et al. 2014). Being a university graduate no longer guarantees employment opportunities in high-skilled jobs with good remuneration. Policymakers and governments are concerned about

[a]Faculty of Business, Economics and Accountancy, UMS
[b]School of Social Sciences, USM
[c]Faculty of Accountancy, Finance and Business, TAR UC
*Corresponding author: cheongqi@ums.edu.my

graduate unemployment as it is considered one of the essential indicators of the health of the economy.

This paper investigated the issue of graduate unemployment in Malaysia. Specifically, it investigated the contributing factors that can explain graduate unemployment in Malaysia. The factors that affect employability such as employability skills, gender bias, experience and family background were investigated to assess whether these factors contribute to unemployment among graduates. This study is important from a policy perspective as more than 290,000 students graduate annually from higher learning institutions in Malaysia, with 1 out of 5 graduates being unemployed 6 months after graduation. The majority of the unemployed youths are Bachelor degree holders, who make up 55% of the total (Michelle, 2019).

Evidently, graduate unemployment can be explained by several factors. In the case of Malaysia, the overall graduate unemployment rate stood at 3.9% in 2018, with the unemployment rates for males and females being 3.4% and 4.4%, respectively; in absolute numbers, graduate unemployment was greater among females than males (DOSM, 2019). Studies by Shackleton (1997), Hedayat et al. (2013), and Storen (2004) found that gender is a factor that contributes to graduate unemployment. Studies in Italy (Ordine & Rose, 2015) and in OECD countries (Storen, 2004) showed that it is easier for male graduates to find jobs compared to female graduates. However, Kong's (2011) study showed that male graduates are more likely to be unemployed than females.

Globally, ethnicity is recognized as one of the factors that contribute to graduate unemployment (Minderjeet, 2019; Shackleton, 1997). In the United Kingdom (UK), Mok's (2006) study showed that the unemployment rate among white graduates is lower (5.5%) than that of graduates of minority ethnic groups (11%), including Pakistani, Bangladeshi, Black African and Chinese graduates. In Malaysia, *Bumiputera* graduates are reported to be at a disadvantage and have greater difficulty in securing employment compared to others (Minderjeet, 2019).

The relationship between unemployment and academic attainment is unclear. In the case of the UK, it was found that academic attainment is not the main reason affecting unemployment among UK engineering graduates (Atkinsona & Pennington, 2012). On the other hand, there is evidence to indicate that graduates with 'good grades' in higher education have a lower probability of being unemployed (Storen, 2004).
Working experience has been found

to be a factor that contributes to graduate unemployment. Graduates with working experience have a higher tendency to be employed (Atkinsona & Pennington, 2012). Omar et al. (2012) found that working experience is a prerequisite for employment in the construction, finance and engineering industries. According to Olufemi et al. (2012), working experience is a determinant that ensures that graduates possess the competencies and skills required for employment. The onset of the Industrial Revolution 4.0 has boosted the demand by employers for digital skills such as digital marketing, software and application development, e-commerce, big data analytics, and database management (Michelle, 2019).

This study revealed the underlying factors contributing to graduate unemployment from the perspective of graduates. The findings of this study may be useful to the Ministry of Education, Malaysia in formulating strategies to increase the marketability of graduates and limit the number of unemployed graduates, which is growing at a fast rate. This study focused on the feedback given by graduates rather than employers. Not many studies in Malaysia have examined graduate unemployment based on the responses and perceptions of the graduates themselves. Hence, this study is relevant to policymakers in tackling the problem of graduate unemployment.

This paper is structured as follows: the methodology (sampling, questionnaire design and method of data analysis, i.e., multivariate regression) is explained in Section II; Section III discusses the results obtained from the survey; and Section IV provides the concluding remarks and recommendations.

Methodology

A pilot survey was conducted to check if the respondents were able to understand the survey questions. Subsequently, the questionnaire was modified in terms of simplifying the questions as well as improving the clarity and sequencing of the questions. The preliminary version of the questionnaire was pre-tested by distributing it to 50 target respondents comprising graduates from the University of Malaya (public university) and Universiti Kuala Lumpur (private university) in Malaysia. Based on the feedback received in the pilot survey as well as the preliminary analysis of the data using the Statistical Package for the Social Sciences (SPSS), the questionnaire was improved by reducing the ambiguity in some questions and ensuring that the relevant questions were included in the questionnaire.

A survey was then conducted in 2019 in the Klang Valley with a targeted sample size of 500 respondents from two public universities (University of Malaya and Universiti Putra Malaysia (UPM) and two private universities (Universiti Kuala Lumpur (UniKL) and UCSI University). The survey adopted the convenience sampling and snowball sampling approach. Quotas were set to reflect the general population in the Klang Valley in terms of ethnicity and gender, with a balanced representation of respondents from both the public and private universities. The information collected from the respondents included their age, active/not active in job search, educational attainment and years of experience. Their employment status was divided into two categories: employed and unemployed. In this study, the term 'unemployed' was defined as respondents who had been jobless for more than six months after their graduation, while the term 'employed' was used to define those respondents who had been able to find work within a short time (three months) after their graduation. By the end of the survey, there were 402 completed questionnaires, i.e., 80.4% of the targeted sample size. The socio-demographic characteristics of the respondents are shown in Table 1.

The questionnaire in this study was developed with a focus on seven factors affecting unemployment among graduates, namely, i) perception of gender bias in the job market; ii) perception of individual employability skills; iii) perception of economic conditions; iv) perception of importance of academic performance for graduate employment; v) parent's working status; vi) working experience; and vii) employment status of graduate.

The measurement scale used for some of the questions in this study was the Likert scale. The Likert scale is used to measure perceptions designed to indicate how strongly respondents agree or disagree with carefully constructed statements (Eisend & Kuss, 2019; Zikmund, 2003). The Likert scale generally uses the prescribed five anchors Cavana et al., 2001; Jenkins-Smith et al., 2017).

The multiple regression analysis in Table 2 was used to examine whether the dependent variable (employment status of graduates) was significantly related to each of the independent variables. The dependent variable in the analysis was a dummy variable that was given a value of 1 if the respondent was unemployed for 6 months or more, and 0 if otherwise.

The model was written as

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \ldots + \beta_k X_{ki} + u_i, \quad (1)$$

where,

$$unemployed_i = C + \beta_1 gender_i + \beta_2 employability\ skills_i + \beta_3 economic\ condition_i + \beta_4\ academic\ performance_i + \beta_5\ experience_i + \beta_6 parent's\ working\ status_i + \beta_7 types\ of\ universities_i + error\ term. \quad (2)$$

This paper utilized the Statistical Package for the Social Sciences (SPSS) to perform the statistical analysis.

