

Minimum Wage and Employment of Malaysian Low-skilled Workers

Kek Jing Wen^a

Lai Wei Sieng^b

Universiti Kebangsaan Malaysia

Abstract: The current study is inspired by inconclusive empirical findings on the impacts of minimum wage on employment. The majority of past studies have concluded that an increase in the minimum wage negatively impacts employment, despite certain scholars discovering either an insignificant or a positive impact. Hence, this study aims to investigate the impact of the Malaysian minimum wage on the employment opportunities of low-skilled workers. The data are collected annually from 1995 to 2020. An autoregressive distributed lag (ARDL) model is employed to examine the impact of the Malaysian minimum wage on the employment of low-skilled workers. The bounds test method and error correction model (ECM) are subsequently utilised to determine both short- and long-term effects. As a result, the employment of low-skilled labour is found to be positively impacted by the minimum wage, with this impact being statistically significant in both the short and long terms. However, when the interaction variables are included, the effect on the employment of low-skilled workers is negative and insignificant. Furthermore, neither increasing labour productivity nor technological advancement significantly altered the impact of the minimum wage on employment.

Keywords: Minimum wage, low-skilled workers, employment, ARDL, Malaysia

JEL classification: J31, O12, O15, P23

1. Introduction

The Malaysian labour force recorded 16.10 million employees in May 2021. Employees are categorised into high-skilled, semi-skilled, and low-skilled workers. According to the International Standard Classification of Occupations, low-skilled work consists of “simple and routine tasks which require the use of hand-held tools and often some physical effort”, such as those performed by office cleaners, freight holders, garden labourers and kitchen assistants. Moreover, a low-skilled worker could be defined as an individual who undertakes low-skilled work not requiring post-secondary degrees or credentials and is compensated with low wages. As such, the minimum wage is stipulated by the government to ensure that employees receive reasonable compensation for the respective labour. The minimum wage varies across regions, states or countries.

^a Faculty of Economics and Management, Universiti Kebangsaan Malaysia, 43600 UKM, Bangi Selangor, Malaysia. Email: p110570@siswa.ukm.edu.my

^b Faculty of Economics and Management, Universiti Kebangsaan Malaysia, 43600 UKM, Bangi Selangor, Malaysia. Email: laiws@ukm.edu.my (Corresponding author)

The first minimum wage policy in Malaysia was introduced in 2012 before being implemented in 2013. Specifically, the hourly rate was RM4.33 and the monthly rate was RM900 in Peninsular Malaysia, with RM3.85 hourly and RM800 monthly in Sabah and Sarawak (Minister of Human Resources, 2012). The Malaysian minimum wage increased to an hourly rate of RM4.81 and a monthly rate of RM1000 in Peninsular Malaysia, with RM4.44 hourly and RM920 monthly in Sabah and Sarawak in 2016 (Minister of Human Resources, 2016). Subsequently, the minimum wage was increased to RM5.29 hourly and RM1100 monthly in 2018, with the alternative rates being effective in the following year (Minister of Human Resources, 2018). In 2018, the minimum wage order was the same across Peninsular Malaysia, Sabah, the Federal Territory of Labuan and Sarawak, which allowed all Malaysian states to receive the same minimum salary.

The Malaysian government increased the minimum wage for workers in the city council or municipal council districts to RM5.77 hourly and RM1200 monthly during the early stages of the coronavirus disease (COVID-19) pandemic in 2020. Nonetheless, the minimum salary for workers in other areas would continue at RM5.29 hourly and RM1100 monthly (Minister of Human Resources, 2020). Dato' Sri Ismail Sabri Yaakob, the former Prime Minister of Malaysia, declared in March 2022 that the minimum wage would be increased to RM1500 monthly from 1 May 2022 onwards, which was an increase from the current RM1200 monthly (Thomas, 2022). Increases in the minimum wage would be implemented in May 2022 for private sector firms with five or more workers and effective in January 2023 for firms with fewer than five workers (Lim, 2022). The legislation resulted from the Ministry of Human Resources reporting in 2012 that 33.8% of private-sector employees were compensated with less than RM700 monthly, which was below the poverty line income (PLI) of RM800 determined in 2009 (Mahyut, 2013). The legislation would guarantee that all employees receive a salary above the poverty threshold, thereby enhancing life quality.

Under the neoclassical economic theory, raising the minimum wage will lead to a reduction in employment following two possible negative reactions from companies. Particularly, increasing minimum wages might compel businesses to increase the prices of respective goods and services, which might result in consumers decreasing demands. Furthermore, low-skilled workers with increased minimum salaries would be substituted by high-skilled employees (Giuliano, 2013; Neumark & Wascher, 2007), which is regarded as the labour substitution effect. Past findings revealed that enterprises would be more inclined to employ high-skilled or non-poverty employees when the minimum wage was increased, thus resulting in a detrimental impact on low-skilled or poor workers (Yamada, 2016).

The positive employment effect may occur in different job types. Previous researchers demonstrated that the minimum wage would negatively impact marginal employment while positively contributing to regular employment (Holtemöller & Pohle, 2019). Tajuddin et al. (2021) scrutinised aggregate employment (2021) and discovered that the Malaysian minimum wage policy led to fewer low-skilled foreign workers while increasing local employees in low-paid industrial employment. In addition, Neumark and Wascher (2008) argued that a higher minimum wage would decrease the demand for less-skilled workers while boosting the demand for skilled workers in

production. Nevertheless, Nordin et al. (2021) indicated that the Malaysian minimum wage significantly and positively impacted all employment types. Thus, aggregate employment data might not accurately illustrate the impact of minimum wages on low-skilled workers.

Statistics from Talentcorp demonstrated that semi- and low-skilled workers accounted for approximately 72% of total Malaysian employment in 2019 and 2020. Investigating the impact of minimum wages on Malaysian low-skilled workers is crucial owing to the direct impact of the minimum wage on low-skilled workers. Nonetheless, limited studies have been conducted on the current topic and the existing literature revealed contradictory findings, thus demonstrating the importance of empirical research to determine the actual impact of minimum wages, either positively or negatively. The present study aims to examine the impact of minimum wage on the employment of low-skilled workers. Moreover, labour productivity and technological advancement are incorporated as moderating variables in the impact of minimum wages on the employment of low-skilled employees. The following section focuses on reviewing the current empirical findings in both developed and developing countries. Subsequently, a description of the data, methodology and estimation equations is provided, before discussing the results and implications.

2. Literature Review

Minimum wages have generated numerous debates concerning relevant employment impacts. Several studies discovered that employment was negatively impacted by the minimum wage, despite insufficient empirical evidence to establish a direct relationship. Nonetheless, Rybczynski and Sen (2017) revealed that minimum wage adjustments between 1981 and 2011 negatively impacted employment rates in 10 Canadian provinces, especially among young locals and immigrants with reduced employment. An Indonesian study also demonstrated that boosting minimum wages would reduce formal-sector employment, with the rate of job loss surpassing the growth of informal-sector employment (Comola & Mello, 2011; Siregar, 2020). Siregar (2020) delineated that the development in the informal sector could be attributed to the relocation of workers terminated from the formal sector. South African low-skilled workers were also subjected to the same negative impacts of the minimum wage (Yamada, 2016). Contrarily, raising the minimum wage might positively impact employment. Wang and Gunderson (2018) discovered that the minimum wage significantly elevated the employment of low-skilled workers in China, although the results were not statistically significant in less developed areas.

Lemos et al. (2004) appraised the impact of the minimum wage on working hours and job availability in Brazil, wherein 0.14% of working hours and 0.02% of jobs were reduced in the short term when the minimum wage was increased by 10%. The cumulative effects were less than 0.5% in the long term, which suggested that increasing the minimum wage only produced a minor impact on employment. Meanwhile, Ding (2010) explicated that the minimum wage impacted urban and rural migrants differently in China due to external factors (the work contracts law and urban dual employment system). Rural migrant workers in Guangdong and Fujian were more

negatively impacted by the increased minimum wage in 2008 than in 2007, particularly low-salary occupations. Comparatively, the impact was negligible on urban employees. Furthermore, the impact on employment varied by region, in which the eastern region received minimal negative impacts, the western region received positive effects, and the central region received insignificant impacts (Ni et al., 2011).

Low-salary employment without requiring high-level skills would be eliminated by the increase in minimum wages (Neumark, 2018), as low-skilled employees are compensated with equivalent to or below the minimum wage. Sabia et al. (2012) demonstrated that employment among less educated youths declined by 20.2% to 21.8% when the minimum wage in New York was raised by \$1.60 per hour. Researchers also discovered that raising the minimum wage by more than \$1 in the United States would reduce low-skilled workers' employment by slightly more than 1 percentage point (Clemens & Strain, 2018). Past research in China investigating the changes in minimum wages revealed a detrimental impact on total employment in the eastern and central regions by combining country-level panel data with microdata from urban household surveys. The negative impacts were evident in young individuals and low-skilled employees, who were susceptible to the increase (Fang & Lin, 2015). Furthermore, approximately 2% of Indonesian production workers with a junior and senior high-school education and 2.9% of non-production workers with a primary education would be decreased with a 10% minimum wage hike (Del Carpio et al., 2015).

Certain studies demonstrated limited evidence regarding the negative impacts of increasing the minimum wage. The OECD research findings reported insignificant disemployment impacts on low-skilled employees, particularly female low-skilled workers and young workers (Sturn, 2018). Langevin (2020) longitudinally assessed the impact of increasing minimum wages on Canadian employment and revealed a statistically insignificant effect, with other developing nations obtaining similar findings. Additionally, Wang and Gunderson (2018) discovered no evidence of the impact on the negative low-skilled employees' employment effect among less developed areas in China. Summarily, multiple empirical studies revealed that the minimum wage was inversely correlated with employment, although the negative impact remained inconclusive when other employment policies, economic factors, regional development level, labour market structure (Munguia Corella, 2020), or job types (Holtemöller & Pohle, 2019) might confound the effect. Therefore, further research should be conducted to determine the actual impact of the minimum wage increase, particularly in Malaysia.

2.1 Minimum Wage, Employment and Labour Productivity

Minimum wages might impact employment depending on labour productivity. Bodnár et al. (2018) revealed that enhancing labour productivity was performed by Central and Eastern European firms instead of reducing employment to resolve the negative impact of increased minimum wages. Wye and Bahri (2021) elucidated that the detrimental effect of minimum wage on employment could be mitigated by labour productivity through capital investment or technical development. Nonetheless, higher

capital utilisation might eliminate numerous low and middle-level jobs. Graetz and Michaels (2018) delineated that robots adversely impacted the employment share of low-skilled workers, despite the total employment rate being insignificantly impacted. In addition, non-manufacturing employers might receive more employment mitigating the negative effect of industrial robots on manufacturing employment. The negative impact of increased technology usage on low-skilled employees could be mitigated by the increase in high-skilled jobs, despite the negative interplay between minimum wage and labour productivity (Wye & Bahri, 2021) on total employment. Summarily, the relationship between minimum wage and labour productivity might produce different impacts on the employment of low-skilled workers rather than on total employment. A more precise depiction regarding the impact of the relationship between the two variables on low-skilled employment in Malaysia is required.

2.2 Minimum Wage, Employment and Technological Advancement

Technological advancement could positively or negatively moderate the effect of minimum wage on low-skilled employment. The increasing automation of labour-intensive jobs evokes fear that emerging technology might render human labour obsolete (Autor, 2015), which would reduce the demand for low and middle-skilled employees while creating a corresponding increase in high-skilled employment. According to Lordan and Neumark (2018), a 10% rise in the minimum wage reduces the proportion of low-skilled employment that could be automated by 0.31 percentage points. Acemoglu and Restrepo (2020) also discovered that substituting a robot for every thousand workers would lower the employment-population ratio by 0.2% and the salary by 0.42%. Nevertheless, Lee and Clarke (2019) demonstrated that low-skilled employees could benefit from the expansion of high-tech sectors. Specifically, every 10 high-tech employment would result in seven local non-tradeable service occupations, with six filled by low-skilled individuals. Several studies also discovered that employment was negatively impacted by minimum wage. Nevertheless, empirical evidence was insufficient to establish a corroborated association. Moreover, previous research indicated the effect of technological advancement on low-skilled employment. Nonetheless, the effect of the interaction between minimum wage and technological advancement on the employment of low-skilled workers was not thoroughly investigated. Thus, assessing the impact of the relationship on the employment of low-skilled workers in Malaysia in detail is crucial.