Results and Discussion

The socio-demographic characteristics of the respondents are given in Table 1. The profile of the sample was described by showing the percentage distribution of respondents for the key socio-demographic variables.

Table 1 Socio-demographic profile of public and private university graduates

Personal Background	**Public Universities**		**Private Universities**		**Total**	
	%	**n**	**%**	**n**	**%**	**n**
Gender						
Male	49.8	101	50.2	101	50.0	202
Female	50.2	100	49.8	100	50.0	200
Ethnic group						
Malay	49.8	100	49.8	100	49.8	200
Chinese	30.8	62	30.3	61	30.6	123
Indian	19.4	39	19.9	40	19.6	79
Age Group						
Less than 22	14.9	30	8.0	16	11.4	46
22-24	77.1	155	77.6	156	77.4	311
25 and above	8.0	16	14.4	29	11.2	45
Job search						
No	23.9	48	25.4	51	24.6	99
Yes	76.1	153	74.6	150	75.4	303
Award of honours						
First class honours	17.9	36	22.4	45	20.1	81
Second class upper honours	48.3	97	49.8	100	49.0	197
Second class lower honours and below	33.8	68	27.8	56	30.9	124
Work Experience						
Without	53.2	107	49.8	100	51.5	207
With	46.8	94	50.2	101	48.5	195
Experience Years						
Nil	53.2	107	49.8	100	51.5	207
1	35.3	71	41.8	84	38.6	155
2 and above	11.5	23	8.4	17	9.9	40
Total	100.0		100.0		100.0	
N	201		201		402	

Note: n (sample size)
% indicate column percentages

With regard to the multiple regression model, the results presented in Table 2 show that all the independent variables were significantly related to the dependent variable (i.e., employment status (unemployed versus employed)). The F-statistic, F (7, 395) = 18.51, $p < 0.05$, indicated that the overall regression model was a good fit of the data in this study.

The regression results in Table 2 show that among all the variables that were examined, the variables that were most significantly related (with a significance level of 1% for their coefficients) to the employment status of graduates were perceptions of gender bias, perceptions of economic conditions, and parent's working status. The perceptions regarding the importance of employability skills and academic performance also had a considerably statistically significant effect on the unemployment status of graduates in the model. Employability skills and academic performance were statistically significant at the 5% level. Finally, working experience and type of university were statistically significant at the 10% level.

The unstandardized coefficient, $\beta 1$, for the constant was equal to 1.066 (Table 3). This means that graduate unemployment was predicted to be 1.066 if all of the independent variables were zero.

Table 2 Multiple regression on employment status of graduates after graduation

Independent Variables	Coefficient B	Standard Error
Job bias by Gender	0.151***	0.035
Employability skills	0.100**	0.042
Economic Condition	0.229***	0.044
Academic Performance	0.066**	0.031
Experience	0.207*	0.043
Parent's Working Status	0.133***	0.049
Types of University	-0.089*	0.049
Constant	1.066	0.269
F(7df)	18.51	
Probability	0.000	
Total observations (N)	402	

Note: ***Significant at the 1 percent level, ** significant at the 5 percent level and * significant at the 10 percent level.

Based on the results in Table 2, it was clear that graduates who perceived the existence of gender bias in the job market were more likely to be unemployed, all other independent variables being constant. This could have been because those graduates who perceived that there was gender bias among employers would not attempt to seek employment in particular occupations if they were of the opinion that employers preferred graduates of the opposite sex for such jobs. Hence, they restricted their job search to a narrower range of jobs, where they thought they stood a better chance of finding employment. Therefore, the probability of unemployment tended to be higher for those graduates who perceived that employers had gender bias, given that these graduates limited their job search to only certain types of occupations, where they expected to encounter less gender bias. In short, the greater the perception of gender bias, the less wide was the job search and the higher the probability of unemployment.

Another determinant of graduate unemployment is individual perception of their employability skills. The positive coefficient for this variable meant that the probability of unemployment was higher for those graduates who gave themselves a better rating for employability skills. This direct relationship suggested that although the graduates viewed themselves as having the necessary skills, it did not have the expected negative relationship with the probability of unemployment. This could have been due to a mismatch of skills; i.e., the type of skills that the graduates perceived they possessed might not necessarily have been the skills demanded by employers. As such, those who perceived they had better employability skills might have encountered a greater probability of unemployment than those who perceived they had low employability skills. Therefore, the key to graduate employment was not based on their perception of their employability skills, but rather on ensuring that they met the market demand with respect to the kind of skills employers deemed to be important. As employers are emphasizing on communication and soft skills, these skills will provide fresh graduates with an advantage to be hired (Michelle, 2019).

One other determinant of graduate unemployment is the graduates' perception of economic conditions; when the economy is healthy and growing, graduates are more likely to be employed and vice-versa. The results of the regression analysis in Table 2 indicated that the perception of unfavourable economic conditions tended to increase the probability of unemployment. This might have been because those graduates who perceived that the economic conditions were adverse would be less enthusiastic in their job search efforts, and this increased the probability of unemployment. It has been argued that the recruitment of graduates is indeed slow when the economy is bad as conservative business sentiments constrict businesses from increasing their labour force (Dass, 2018).

The model also included another variable, i.e., graduates' perception of the importance of academic performance. The more the graduate perceived the CGPA as being important for graduate employment, the higher the probability of unemployment, other factors being constant. This might perhaps have been because those graduates who placed too much emphasis on the importance of scoring a high CGPA tended to ignore the non-academic aspects of employability (such as participation in co-curricular activities, etc.), which are also important for graduate employment. Very often, employers do not simply focus on the academic performance of graduates, but look at their other qualities as well.

In this study, the sample comprised fresh graduates who generally did not have work experience, and the variable that was used here was the perception of the respondents concerning work experience. The higher the rating given for experience as a prerequisite for employment, the greater was the probability of graduate unemployment. Those graduates who opined that employers emphasized experience as a key criterion for the selection of workers might have been discouraged from applying for many jobs simply because they felt they lacked the necessary experience sought by employers, and this increased the probability of unemployment. Studies have shown that fresh graduates who enter the labour force for the first time have greater difficulty in securing a job compared to adults with a lengthier history of job experience (Balakrishnan, 2017; Dass, 2018; Michelle, 2019).

The parent's working status also influenced the probability of graduate unemployment. Individuals with employed parents were more likely to be unemployed than those whose parents were unemployed or retired. This could be attributed to the fact that graduates with working parents felt less pressured to get a job since their parents could provide them with an income/allowance to sustain their livelihood. Dass (2018) argued that having the financial support of the family provides graduates with a prolonged period to search for a job, and this will enable them to search for a job that is more suitable for them.