3. Methodology and Data Analysis

26 years of annual data collected in Malaysia from 1995 to 2020 were utilised to explore the impact of minimum wages on low-skilled employment. All data were collected from the Department of Statistics Malaysia, Economic Planning Unit and World Development Indicators, with low-skilled employees possessing below a secondary educational level as the dependent variable (Wang & Gunderson, 2018). Meanwhile, the independent variable was the minimum wage indicator with values 0 and 1, wherein the value of 0 reflected the year before Malaysia enacted the policy

and the value of 1 the year after (Nordin et al., 2021). The gross domestic product (GDP) per capita, net inflow of foreign direct investment (FDI), labour productivity, and technical progression were employed as control variables (Lee & Clarke, 2019; Ni et al., 2011; Siregar, 2020; Wye & Abdul Bahri, 2021). The GDP per capita is a measure of national economic production per individual. Growing GDP per capita and household expenditure could boost long-term employment. Maitah et al. (2015) delineated that a 1% gain in GDP per capita would significantly increase employment.

Employment would be influenced by the net FDI inflow, which refers to foreign investors' direct investments in Malaysia. Foreign corporations who invest and develop businesses in Malaysia will provide additional job opportunities, thereby resulting in higher employment. Vacaflares (2011) observed the same association in Latin American economies. Higher labour force productivity, which was measured by dividing GDP by the number of employees, increased employment. Increased productivity would also enhance business outputs and profits while elevating the demand for investment and labour. Tadjoeddin (2016) discovered that productivity increased incomes in the Indonesian manufacturing sector, which subsequently promoted employment. Furthermore, technical progression would influence low-skilled employment as technological advancement would substitute low-skilled jobs with more high-skilled occupations (Hotte et al., 2023). Autor et al. (2003) elucidated that technological advancement would reduce the need for low-skilled workers to perform regular mechanised tasks while increasing the demand for high-skilled employees to perform technical and analytical work. Nonetheless, Lee and Clarke (2019) demonstrated that technological advancement created jobs for low-skilled employees. As such, the current study employed the total number of technological patents as a proxy for technical progression. Table 1 describes the study variables and data sources.

Table 1. Study variables and data sources

Variable	Description	Measurement unit	Source
EMPL	Employment of low-skilled workers	A thousand individuals	Economic Planning Unit
MW ₀	Dummy for minimum wage	D=1 on and after 2013, otherwise 0	
GDPC	GDP per capita	RM	Economic Planning Unit
FDI	Net FDI inflow	RM million	World Development Indicators Converting from US dollars to RM using the official exchange rate
LP	Labour productivity	RM	Economic Planning Unit based on the author's calculation
TECH	Technical progression	Unit	World Intellectual Property Organisation

3.1 Model Specification

Neumark and Wascher (2008) emphasised that empirical research should allow adequate time for the impacts of minimum wage to become apparent in the collected data, which highlighted the importance of analysing the impact in both short and long terms. The autoregressive distributed lags (ARDL) bounds test established by Pesaran et al. (2001) was employed to identify variable integration, which is suitable for small study samples to determine the short- and long-term impact of minimum wages on the employment of low-skilled workers. Moreover, the ARDL model is appropriate for combination variables that are stationary at Level $I(0)$ and First Difference $I(1)$, although the model was infeasible when Variable $I(2)$ was included (Pesaran et al., 2001). The model is also feasible for calculating short- and long-term elasticities through a small sample size by following the ordinary least square (OLS) technique for cointegration among variables (Nasrullah, et al., 2021). The following models were developed to accomplish the study objectives:

$$EMPL = f(MW_D, RGDP, FDI, LP, TECH) \quad (1)$$

The econometric models are expressed below:

$$EMPL_t = \beta_0 + \beta_1 MW_{D_t} + \beta_2 GDPC_t + \beta_3 FDI_t + \beta_4 LP_t + \beta_5 TECH_t + \epsilon_t \quad (2)$$

where $EMPL$ represents an employed individual with a low educational level, MW_D represents the dummy variable of minimum wage with 1 indicating the year after implementing the minimum wage policy. The symbols, namely $GDPC$, FDI , LP and $TECH$, represents GDP per capita, net FDI inflow, labour productivity, and technical progression respectively. β_0 denotes the constant, while β_1 to β_5 represent the coefficients of each variable. The error term is represented by ϵ_t . Meanwhile, log transformations were performed on variables to assist in estimating outcomes and reducing projected heteroscedasticity (Alimawi et al., 2020). The log transformation model was constructed as follows:

$$\ln EMPL_t = \beta_0 + \beta_1 MW_{D_t} + \beta_2 \ln GDPC_t + \beta_3 \ln FDI_t + \beta_4 \ln LP_t + \beta_5 TECH_t + \epsilon_t \quad (3)$$

The role of labour productivity and technological advancement were assessed to account for the impact of minimum wages on employment through the interaction of the minimum wage with labour productivity and technological advancement respectively. The main model and interaction variables were developed as follows:

$$\ln EMPL_t = \beta_0 + \beta_1 MW_{D_t} + \beta_2 \ln GDPC_t + \beta_3 \ln FDI_t + \beta_4 \ln LP_t + \beta_5 TECH_t + \beta_6 (MW_D \times \ln LP) + \beta_7 (MW_D \times \ln TECH) + \epsilon_t \quad (4)$$