Graduates of public universities are less likely to be unemployed, when all other independent variables are held constant. Although there are some stereotypes in the labour market that put public university graduates at a disadvantage, this trend is changing since many public universities in Malaysia nowadays are performing better than private universities. According to Balakrishnan (2017), only 51% of unemployed fresh graduates are from public universities and higher learning institutions. Furthermore, it has been noted that 64% of the employers who participated in a JobStreet survey mentioned that they did not differentiate between graduates from public, private or foreign universities when they hired workers.

Conclusions and Recommendations

The results revealed that all the seven variables in the regression model were significantly related to the employment status of Malaysian graduates in the Klang Valley. The results showed that the probability of unemployment tended to be greater for graduates who (i) perceived there was gender bias among employers, (ii) perceived they had employability skills, (iii) perceived economic conditions could influence their job prospects, (iv) perceived that academic performance would ensure employability, (v) perceived work experience as a key factor for employment, (vi) had working parents, and (vii) had graduated from a private institution of higher learning.

Several recommendations can be made based on the findings of this study. First, it has been found that the perception of gender bias among graduates can increase the probability of graduate unemployment. To reduce graduate unemployment, gender bias should be tackled from the supply and demand side. From the demand side, employers should not demonstrate any form of gender bias in hiring workers. In addition, graduate unemployment can also be curbed from the supply side by ensuring that the graduates themselves do not have misconceptions about gender bias in the labour market that may inhibit their job search and reduce their probability of finding employment. Thus, attempts by the government to address any form of gender discrimination in the labour market will reassure graduates that gender bias in the labour market is not an obstacle to their employment prospects, and this will encourage them to apply for a wider variety of jobs, and thereby, reduce the probability of graduate unemployment.

Next, the perception of one's employability skills has been found to be positively related to the probability of graduate unemployment. The positive coefficient implies that the probability of unemployment is higher for graduates who perceive that they have the necessary skills; i.e., in spite of a positive self-evaluation of employability skills, these graduates have a higher probability of unemployment. This may be because graduates tend to overrate their own employability skills or their perception of employability skills may differ from the expectations of employers. Hence, it is suggested that the government and institutions of higher learning should be given the onus to ensure that graduates are equipped with the relevant skills that are actually needed by employers rather than allow graduates to equip themselves with the level and type of skills that they perceive are necessary for employment.

The model showed that another determinant of graduate unemployment is the graduates' perception of economic conditions. The results of the regression analysis indicate that the perception of unfavourable economic conditions tends to increase the probability of unemployment. This may be because graduates who perceive that economic conditions are adverse are less active in their job search efforts, and this will increase the probability of unemployment. Adverse economic conditions can indeed reduce the chances of finding paid/salaried employment, and thus, increase the probability of graduate unemployment. However, the probability of graduates finding a job can be improved, even in times of economic adversity, by encouraging graduates to be self-employed. It is recommended that institutions of higher learning make concerted efforts to train and prepare graduates for the business world so that more graduates will venture into self-employment and entrepreneurship.

The model also included another variable, i.e., graduates' perception of the importance of academic performance. The more one perceives the CGPA as being important for graduate employment, the higher the probability of unemployment, other factors being constant. This may be because graduates who over-emphasize the importance of a high CGPA may compromise their achievement in other aspects, such as participation in co-curricular activities, which are also valued by employers. Very often, employers do not simply select or hire workers based on academic performance but instead consider their overall achievements, i.e., academic as well non-academic performance. Therefore, institutions of higher learning should re-design their undergraduate programs in order to produce well-balanced and holistic graduates.

In this study, the perception of the respondents about work experience was also included in the model. The more one perceives work experience as a ticket to employment, the greater the probability of graduate unemployment. Graduates who opine that employers emphasize experience as an essential factor in the hiring of workers may be deterred from applying for many jobs simply because they regard themselves as unsuitable candidates due to their lack of work experience that is desired by employers, and this will increase the probability of unemployment. In order to increase the probability of graduate employment, graduates should be encouraged to apply for jobs in the private and public sectors despite of their lack of experience by giving them entry-level jobs, providing them with on-the-job training and paying them lower starting salaries during the training period to compensate for their lower productivity as they learn the ropes at the workplace.

The findings of this study showed that the root of the graduate unemployment problem is not limited to factors related to the demand side (employers), but also encompasses factors on the supply side (graduates). On the supply side, the variables that were focused on in this study were the perceptions of graduates about various employment-related factors and how each variable influenced the probability of graduate unemployment. Following this, several recommendations have been put forward as to how to reduce the probability of graduate unemployment in line with the findings of this study.

Finally, this study was done on a sample of fresh graduates from public and private institutions in the Klang Valley. It is suggested that further studies be undertaken involving a larger sample throughout other states in the country to take into account the perceptions of fresh graduates, which may vary according to their geographical location. In addition, future research can combine the perspectives of both employers and graduates to provide a more comprehensive analysis of graduate unemployment.

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Demographic Factors Affecting Speed of Job Placements: An Empirical Analysis using Administrative Data

Mohammad Azmeer Abu Bakar[a], Mohd Alzaiery Abdul[b,c]*, Muhamad Zharif Luqman Hashim[a,c]

Abstract

Motivation and Aim: Reopening the economy after a lockdown has accelerated the placement rate among retrenched workers signalling that the Malaysia's labour market still in the recovery phase. However, most of the vacancies offered are allied to the low-skilled jobs category but not aligned to the supply side, which mostly high-skilled workers. It is this imbalance that motivated this study to examine the educational level importance in boosting the placements speed in the post-Movement Control Order (MCO) period.

Methods and Materials: Administrative data of 8,848 jobseekers who lost their jobs and obtained placements from July to December 2020 were provided by the Employment Insurance System (EIS). The ordinary least squares (OLS) regression was utilised alongside other diagnostic tests, namely a heteroscedasticity test, normality test, and misspecification test.

Key Findings: Findings showed that jobseekers with higher education backgrounds took a longer time to receive job placements. Other demographic factors indicated that males seemed to get jobs earlier by two days than females, while married people appeared to get placements faster than singles.

Policy Implications: The government's actions in handling the current labour marker issues caused by the pandemic appear to be successful as numerous vacancies are being offered. However, the vacancies do not reflect the needs of jobseekers. Generating high-skilled jobs, rapid involvement in the curriculum of universities, and matching industries demands with the supply from universities are some of the initiatives proposed in this study.