Equations (3) and (4) were written in terms of the conditional error correction model or unconstrained error correction regression (Pesaran et al., 2001), which is an ARDL equation for assessing the presence of a long-term connection between the employment of low-skilled employees and corresponding determinants:

$$\begin{aligned} \Delta \ln EMPL = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta \ln EMPL_{t-i} + \sum_{i=0}^p \beta_2 \Delta \ln GDPC_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln FDI_{t-i} + \\ & \sum_{i=0}^p \beta_4 \Delta \ln LP_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln TECH_{t-i} + \beta_6 \ln EMPL_{t-1} + \beta_7 MW_{D_{t-1}} + \\ & \beta_8 \ln GDPC_{t-1} + \beta_9 \ln FDI_{t-1} + \beta_{10} \ln LP_{t-1} + \beta_{11} \ln TECH_{t-1} + \epsilon_t \end{aligned} \quad (5)$$

$$\begin{aligned} \Delta \ln EMPL = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta \ln EMPL_{t-i} + \sum_{i=0}^p \beta_2 \Delta \ln GDPC_{t-i} + \sum_{i=0}^p \beta_3 \Delta \ln FDI_{t-i} + \\ & \sum_{i=0}^p \beta_4 \Delta \ln LP_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln TECH_{t-i} + \sum_{i=0}^p \beta_6 (MW_{D_{t-1}} \times \Delta \ln LP_{t-i}) + \\ & \sum_{i=0}^p \beta_7 (MW_{D_{t-1}} \times \Delta \ln TECH_{t-i}) + \beta_8 \ln EMPL_{t-1} + \beta_9 MW_{D_{t-1}} + \\ & \beta_{10} \ln GDPC_{t-1} + \beta_{11} \ln FDI_{t-1} + \beta_{12} \ln LP_{t-1} + \beta_{13} \ln TECH_{t-1} + \\ & \beta_{14} (MW_{D_{t-1}} \times \ln LP_{t-i}) + \beta_{15} (MW_{D_{t-1}} \times \ln TECH_{t-1}) + \epsilon_t \end{aligned} \quad (6)$$

where β_0 represents the drift component while Δ indicates the first difference operator. p portrays the optimal lag length and ϵ_t depicts the white noise. The bound test was utilised to analyse Equation (4) in determining the existence of a long-term correlation between the study variables, which involved evaluating the significance of the lagged variable coefficients via an F-test. Cointegration and non-cointegration were investigated through the following hypotheses:

$$H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$$

$$H_0: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq 0$$

The F-statistics and critical values assisted in the hypothesis testing decisions. The null hypothesis (H_0) would be rejected when F-statistics exceeded the upper-limit critical value I(1) series, which suggested that long-term relationships existed between the variables. F-statistics below the lower-limit critical value I(0) would indicate that long-term correlations did not exist between the variables, which would not reject the null hypothesis. The results would be considered inconclusive when F-statistics were between the upper and lower limit critical values. The following long-term model was estimated by assuming that the variables were cointegrated:

$$\begin{aligned} \ln EMPL_t = & \beta_0 + \sum_{i=1}^p \beta_1 \ln EMPL_{t-i} + \sum_{i=0}^p \beta_2 MW_{D_{t-1}} + \sum_{i=0}^p \beta_3 \ln GDPC_{t-i} + \\ & \sum_{i=0}^p \beta_4 \ln FDI_{t-i} + \sum_{i=0}^p \beta_5 \ln LP_{t-i} + \sum_{i=0}^p \beta_6 \ln TECH_{t-i} + \epsilon_t \end{aligned} \quad (7)$$

$$\begin{aligned} \ln EMPL_t = & \beta_0 + \sum_{i=1}^p \beta_1 \ln EMPL_{t-i} + \sum_{i=0}^p \beta_2 MW_{D_{t-1}} + \sum_{i=0}^p \beta_3 \ln GDPC_{t-i} + \\ & \sum_{i=0}^p \beta_4 \ln FDI_{t-i} + \sum_{i=0}^p \beta_5 \ln LP_{t-i} + \sum_{i=0}^p \beta_6 \ln TECH_{t-i} + \\ & \sum_{i=0}^p \beta_7 (MW_{D_{t-1}} \times \ln LP_{t-i}) + \sum_{i=0}^p \beta_8 (MW_{D_{t-1}} \times \ln TECH_{t-i}) + \epsilon_t \end{aligned} \quad (8)$$

where p is the optimal lag order for each variable determined by Akaike Information Criteria (AIC). Long-run estimates could be employed to determine short-term dynamic parameters through an error correction model as follows:

$$\Delta \ln EMPL = \beta_0 + \sum_{i=1}^p \beta_1 \Delta \ln EMPL_{t-i} + \sum_{i=0}^p \beta_2 \Delta MW_{t-1} + \sum_{i=0}^p \beta_3 \Delta \ln GDPC_{t-i} + \sum_{i=0}^p \beta_4 \Delta \ln FDI_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln LP_{t-i} + \sum_{i=0}^p \beta_6 \Delta \ln TECH_{t-i} + \vartheta ec_{m,t-1} + \epsilon_t \quad (9)$$

$$\Delta \ln EMPL = \beta_0 + \sum_{i=1}^p \beta_1 \Delta \ln EMPL_{t-i} + \sum_{i=0}^p \beta_2 \Delta MW_{t-1} + \sum_{i=0}^p \beta_3 \Delta \ln GDPC_{t-i} + \sum_{i=0}^p \beta_4 \Delta \ln FDI_{t-i} + \sum_{i=0}^p \beta_5 \Delta \ln LP_{t-i} + \sum_{i=0}^p \beta_6 \Delta \ln TECH_{t-i} + \sum_{i=0}^p \beta_7 (MW_{D,t-1} \times \ln LP_{t-i}) + \sum_{i=0}^p \beta_8 (MW_{D,t-1} \times \ln TECH_{t-i}) + \vartheta ec_{m,t-1} + \epsilon_t \quad (10)$$

where β_1 to β_8 are the short-term dynamic coefficients and ϑ indicates the rate of long-term equilibrium adjustment. Diagnostic tests were conducted as part of the estimation process to evaluate the reliability and efficiency of the estimates. The ARDL cointegration technique could determine the existence of either a long- or short-term cointegration, although the technique would not specify the direction of the relationships between variables. The Granger causality test was performed to identify the causality of the study variables.

4. Findings and Discussion

4.1 Descriptive Statistics

Table 2 illustrates that all variables are normally distributed, with all p-values of the Jarque-Bera test higher than the 5% significance level. Approximately 8,839,000 individuals were employed as low-skilled workers. The minimum GDP per capita was RM10,754 and the maximum GDP per capita was RM48,521 from 1995 to 2020, with an average amount of RM27,394. Furthermore, the average FDI amount was RM23,915 million and ranged from RM404 million to RM55,878 million. Meanwhile, the average labour productivity and technical progression were RM61,528 and 319 units, respectively.