Keyword: COVID-19, Duration of Unemployed, Education, Loss of Employment, Job Placement

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[a]School of Business and Economics, Universiti Putra Malaysia, Serdang, Malaysia
[b]Institute of Tropical Agriculture and Food Security, Universiti Putra Malaysia
[c]EIS-UPMCS Centre for Future Labour Market Studies, Menara PERKESO, Putrajaya, Malaysia
*Corresponding author: zaiery0211@gmail.com

Introduction

The emergence of the Covid-19 pandemic has led to a domino effect that is threatening the lives and livelihoods of human beings across the globe. The World Bank (2020) projected that many countries would be facing recessions in 2020 as the pandemic will bring down their GDP per capita income to the lowest since it was first recorded in 1870. Meanwhile, the Asian Development Bank (2020) declared that the Covid-19 pandemic would cost the global economy about $5.8 trillion to $8.8 trillion in the second quarter (Q2) of 2020. The World Health Organization (2020) reported that nearly half of the world's 3.3 billion workers are in jeopardy of losing their jobs as the labour force is unable to enter the labour market due to border closures, import barriers, and confinement controls.

The International Labour Organization (ILO, 2021) reported that the global unemployment rate in 2020 rose to 6.5%, which was higher than that of the global financial crisis in 2009. This unnerving phenomenon has triggered governments around the world to take pragmatic actions by providing unemployment benefits for retrenched workers. In the case of Malaysia, the implementation of the Movement Control Order (MCO) in March 2020 forced firms to take the unprecedented action of downsizing inputs and outputs, which significantly reduced their profits. As a consequence of inadequate industrial revenue, more workers are being laid off. Therefore, one of the hiring incentives that is being provided by the Malaysian Government is an unemployment benefit (UB) known as a Job Search Allowance (JSA)[1]. This unemployment benefit, which is provided under the Social Security Organisation (SOCSO) scheme, is meant to assist retrenched employees.

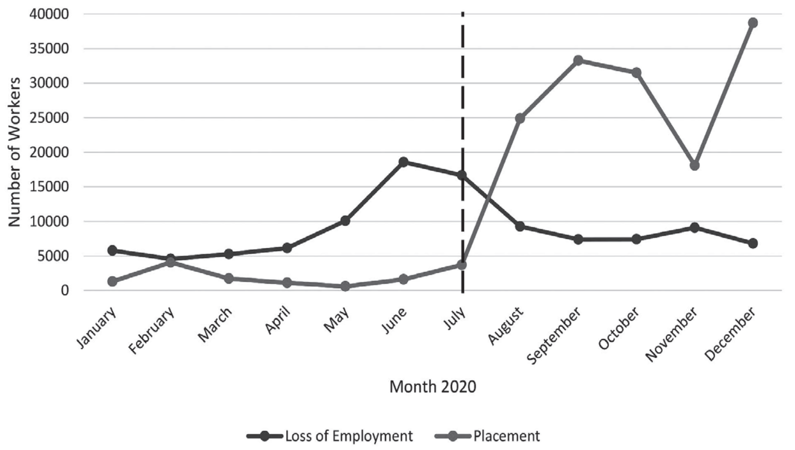
The unique feature of the JSA is that if jobseekers manage to secure a job within six months, they are entitled to an Early Reemployment Allowance (ERA), which is 25% of the balance JSA payment in a lump sum. This policy is meant to motivate JSA receivers to attempt to secure a job within the six-month period. Based on the Employment Insurance System 2021 Report (EIS, 2021), 4,757 jobseekers benefited from the ERA incentive in the year 2020. These initiatives, together with the government's enforcement of the Recovery Movement Control Order, helped to improve the placement rate (see Figure 1), especially in the

[1] A Job Search Allowance (JSA) is an unemployment benefit that is projected for a maximum of 6 months, with a diminishing marginal percentage of wages.

third quarter of 2020. Despite the improvement in the labour market, the role of education in helping to accelerate job placements in the post-MCO period is still questionable as the effects of the Covid-19 crisis are still daunting to jobseekers, especially high-skilled jobseekers, because of the limited job offers in the labour market.

Therefore, the aim of this study was to identify the demographic factors affecting the speed of placements in the post-MCO period. To study the factor of placement speed, administrative data on job placements between 1 July 2020 and 31 December 2020 were obtained from the Department of Employment Information Analysis Services, Employment Insurance System Office of the Social Security Organisation (SOCSO). The contribution of this paper to scientific knowledge is essentially an empirical analysis to determine the demographic factors that drive the speed of placements during this era as such studies are very limited in the current literature. This paper is also expected to provide policy responses that reflect the findings of this study.

This paper is structured into five sections, with the next section discussing related previous studies that guide in understanding the subject matter. Section 3 explains the procedures involved in filtering the data methodology used. The functional form of the regression model and a detailed summary of the measurement used for every variable are also described meticulously in this section. Section 4 discusses the use of the OLS regression analysis to achieve the objectives of the study. Last, but not least, the paper ends with a summary of the overall interpretation of the results, while providing a few policy recommendations based on the insightful findings.



Source: Employment Information Analysis System (EIAS)

Figure 1 Loss of employment and placement for the year 2020

Literature Review

In this section, the literature review emphasised the impact of unemployment benefits worldwide, and the effects of education and demographic factors on the speed of placements.

Impact of Unemployment Benefits Worldwide

According to the standard search-theoretic model, increasing unemployment benefits will lower the net cost to jobseekers in their search for jobs, resulting in an increase in reservation wages, thereby significantly reducing the speed of placements due to the moral hazard (Chetty, 2008). The effectiveness of unemployment benefits has a two-sided effect as it varies across countries. In Australia, a longer period of unemployment benefits (Newstart Allowance)[2] leads to more financial stress as jobseekers need to cope with rising costs of living and diminishing reservation wages (Morris & Wilson, 2014). Moreover, those who are entitled to a longer period of unemployment benefits do not show any match in quality, whether in salary or job period (Card, 2007). Schmieder (2016) added that a 6-month rise in the unemployment insurance (UI) period specifically reduces daily wages by 1%. Likewise, Fujita and Moscarini (2017)

[2] NSA is an Australian income support payment that provides financial assistance to people aged 22 years or older but under pension age who are unemployed or treated as unemployed and, unless exempted from mutual obligation requirements. NSA is calculated on a daily basis and is paid in arrears.

also found a promising association in Austria between the expansion of comparatively short baseline UI benefits and reemployment incomes. They also found that the unemployment period is negatively associated with income.

Providing unemployment benefits for a longer period has a negative effect on the job search rate (Gutierrez, 2019). Lichter (2016) proved that people who benefit from unemployment insurance for more than two months after their application period are associated with lower job search severity. Meyer (2002) concluded that a massive amount of UI payments is linked to a longer period of unemployment, where jobseekers take a longer time to get placements. On the other hand, a longer job placement period is said to have no effect on the reservation wages that jobseekers receive when they register as unemployed persons (Le Barbanchon, 2017). Nichols (2013) mentioned that although the unemployment rate is declining over time, the duration of unemployment for the individual is increasing.