Table 2. Descriptive statistics

Variable	EMPL	MW_D	GDPC	FDI	LP	TECH
Mean	8829.335	0.307692	27393.46	23914.66	61527.49	318.8846
Median	8385.600	0.000000	28029.98	21695.16	61660.77	259.0000
Maximum	10638.20	1.000000	48520.39	55877.98	100385.9	798.0000
Minimum	6792.900	0.000000	10753.20	404.1351	29100.46	29.00000
Std. dev.	1197.929	0.470679	12148.38	14188.26	23595.06	275.1772
Skewness	0.206055	0.833333	0.201411	0.311850	0.142667	0.493375
Kurtosis	1.608084	1.694444	1.726830	2.275628	1.668163	1.649874
Jarque-Bera	2.282871	4.855774	1.931830	0.989860	2.009806	3.029561
Probability	0.319360	0.088223	0.380635	0.609614	0.366080	0.219856
Observations	26	26	26	26	26	26

Note: The results were extracted before log transformation.

4.2 Unit Root Test

All series must be scrutinised for stationary conditions as a first step in model estimation, despite ARDL cointegration not requiring pre-tests for unit roots. The ARDL models would fail in the presence of integrated stochastic trends from I(2). According to Nasrullah et al. (2021), the integration order was determined through the Philips-Perron (PP) and Augmented Dickey-Fuller (ADF) unit roots tests. Table 3 depicts ADF estimates and PP unit root tests. Net FDI inflows were stationary at Level I(0), whereas low-skilled employees, minimum wage, GDP per capita, labour productivity, and technical progression were stationary at First Difference I(1). All variables fulfilled the ARDL cointegration prerequisites in the absence of Second Difference I(2).

Table 3. Unit root test

Variable	ADF		PP	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend
lnEMPL	-1.740366	-1.873319	-1.740366	-2.069331
MW _D	-0.615486	-1.938933	-0.615486	-1.938933
lnGDPC	-1.507204	-1.304811	-1.762076	-1.286703
lnFDI	-4.202695***	-5.065854***	-4.202695***	-5.408095***
lnLP	-1.260258	-1.484781	-1.433908	-1.484781
lnTECH	-1.580658	-0.879592	-1.627511	-0.733755
MW _D × lnLP	-0.583245	-1.918164	-0.583245	-1.918164
MW _D × lnTECH	-0.836987	-1.949313	-0.836987	-1.949313
DlnEMPL	-4.590243***	-4.537965***	-4.593754***	-4.544796***
DMW _D	-4.898979***	-4.881719***	-4.898998***	-4.881660***
DlnGDPC	-4.267030***	-4.382285**	-4.168172***	-4.298523**
DlnFDI	-5.753987***	-5.606395***	-20.36079***	-19.65399***
DlnLP	-5.781889***	-5.984669***	-5.819077***	-6.102782***
DlnTECH	-4.697650***	-5.631788***	-5.067872***	-8.368184***
D(MW _D × lnLP)	-4.880285***	-4.868788***	-4.880264***	-4.868685***
D(MW _D × lnTECH)	-4.676553***	-4.600545***	-4.676422***	-4.600451***

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

4.3 Lag Length Selection

The study variables should contain the appropriate lag order before conducting the test to ensure a successful ARDL bound test. The current study employed the optimum lag order of the vector autoregression (VAR) model by selecting an acceptable lag order. Table 4 portrays lag selection criteria, with the results postulating that the ARDL bound test performs more effectively at Lag 1 for both models.

Table 4. Lag length selection

	Lag	LogL	LR	FPE	AIC	SC	HQ
Without interaction term	0	51.91675	NA	1.02e-09	-3.673340	-3.380810	-3.592205
	1	172.0808	173.0362*	1.34e-12*	-10.40646*	-8.358750*	-9.838513*
With interaction term	0	110.2506	NA	3.87e-14	-8.180051	-7.790011	-8.071870
	1	314.5936	261.5590*	6.74e-19*	-19.40749*	-15.89713*	-18.43386*

Note: * indicates the lag order selection criteria.

4.4 ARDL Bound Test

The bound test was utilised to determine the existence of a long-term association. The null hypothesis asserts that a long-term relationship does not exist while the alternative hypothesis asserts the opposite through several criteria. Specifically, F-statistic values lower than $I(0)$ would not reject the null hypothesis while the null hypothesis would be rejected if the F-statistic exceeds $I(1)$. The result remains inconclusive if F-statistics are within the range of $I(0)$ and $I(1)$. Table 5 indicates a long-term correlation for both models, as the F-statistics exceed the upper limit of $I(1)$.

Table 5. ARDL bound test

	Test statistics	Value	Significant level	$I(0)$	$I(1)$
Without interaction term	F-statistics	4.242405****	10%	2.08	3.00
	k	4	5%	2.39	3.38
			2.5%	2.70	3.73
			1%	3.06	4.15
With interaction term	F-statistics	3.413747**	10%	1.92	2.89
	k	7	5%	2.17	3.21
			2.5%	2.43	3.51
			1%	2.73	3.90

Note: ****, ***, **, * represents 1%, 2.5%, 5% and 10% significance levels.

4.5 Long- and Short-term Parameter Estimates

The ARDL bound test determines long- and short-term variables based on the long-term association. Tables 6 and 7 demonstrate both long- and short-term empirical findings between low-skilled workers' employment, minimum wage, GDP per capita, FDI net inflow, labour productivity and technical progression. The employment of low-skilled employees significantly increased by 0.09% in the long term after implementing the minimum wage policy. Similarly, the employment of low-skilled workers in the short term was significantly boosted by 0.05% after the minimum wage policy was implemented. The findings were in line with Nordin et al. (2021) and Pratama et al. (2020). Firms would be more equipped to adapt to government minimum wage laws

Table 6. ARDL model parameters (long-term estimation)

Variable	Without interaction term		With interaction term	
	Coefficient	Std. error	Coefficient	Std. error
MW _D	0.094931***	0.029952	1.080598	2.279353
lnGDPC	-0.640622	0.372579	-0.779130*	0.408490
lnFDI	-0.011433	0.019514	-0.024153	0.020117
lnLP	0.776608*	0.438590	0.843343	0.513167
lnTECH	0.071380**	0.030635	0.105186*	0.048842
MW _D × lnLP	–	–	-0.035736	0.193896
MW _D × lnTECH	–	–	-0.085934	0.060872
c	6.788956***	1.218617	7.375137***	1.796908

Notes: *, **, *** represent 10, 5 and 1% significance levels. Low-skilled employees are the dependent variable. The ARDL (1, 0, 1, 1, 1, 1, 0, 0) model is based on Akaike information criteria.

Table 7. ARDL model parameters (short-term estimation)

Variable	Without interaction term		With interaction term	
	Coefficient	Std. error	Coefficient	Std. error
MW _D	0.049200**	0.021937	0.651330	1.396862
DlnGDPC	0.013165	0.101681	-0.048507	0.098913
DlnGDPC _{t-1}	-0.332016*	0.188223	-0.469621*	0.256573
DlnFDI	0.007307**	0.002851	-0.003265	0.003311
DlnFDI _{t-1}	-0.005925	0.009686	-0.014558	0.011845
DlnLP	-0.095865	0.115188	0.114522	0.116009
DlnLP _{t-1}	0.402494	0.234699	0.508325	0.327368
DlnTECH	0.011855	0.007316	0.031202***	0.006892
DlnTECH _{t-1}	0.036994**	0.012911	0.063401*	0.029274
D(MW _D × lnLP)	–	–	-0.021540	0.117363
D(MW _D × lnTECH)	–	–	-0.051797	0.039880
ECM	-0.518272***	0.079570	-0.602750***	0.084232
c	3.518526***	1.106386	4.445361	1.530650
R ²	0.781061		0.808064	
Adj. R ²	0.737274		0.769677	

Notes: *, **, *** represent 10, 5 and 1% significance levels. Low-skilled employees are the dependent variable. The ARDL (1, 0, 1, 1, 1, 1, 0, 0) model is based on Akaike information criteria.

in the long term when aiming to earn long-term profits (Pratama et al., 2020). A higher minimum wage would also enhance individuals' buying power, thereby leading to stronger aggregate demand and domestic consumption that boost employment.

The impact of implementing minimum wages for low-skilled employees in both the short and long term was insignificantly positive when considering the interaction variables (Wang & Gunderson, 2018). Meanwhile, the interaction term between the minimum wage and labour productivity with low-skilled employment was negative in the short and long terms. The finding was inconsistent with Wye and Abdul Bahri (2021), which could result from the growth in labour productivity not entirely related to the increase in labour capacity and instead partially dependent on technological advancement. Therefore, employers may decrease routine jobs that could be replaced by technology and frequently performed by less competent employees when labour productivity increases from higher technology usage and the adoption of minimum wage. Nevertheless, the results were statistically insignificant, which could not be regarded as an indication of a negative impact on low-skilled employment.

The interaction between minimum wage and technical progression with low-skilled employment in the short and long terms was insignificantly negative (Lordan & Neumark, 2018). Technological advancement would substitute low-skilled workers performing ordinary tasks or less-skilled occupations, which decreases the employment of low-skilled employees. Table 7 depicts that the computed ECM coefficient is statically significant and negative, thereby suggesting cointegration. The ECM forecasts the pace of reactions to short-term shocks in equilibrium over the long term. The ECM coefficient without the interaction term for low-skilled employment in Malaysia was 0.5183, which propounded that approximately 52% of the difference between the short term and the long term was recalibrated annually. Moreover, approximately 60% of the difference between the short term and long term would be adjusted annually when the interaction terms were incorporated.

4.6 Diagnostic Tests

Table 8 portrays the diagnostic test results, wherein the Jarque-Bera test discovers that the data are normally distributed. Furthermore, the Breusch-Godfrey test did not reveal that a serial correlation existed. The Breusch-Pagan-Godfrey and ARCH tests were also conducted to determine the presence of heteroscedasticity, which indicated that heteroscedasticity did not exist. Summarily, both models were normally distributed without serial correlation and heteroscedasticity issues.

Table 8. Diagnostic tests

		Without interaction term	With interaction term
Normality	Jarque-Bera Test	0.566152 (0.7535)	0.433526 (0.8051)
Serial Correlation	Breusch-Godfrey Test	3.995553 (0.1356)	3.130543 (0.2090)
Heteroscedasticity	Breusch-Pagan-Godfrey Test	7.611927 (0.6667)	10.510180 (0.5713)
	ARCH Test	1.683102 (0.1945)	1.040036 (0.3078)

Note: Values in parentheses represent the p-value.

4.7 Stability Check

Both short- and long-term coefficients were investigated through the cumulative sum (CUSUM) tests and cumulative sum of squares (CUSUMSQ), as suggested by Brown et al. (1975). The CUSUM and CUSUMSQ lines indicated that the ARDL model was stable and fit at the 5% level across periods. Figures 1 and 2 present the findings obtained through the CUSUM and CUSUMSQ for both models without interaction terms respectively. Figures 3 and 4 illustrate the CUSUM and CUSUMSQ results for both models with interaction terms respectively.

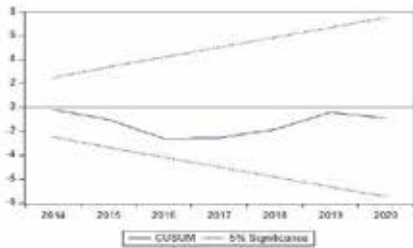


Figure 1. The CUSUM stability test of the ARDL (1,0,1,1,1,1) model without interaction terms

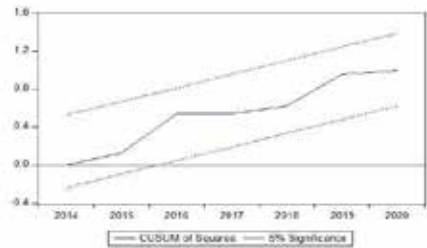


Figure 2. The CUSUMSQ stability test of the ARDL (1,0,1,1,1,1) model without interaction terms

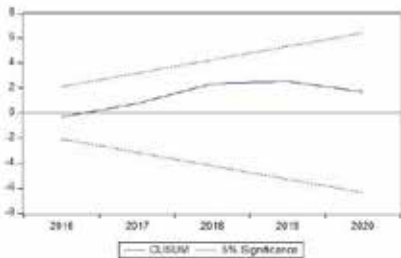


Figure 3. The CUSUM stability test of the ARDL (1,0,1,1,1,1,0,0) model with interaction terms