Moreover, the extended unemployment benefits add a significant positive recovery to the labour market, where the expansion of welfare helps jobseekers to find jobs with higher wages (Barro, 2010; Hagedorn et al., 2015). Recent research in this area has discovered that compensation extensions have a minor impact on individual job search rates and unemployment periods (Farber & Valletta, 2015; Rothstein, 2011). Furthermore, providing adequate time for job searches through extended unemployment benefits significantly enhances job matching (Farooq, 2020). In the United States (U.S.), the UI scheme is considered to be a success since the replacement rate was 76% during the Covid-19 pandemic, with 60% being granted with the scheme (Ganong et al., 2020).

Apart from providing allowances to jobseekers, unemployment benefits assist them in getting better job prospects and act as a survival income. For instance, the Federal Pandemic Unemployment Compensation (FPUC) in the United States has shown that individuals collecting benefits tend to receive better job offers than those who do not collect benefits (Ganong et al., 2020). Based on the Bureau of Labour Statistics (2021), the unemployment rate in the United States in March 2021 was reduced to 6.0% primarily due to the bold policy measures implemented by the government in ensuring that humanitarian and relief aid reached the most vulnerable people.

In New Zealand, job search assistance seems to be the most effective and least expensive of interventions (Andrews & De Raad, 2009). In Vietnam, the UI scheme has contributed to numerous job placements and vocational training (Park, 2016). Apart from that, Michelacci and Ruffo (2015) suggested that unemployment insurance should be more generous to the young generation who have low savings since it motivates them to pursue jobs.

The impact of unemployment benefits (UBs) on job placements varies across countries. Based on the previous studies mentioned above, it can be summarised that a shorter period of unemployment benefits has a significant and positive impact on job placements. In comparison, a longer period of unemployment benefits has a negative impact on income, where income decreases when the UB period is extended, and jobseekers become demotivated in seeking for jobs.

Effect of Educational Background on Duration of Placement

The educational background of jobseekers seems to affect their speed of placement. Based on the review, jobseekers with higher education tend to get placements earlier and go through a shorter duration of unemployment than those without qualifications or with basic vocational or intermediate qualifications for most European countries (Brooks & Youngson, 2016). Li et al. (2008) discovered that students with minor or major specifications are more likely to get hired faster than those without specifications. Additionally, employers see the benefit of replacing jobs with graduates who can bring new talent into their businesses, and provide high-quality work at low cost. Such jobseekers are often hired for permanent positions, which will probably shorten the duration of unemployment for graduates (Brooks & Youngson, 2016).

Nevertheless, being a first-class degree holder in Malaysia is still not a guarantee that the graduate will secure a job on graduation, as the quality of the graduate in terms of skills may still be lacking (Ismail, 2011; Hanapi & Nordin, 2014). Mohamed (2004) underlined as many as eleven reasons that lead to a longer duration of unemployment for graduates, the most common of which is the quality of the education, which may not be related to the working scope of industries. In addition, fresh graduates lack communication skills, especially during a presentation. In line with that, the OECD (2006) reported that the globalisation of higher education has resulted in an overabundance of college graduates, resulting in a competitive labour market. Graduates from tertiary education backgrounds have encountered numerous hindrances and barriers in seeking jobs (FengLiang et al., 2009). Meanwhile, some graduates have accepted positions in which they are insufficiently compensated for their degree, resulting in so-called "over-education" and "crowding-out" issues. (Tomlinson, 2008).

Therefore, Linn (2015) proposed that one way to boost job placement is to make internship a compulsory subject for university students as employers prefer hiring graduates with ample working experience. Plus, internship courses are gradually being touted as a panacea for bridging the gap between employers seeking qualified graduates and the onus of universities to provide quality graduates (Du-Babcock, 2016). Hesketh (2000) found that communication skills, working in a team, problem-solving, and the ability to learn are the top four priorities sought by employers and that induce fast hiring. Bai (2006) also suggested that Chinese higher education institutions should diversify their curricula and provide graduates with expertise and skills that meet business demands in order to reduce the duration of graduate unemployment.

Various Demographic Factors Resulting in Different Speeds of Placement

Based on the review, various demographic backgrounds also produce different results for speed of placements. For instance, the labour demand side is concerned about the age factor as they believe that hiring older workers will lead to higher training costs, which will eventually be reflected in a lower demand by firms for older workers (Heywood & Siebert, 2008). On the labour supply side, poor health conditions and poor adaptability levels will lead to a longer job placement period for older jobseekers (Schirle, 2008). Moreover, Gringart and Helmes (2001) believed that discrimination in terms of age results in younger applicants getting a faster response and placement compared to older applicants in Western Australia. In work-related contexts such as recruitment, workforce allocation, performance assessment, advancement decisions, and training, age discrimination can result is biased decision-making, derogatory judgments, and unequal practices (Zacher & Henriette, 2015).

In addition, the race or ethnicity of jobseekers can also affect their speed of placement. In developed countries, ethnic minorities have significantly lower hiring opportunities than the majority ethnic population and take a longer time to get a job placement (Lancee, 2021). Despite the increased achievement, employment conditions are not universally changed after work placements, with more employment drawbacks being observed among Black and minority ethnic (BME) groups. Those with a lower socioeconomic status tend to get placements late and are hardly called for an interview (Moores, 2017). Moreover, discrimination is common among races with a greater social distance from the mainstream, such as in Muslim and African or Middle Eastern countries (Hagendoorn, 1995).

Nevertheless, Khalid (2016) found that ethnic minorities[3] in developing countries, such as Malaysia, tend to get placements first compared to the ethnic majority. It is believed that stereotypes are linked to such systemic cognitive and behavioural tendencies (Cuddy, 2009).

Besides, the role of gender can also affect the speed of placements. For instance, male jobseekers in France and West Germany take a shorter time than female jobseekers to get placements (Lauer, 2003). In addition, they are sometimes justified by higher communal ideals that perpetuate a dominant power structure (Glick, 2013). As a result, males are expected to be better able to step into managerial roles than females, resulting in a lower chance of females being recruited into managerial positions (Eagly, 2002). Carlsson (2011) stated that no signs ofgender inequality are being exhibited in the labour market, while Blommaert (2014) found positive factors favouring females over males. Likewise, females are thought to have more communal characteristics associated with a nurturing behaviour, which are favoured by employers (Cuddy, 2014). Married males have traditionally been assigned a social position to make money at work. In contrast, married females have traditionally been assigned the social role of performing domestic duties, thus, reinforcing the notion that males are favoured to be hired faster by employers compared to females (Eagly, 2013).

Furthermore, the factor of the marital status of females was also at the centre of discussions in the literature compared to ethnicity, age, or weight due to its moral justification (Morris, 2007). In urban China, married females and mothers face major drawbacks in terms of jobs and earnings, which have resulted in their late placements (Zhang, 2008). Hughes and Maurer-Fazio (2002) added that marriage significantly lowers the economic status of females compared to males, while single females tend to get placements earlier than married females. Some observational data have shown that industries give greater consideration to single people compared to married people because of the ability and willingness of the former to work longer hours (DePaulo, 2006). Traditional notions of marriage such as it entails greater social obligations outside the workplace for females can contribute to the belief that married females are less appropriate for jobs than single females (Hoobler, 2009). Married partners tend to get placements late since they can rely on their partner for an alternative income

[3] Out of 3,000 resumes that were sent out, 22.1% of the Chinese applicants and only 4.2% of the Malay applicants were called back for interviews

while continuing to receive consistent unemployment benefits, which represent their reservation wages (Ahn et al., 2004).

Research Gap

Previous studies in the literature debated the positive and negative sides of unemployment benefits. This encouraged the researchers to conduct an in-depth study on the effectiveness of unemployment benefits on speed of placements. Past research also mainly collected demographic data randomly without any targeted field. In this study, demographic data on the receivers of unemployment benefits were collected to observe the effectiveness of unemployment benefits on the speed of placements. Besides, most studies prioritised external factors such as economic recession, mismatch in job creation, and government policies, and only a few studies included demographic factors. Hence, this study used demographic factors to fill the gap. Moreover, the influence of demographic factors on the speed of placements has been widely studied in developed countries. Therefore, this study focused on developing countries since their labour market structure and economic environment are different from those of developed countries.

The factors affecting the speed of placements vary across developed and developing countries. For example, a study in a developing country such as Vietnam illustrated that family income, accepted salary and location are some of the factors that contribute to fast placements (Nghi & Ni, 2020). A study in a developed country such as Australia outlined that housing prices are one of the factors affecting the speed of placements because Australians will find jobs faster if they are burdened with a heavy housing debt (Morris & Wilson, 2014).

Methodology

The discussions in this section are mainly on the procedures for the collection and cleaning of administrative data, the formulation of the econometric model, and the selection of a regression method. A few diagnostic tests are also explained and applied in the model to ensure its stability and reliability.

This study used the ordinary least squares (OLS) regression method to find the unknown parameters in the model (Gujarati et al., 2012). By using this method, the variance can be minimised without violating the Best Linear Unbiased Estimator (BLUE) assumption (Freedman, 2009). Furthermore, the OLS can detect noisy data in a sample of data and straightaway eliminate that particular variable to obtain more accurate results (Huang, 2018). The majority of the literature used the

OLS method because it involves the relationship between two variables, and the incentives of unemployment benefits are limited (Caliendo, 2013). Besides, an Autoregressive Distributed Lag (ARDL) cointegration model was also used in a previous study to find the long-term relationship between the factors and speed of placements (Karikari-Apau & Abeti, 2019).

A few processes are involved in the cleaning of data, starting with the consistency of the data. All the components of various sizes in the sample are considered. The second process is for simplicity, as fractal measurements can be conveniently measured in standard applications such as Excel, SPSS, STATA and Mat lab. In this study, Stata was used as its features are more visible at the advanced end, it is easier to get assistance for Stata, and it is more commonly used in academia than SPSS and Excel (Baum, 2006).

When using a regression analysis to measure fractal dimensions, an adequate data sample needs to be taken into consideration. If these issues are not addressed correctly, the measurement and performance of the study can be negatively impacted. After all the above measures had been considered, the general functional form of the regression was constructed as follows:

$$Duration_t = \beta_0 + \beta_1\ Education_t + \beta_2\ Age_t + \beta_3\ Age2_t + \beta_4\ Gender_t + \beta_5\ Marital\ status_t + \beta_6\ Races_t + \varepsilon_t \qquad (1)$$

where the descriptions of the variables are explained in the following table.

Table 1 Variables, descriptions and abbreviation

Variables	Descriptions	Abbreviation
Duration	Duration is taken from the period of being unemployed until secure a job. Duration is being measured in days.	Duration
Education	Education has been divided into 2 categories where High education = 1 or Low education = 0 High education incorporated from Diploma, Degree, Master and PhD. Low education consists of UPSR, PT3, SPM & STPM.	Dum_education
Age	Age of candidates is in continuous numeric.	Age
Age Square	Age square has been included in this study to find the long-term impact of age on the duration to get placement.	Age2
Gender	Dummy Gender is being used as Male = 1 and Female = 0	Dum_male
Marital Status	Marital Status has been divided into 2 categories, namely Married =1 or Single = 0.	Dum_married
Races	Malay coded as 1 while Others as 0. Others compromise of Chinese, Indian, Bumiputera Sabah, Bumiputera Sarawak and Orang Asli (Peninsular).	Dum_malay

Dummies were used for education, marital status, gender and race because these variables have more than 2 attributes. OLS regression models treat all independent variables as numerical data such as in the form of intervals or ratios. Therefore, the attributes had to be replaced with numerical codes before the OLS regression analysis could be used.

After the variables in Equation (1) had been incorporated into the dummy variables, a new regression model was generated as follows:

$$Duration_t = \beta_0 + \beta_1\ Dum\_education + \beta_2\ Age_t + B_3\ Age2_t + \beta_4\ Dum\_male + \beta_5\ Dum\_marrried + \beta_6\ Dum\_malay + \varepsilon_t \quad (2)$$

Data

The data were requested from the Department of Employment Information Analysis Services (EIAS), Employment Insurance System. The samples consisted of jobseekers who had lost their jobs and obtained placements between 1 July 2020 to 31 December 2020. The significance of using the data was primarily because the labour market was already in the recovery phase after receiving a tremendous hit from the impact of the Covid-19 pandemic. At the same time, it could also be used to measure how crucial the educational level was to the labour market in the post-MCO period. The raw data in the early stage was comprised of 51,248 samples. However, some of these samples were duplicates and the questionnaires had not been completed by the individuals as the information was optional. In order to achieve the objective of this study, the educational background together with several demographic variables were required. Thus, these variables needed to be fulfilled if they were to be included in the developed model. After cleaning the samples of blank data, what remained finally were 8,848 samples. These samples were sufficient enough to run the regression analysis following the calculation provided by Bam (1992), which set the minimum sample size at 10% of the population.

The data sample was comprised of individuals aged 18 to 61 years of different educational backgrounds, races, and marital status. The variety of variables created a complex data set. Therefore, some of these variables had to be grouped into new classifications. In research work, it is highly recommended that variables be grouped so that they can be easily interpreted according to the classifications.