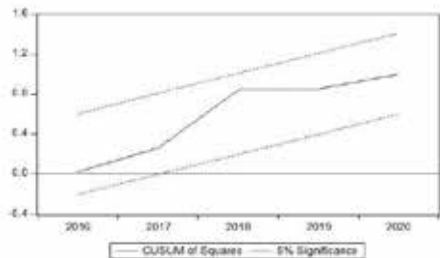


Figure 4. The CUSUMSQ stability test of the ARDL (1,0,1,1,1,1,0,0) model with interaction terms

4.8 Pairwise Granger Causality Test

Table 9 illustrates the Granger causality test results, in which a unidirectional causality relationship exists between technological advancement and the employment of low-skilled workers, GDP per capita, net FDI inflow and labour productivity. The relationship direction flows from technological advancement towards the latter variables, which supported past findings regarding the unidirectional influence of technological advancement on labour productivity and employment. The employment of low-skilled workers also demonstrated a unidirectional causality relationship with the minimum wage and net FDI inflow with the relationship direction from low-skilled employment towards minimum wage and net FDI inflow.

Table 9. Pairwise Granger causality test

Dependent variable	F-statistic						Direction of causality
	InEMPL	MW ₀	InGDPC	InFDI	InLP	InTECH	
InEMPL		1.18775	0.88496	3.36278	1.45838	9.33535**	TECH → EMPL
MW ₀	7.92322**		3.18218	0.64789	3.28873	4.12004	EMPL → MWD
InGDPC	0.33360	0.02903		1.26028	1.08293	16.3544**	TECH → GDPC
InFDI	6.14253**	3.98906	3.26999		3.37957	10.3961**	EMPL → FDI
InLP	0.19406	0.01870	0.96244	0.44247		18.4352**	TECH → FDI
InTECH	0.01011	0.82754	0.67796	1.18075	0.58042		TECH → LP

Note: ** represents the 5% significance level.

5. Conclusion

The present study aims to examine the impact of minimum wages on the employment of low-skilled workers in both the short and long terms. The short- and long-term effects of the minimum wage on low-skilled workers' employment were examined via the ARDL cointegration model with data from 1995 to 2020. The ADF, PP and breakpoint unit root tests discovered that no variables were stationary at $I(2)$. In addition, the ARDL bound test indicated the presence of both short- and long-term associations, which posited that the minimum wage significantly and positively impacted the employment of low-skilled workers in both the short and long terms. Nevertheless, the impact of the minimum wage policy on the employment of low-skilled workers was insignificant when the interaction variables were considered. The interactions between minimum wage and labour productivity and minimum wage and technical progression insignificantly and negatively impacted the employment of low-skilled workers respectively. No sufficient evidence was found to demonstrate that high labour productivity and technological advancement would enhance or diminish the employment impact of minimum wages. Meanwhile, a unidirectional causation association existed between technological improvement and low-skilled employment, GDP per capita, FDI net inflow and labour productivity. The employment of low-skilled workers also demonstrated unidirectional causation with the minimum wage and FDI net inflow.

The findings provided significant implications and recommendations for Malaysian policymakers. Policymakers could continue highlighting and supporting the importance of upskilling and reskilling low-skilled workers to prevent the mismatch between skill demand and supply in the labour market, which may lead to unemployment. Furthermore, the government should consider external factors, such as labour productivity and technological innovation, when adjusting the minimum wage. Both factors could alter company revenues and the employment of individuals with low education and training levels. This study was conducted on an aggregate basis and targeted low-skilled workers. As the impact of minimum wage laws is contingent on the elasticity of labour supply and demand in specific sectors or industries, further research on the low-skilled employment impact should focus on sectors or industries. The impact would vary across sectors. Moreover, further studies should determine the corresponding impact based on the threshold level of the Malaysian minimum wage to ensure a positive employment impact rather than a negative effect. Future researchers could appraise whether firms would alleviate the impact of minimum wages by discontinuing non-salary benefits or altering the job structure to ensure the total salary remains the same while reducing the financial burden from providing non-salary-related employment benefits.

References

- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor market. *Journal of Political Economy*, 128(6), 2218–2244. <https://doi.org/10.1086/705716>
- Alimawi, M.Y.S., Lai, W.S., & Baharin, R. (2020). Impact of macroeconomics variables on exports in Indonesia, Philippines, Malaysia and Thailand. *Journal of Contemporary Issues and Thought*, 10(2), 46–57. <https://doi.org/10.37134/jcit.vol10.sp.5.2020>