Diagnostic Tests

Heteroscedasticity Test

Heteroscedasticity suggests that there is no constant variance in error terms, and it relies on the importance of the explanatory variable (Knaub, 2007). The most suitable tool to detect heteroscedasticity in time series data is the Breusch-Pagan Godfrey test (Breusch, 1979). The null heteroscedasticity test hypothesis is established if the series is homoscedastic, while the alternative hypothesis is identified if the series is not homoscedastic. If the p-value of $\chi 2$ is smaller than the significance level (α), then, the H_0 will be rejected at 1%, 5%, or 10%. A heteroscedasticity test can be obtained by using Stata.

Misspecification Test

The Ramsey RESET test is primarily used to observe the incorrect functional forms of dependent and independent variables (Shukur & Edgerton, 2002). If the model specification is correctly developed, the H_0 of the Ramsey RESET test is implied, while the alternative hypothesis is demonstrated if the model specification is falsely formed (Ramsey, 1969). If the p-value of the F-statistic is less than the significance level (α), then, the null hypothesis will be rejected at 1%, 5%, or 10%. Stata can be used to detect the specification error in a series.

Results

A statistical analysis of the relationship between the variables was conducted based on the administrative data collected in the Methodology section, starting with the descriptive statistics, where details of the data tabulation were presented in numerical form. Then, the relationship between the variables was analysed using a correlation matrix to test multicollinearity, before proceeding with the OLS regression. After discussing the results of the ordinary least squares (OLS) regression, a few diagnostic tests were also carried out to ensure that there was no econometric problem in the model.

Descriptive Statistics

Table 2 presents the descriptive statistics of the mean, standard deviation, and minimum and maximum values for the dependent and independent variables. Descriptive statistics are important for presenting complex data in a meaningful way and have to do with the variability of the dataset.

Based on the table of descriptive statistics above, the mean for the duration showed that the average duration for jobseekers to get placements was 66 days. The standard deviation for the *duration* was 40, which illustrated the spread of the data towards the mean. The minimum value for the duration to obtain a placement was 0 days, indicating that there was a jobseeker who managed to secure a job on the same day after being laid off. The maximum number of days was 171, meaning it took almost five months to secure a job.

The arrangement of the variables in a vertical form implied the duration of days to get a placement. Tertiary-level holders secured placements within 68 days compared to non-tertiary-level holders, who took 65 days. Male jobseekers required 65 days to get a placement, while female jobseekers needed 68 days to be hired. Married jobseekers took 65 days, while singles took 67 days to get a placement. Malays and other races required 66 days to get a placement.

Table 2 Descriptive statistics

Variables	Mean	Maximum	Minimum	Std. Dev.	Jarque-Bera
Duration (days)	66	171	0	40.782	290.1398
Age	33.865	61	18	9.295	1531.657
Age2	1233.255	3721	324	686.768	1474.817

Correlation Matrix

The correlation matrix in Table 3 describes the strength of the correlation between two random variables ranging from 0 to 1. A correlation matrix is crucial in understanding the nature and degree of a relationship for forecasting and future planning.

A value of 1.00 indicates that a variable is highly collinear with the respective variable in the correlation matrix part, while 0 indicates that there is no correlation between both variables. A value of more than 0.50 indicates a strong positive relationship between the variables, while a value of 0.49 and below indicates a weak positive correlation between the variables. In the study sample, all the independent variables had a weak collinear relationship with the dependent variable, which was the duration to get a placement. This was a good indicator as the selected independent variables depended on the dependent variable, which could violate the analysis.

Table 3 Correlation matrix

Variables	Durations	Education	Age	Age2	Male	Married	Malay
Dum_education	0.0283	1.0000					
Age	-0.0075	-0.1749	1.0000				
Age2	-0.0092	0.1882	0.9913	1.0000			
Dum_male	-0.0339	-0.1371	0.0863	0.0781	1.0000		
Dum_married	-0.0232	-0.1600	0.4767	0.4427	0.2143	1.0000	
Dum_malay	-0.0002	-0.1069	-0.1609	-0.1610	0.1227	0.0964	1.0000

OLS regression

Based on the OLS regression result (Table 4), the F-statistic was 3.39, indicating that the model was statistically significant at 5%, while the R-squared and adjusted R-squared were 0.002. This showed that the model explained 2% of the variance. A low R-squared value was obtained because humans are typically very heterogonous in their attitudes, actions and behaviours, which will tend to have R-squared values of less than 50% (Frost, 2019).

Table 4 OLS regression result

No. of Observation	8,848			
F-statistics (6, 8841)	3.39			
R-squared	0.002			
Adj. R-squared	0.002			
Variable	Coefficient	Std. Error	t-statistics	Probability
Dum_education	1.766*	0.909	1.94	0.052
Age	0.644*	0.379	1.70	0.089
Age2	-0.008	0.005	-1.61	0.108
Dum_male	-2.397***	0.909	-2.64	0.008
Dum_married	-1.980*	1.066	-1.89	0.063
Dum_malay	0.806	0.933	0.86	0.387
C	55.690***	6.615	8.42	0.000

Notes: ***, ** and *referring to the rejection level of null hypothesis at significance level of 1%, 5% and 10% respectively.

Impact of Education on the Speed of Placements

The regression results showed that *education* had a positive coefficient and was statistically significant. As high education was a dummy for the *education* variable, jobseekers with high education backgrounds took a longer duration to get a placement compared to jobseekers with low education. This result contradicted the findings in the existing literature (Smith, 2018; Lettmayr, 2012; Lauer, 2003) because of the nature of the job vacancies offered in Malaysia from the demand side is inclined towards low-skilled occupations. According to the EU-ERA Quarterly Report (EU-ERA, 2021), the vacancies available for the fourth quarter of 2020 were more concentrated on the low-skill categories (70% of the total vacancies offered), which did not require jobseekers with high educational skills. Meanwhile, high-skilled jobseekers comprised 45.5% of the total number of jobseekers, indicating that job vacancies for high-skilled jobseekers are still lacking in Malaysia compared to vacancies for low-skilled jobseekers.

In addition, Ismail (2011) argued that high-skilled jobseekers in Malaysia still lack skills, even if they have outstanding academic achievements. Mohamed (2004) mentioned as many as eleven reasons[4] for the longer duration

[4] A capital-intensive economy, quality of education, potential of candidates, lack of training experience, poor skills and personalities, evolution of education, surge in graduates' workforce, miscommunication between universities and industry, swift increase in number of population but low mortality rate and economic downturn are among reasons contributing to the longer unemployment duration for Malaysian graduates (Mohamed, 2004)

for unemployed graduates to secure a job, some of which are poor skills and personality. In line with that, the World Bank (2019) reported that enrolment for tertiary education in Malaysia showed a downtrend from 2016 to 2019. As a result, graduates are having a tough time, especially in finding jobs that match their qualifications.

This is a troubling scenario as the contributions of higher education to a complacent future generation appears to be vague. There is concern that the prolonged persistence of this dilemma will push the unemployment rate up among high-skilled jobseekers. The situation will build a sceptical perspective and dampen the motivation of students to achieve their passion in pursuing higher education to the level of a Diploma and Degree. This problem will lead to a catastrophic loss in educational investment and impede potential high-skilled jobseekers, and will eventually demoralise future generations in their passion to enrol in higher education.

Impact of Age on the Speed of Placements

Age was shown to have had a significant positive impact on the duration to get a placement, which implied that a one-year increase in the age of jobseekers led to a delay of 0.64 days in getting a placement. The result showed that older adults were hardly getting placements earlier compared to youngsters. It is argued that the reason behind this is the nature of the vacancies that are available in the employment market, where only entry-level jobseekers with less experience are required. The EU-ERA Quarterly Report (EU-ERA, 2021) supports the argument that the vacancies being offered are concentrated in the low-skilled occupations. The nature of the jobs being offered calls for longer working hours, which is not suitable for older workers (Wilson, 2007).

The findings of this study showed that the *Age2* variable was also not significant to show that experienced jobseekers were not affecting the speed of placements in any way. As mentioned above, the *Age2* variable was intentionally included in the model to enable the effect of differing ages to be modelled. Therefore, it was concluded that the nature of the available vacancies influenced the age of jobseekers in getting placements.

Impact of Gender and Marital Status on the Speed of Placements

Both gender and marital status were significant and negatively related to the speed of placements. Here, *Dum_male* and *Dum_married* were used as the dummies for gender and marital status, respectively. Based on the result, it was found that males were getting jobs faster by two days than females.

It is believed that relatively fewer jobs were specifically offered for females compared to males, and thus, they took a longer time to get a placement. Huffman (2010) found the same result, and explained that females have little access to the most prominent positions in institutions and to stable jobs, thus forcing them to take more time in seeking other job opportunities.

Furthermore, Blau (2006) stated that females take more time to secure a job due to their salary preference. It is believed that they are paid lower than males for similar positions. Moreover, Petit (2007) argued that job recruiters also prefer males rather than females due to maternity issues, resulting in females having less chances of securing a job compared to males. Tripathi (2012) explained that married females are most vulnerable to stress, which eventually will affect their health. This discourages employers from hiring them, unless necessary. These stereotypes have given rise to the belief that married men are more driven and committed to their jobs, while married females are more motivated and dedicated to their families.

By using *Dum_married* as the dummy for marital status, the regression result showed that married partners tended to get placements faster by two days compared to single jobseekers. According to Herzog Jr (2000), the married partner is motivated by financial factors to diligently seek for a job to support the family compared to a single jobseeker, even though the latter can work longer hours and has fewer external commitments.

Impact of Race on the Speed of Placements

The *Dum_malay* variable did not have any significant impact on the duration of the placements. This showed that every jobseeker, regardless of their race, had the same chance to get a job placement. In this study, the Malays, who are the majority in Malaysia, were equal with the rest of the races when it came to getting job placements. This scenario illustrated that the employment market in Malaysia is becoming fair and equal in terms of racial discrimination compared to the finding by Khalid (2016). He stated that the ethnic minorities in Malaysia tend to get placements first compared to the Malays. It is believed that stereotypes are linked in a systemic way to such cognitive and behavioural tendencies (Cuddy, 2009).

Diagnostic Tests

In an attempt to validate that the model used was stable and free from econometric problems, a few diagnostic tests were applied to the model (see Table 5). The Breusch-Pagan Godfrey test, which checked for heteroscedasticity, showed that the p-value was statistically significant at the 1% significance level, thereby showing that the series was homoscedastic. On the other hand, the Jarque-Bera normality test, which identified the distribution of the series, showed that the p-value was highly significant at 1%, which means that the tabulation was normally distributed. A Ramsay RESET test was also conducted in this study to ensure that the model had no misspecification errors. The result of the test showed that the p-value was larger than the critical value, and thus, the study failed to reject the null hypothesis of no misspecification to conclude that the series was free of any bias.

Table 5 Diagnostic test

Diagnostic Test	Chi-Square/F-Stats	P-value	Conclusion
Heteroscedasticity Breusch-Pagan Godfrey	1.300	0.254	Series are homoscedastic
Ramsey Reset Test	0.408	0.408	No misspecification bias

Conclusions and Recommendations

The increasing trend of the placement rate has given rise to the question of whether demographic factors, especially educational background, influenced the speed of placements in the post-MCO period. An OLS regression model was designed and analysed based on 8,848 samples. Interestingly, the findings showed that jobseekers with high education, who were older, female and single spent more time getting placements compared to jobseekers with a low education, who were younger, male, and married, in the post-MCO period. Ethnicity did not significantly impact the placements, showing that every jobseeker, regardless of their race, had the same chance to get a job placement. The results of the diagnostic tests verified the findings as the model was free of any econometric problem.

The main finding of the present study is a signal to policymakers to restructure the economy in the post-MCO period. Finding a fair balance between the talents of the people and labour market demands is critical to ensuring the country fully utilises all the resources at its disposal. The current situation shows that talents are not being fully utilised due to a lack of demand from the industrial side, while at the same time, the supply side keeps producing graduates who are touted as high-skilled employees. In the long run, if this issue is not addressed, there will be an abundance of talents and the existing educational mismatch in the job market will become a permanent one.

Thus, it is proposed more investments be poured into potential sectors that can generate high value-added benefits along the supply chain. This will not only create more job opportunities for high-skilled workers, but, most importantly, can transform the country into a high-income country. Besides, the readiness of graduates from the supply side to enter the job market should also be emphasised by institutions. The syllabus provided by the institutions should be aligned with the skills, knowledge, and abilities demanded by industries. An ideal way to ensure that the supply side produces graduates who are reliable in meeting the demands of industries seems to be to involve industry players in the development of the curriculum framework. For instance, universities should invite employers to take part as tutors or visiting lecturers in certain subjects that require highly experienced employees. These steps will give some early exposure to university students in certain fields, such as in those requiring technical and analytical skills. Moreover, universities can also conduct field trips to industries during semester breaks, where students can experience a real industrial environment. Last, but not least, matching university courses with the job scope of industries is highly recommended as fresh graduates will have an overall picture of their future job scope. This will boost the hiring rate for candidates with knowledge of the industry rather than having zero knowledge. Hopefully, the proposed initiatives will help to reduce the educational mismatch in the employment market.

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Editor-in-Chief
Review of Labour Market Policy
EIS-UPMCS Centre for Future Labour Market Studies (EU-ERA)
Office of Employment Insurance System (EIS)
Level 2, Wisma PERKESO Putrajaya
No 6, Persiaran Perdana, Presint 2,
62100 Putrajaya.
Email: editor.rlmp@gmail.com

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