- Autor, D.H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>
- Autor, D.H., Levy, F., & Murnane, R.J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279–1333.
- Bodnár, K., Fadejeva, L., Iordache, S., Malk, L., Paskaleva, D., Pesliakaitė, J., Jemec, N.T., Tóth, P., & Wyszynski, R. (2018). How do firms adjust to rises in the minimum wage? Survey evidence from Central and Eastern Europe. *IZA Journal of Labor Policy*, 7(11), 1–30. <https://doi.org/10.1186/s40173-018-0104-x>
- Brown, R.L., Durbin, J., & Evans, J.M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society*, 37(2), 149–192.
- Clemens, J., & Strain, M.R. (2018). The short-run employment effects of recent minimum wage changes: Evidence from the American community survey. *Contemporary Economic Policy*, 36(4), 711–722. <https://doi.org/10.1111/coep.12279>
- Comola, M., & De Mello, L. (2011). How does decentralized minimum wage setting affect employment and informality? The case of Indonesia. *Review of Income and Wealth*, 57(s1), 79–99. <https://doi.org/10.1111/j.1475-4991.2011.00451.x>
- Del Carpio, X., Nguyen, H., Pabon, L., & Wang, L.C. (2015). Do minimum wages affect employment? Evidence from the manufacturing sector in Indonesia. *IZA Journal of Labor & Development*, 4(17), 1–30. <https://doi.org/10.1186/s40175-015-0040-8>
- Ding, S.H. (2010). Employment effects of minimum wage regulation and cross effect of the employment contracts law. *Social Sciences in China*, 31(3), 146–167. <https://doi.org/10.1080/02529203.2010.503079>
- Fang, T., & Lin, C. (2015). Minimum wages and employment in China. *IZA Journal of Labor Policy*, 4(22), 1–30. <https://doi.org/10.1186/s40173-015-0050-9>
- Giuliano, L. (2013). Minimum wage effects on employment, substitution, and the teenage labor supply: Evidence from personnel data. *Journal of Labor Economics*, 31(1), 155–194. <https://doi.org/10.1086/666921>
- Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5), 753–768.
- Holtemöller, O., & Pohle, F. (2019). Employment effects of introducing a minimum wage: The case of Germany. *Economic Modelling*, 89, 108–121. <https://doi.org/10.1016/j.econmod.2019.10.006>
- Hotte, K., Somers, M., & Theodorakopoulos, A. (2023). Technology and jobs: A systematic literature review. *Technological Forecasting and Social Change*, 194, Article 122750. <https://doi.org/10.1016/j.techfore.2023.122750>
- Langevin, R. (2020). *Revisiting the minimum wage–employment debate for young workers: Evidence from Canada* (Working paper, McGill University). https://www.researchgate.net/publication/343180324_Revisiting_the_Minimum_Wage-Employment_Debate_for_Young_Workers_Evidence_from_Canada
- Lee, N., & Clarke, S. (2019). Do low-skilled workers gain from high-tech employment growth? High-technology multipliers, employment and wages in Britain. *Research Policy*, 48(9), Article 103803. <https://doi.org/10.1016/j.respol.2019.05.012>
- Lemos, S., Rigobon, R., & Lang, K. (2004). Minimum wage policy and employment effects: Evidence from Brazil. *Economia*, 5(1), 219–266.
- Lim, I. (2022, April 28). It's official: Malaysia to start RM1,500 minimum wage from May 1; firms with fewer than five staff to follow in Jan 2023. *Malay Mail*. <https://www.malaymail.com/news/malaysia/2022/04/28/its-official-malaysia-to-start-rm1500-minimum-wage-from-may-1-firms-with-fe/2056088>
- Lordan, G., & Neumark, D. (2018). People versus machine: The impact of minimum wages on automatable jobs. *Labour Economics*, 52, 40–53. <https://doi.org/10.1016/j.labeco.2018.03.006>

- Mahyut, S.M. (2013). Minimum wage in Malaysia: The challenge on the implementation of the law. *International Journal of Business, Economics and Law*, 3(3), 30–37.
- Maitah, M., Toth, D., & Kuzmenko, E. (2015). The effect of GDP per capita on employment growth in Germany, Austria and the Czech Republic: Macroeconomic analysis. *Review of European Studies*, 7(11), 240–251. <https://doi.org/10.5539/res.v7n11p240>
- Minister of Human Resources. (2012). *Minimum Wages Order 2012*. Attorney General's Chambers of Malaysia. <https://www.fmm.org.my/images/articles/Announcement/GAZETTE%20ON%20MINIMUM%20WAGES%20ORDER%202012.pdf>
- Minister of Human Resources. (2016). *Minimum Wages Order 2016*. Attorney General's Chambers of Malaysia. https://www.jtkswk.gov.my/images/BM/hebahan/P.U.A116-Perintah_Gaji_Minimum_2016.pdf
- Minister of Human Resources. (2018). *Minimum Wages Order (Amendment) 2018*. Attorney General's Chambers of Malaysia. [https://www.jtkswk.gov.my/images/BM/hebahan/pua_20181128_P.U.\(A\)305.pdf](https://www.jtkswk.gov.my/images/BM/hebahan/pua_20181128_P.U.(A)305.pdf)
- Minister of Human Resources. (2020). *Minimum Wages Order 2020*. Attorney General's Chambers of Malaysia. https://www.mohr.gov.my/images/pdf/ukk/WartaPGM2020_P_U_A_5.pdf
- Munguia Corella, L F. (2020). Minimum wages in monopsonistic labor markets. *IZA Journal of Labour Economics*, 9(7), 1–28. <https://doi.org/10.2478/izajole-2020-0007>
- Nasrullah, M., Rizwanullah, M., Yu, X.Y., Jo, H.S., Sohail, M.T., & Liang, L.Z. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. *Journal of Water and Climate Change*, 12(6), 2256–2270. <https://doi.org/10.2166/wcc.2021.030>
- Neumark, D. (2018). Employment effects of minimum wages. *IZA World of Labor*, 1–10. <https://doi.org/10.15185/izawol.6.v2>
- Neumark, D., & Wascher, W.L. (2007). Minimum wages and employment. *Foundations and Trends in Microeconomics*, 3(1–2), 1–182. <https://doi.org/10.1561/07000000015>
- Neumark, D., & Wascher, W.L. (2008). *Minimum Wages*. MIT Press.
- Ni, J.L., Wang, G.X., & Yao, X.G. (2011). Impact of minimum wages on employment. *Chinese Economy*, 44(1), 18–38.
- Nordin, N., Nordin, N., Yusoff, N.M., & Zainudin, N. (2021). The impact of minimum wage on employment in Malaysia. In B. Alareeni, A. Hamdan and I. Elgedawy (eds), *The importance of new technologies and entrepreneurship in business development: In the context of economic diversity in developing countries* (pp. 858–869). Springer Cham.
- Pesaran, M.H., Shin, Y., & Smith, R.J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326. <https://doi.org/10.1002/jae.616>
- Pratama, R.A., Muhammad, S., & Silvia, V. (2020). Do minimum wage and economic growth matter for labor absorption in Sumatera Island, Indonesia? *East African Scholars Journal of Economics, Business and Management*, 3(1), 54–61.
- Rybczynski, K., & Sen, A. (2017). Employment effects of the minimum wage: Panel data evidence from Canadian provinces. *Contemporary Economic Policy*, 36(1), 116–135. <https://doi.org/10.1111/coep.12241>
- Sabia, J.J., Burkhauser, R.V., & Hansen, B. (2012). Are the effects of minimum wage increases always small? New evidence from a case study of New York State. *Industrial and Labor Relations Review*, 65(2), 350–376. <https://doi.org/10.1177/001979391206500207>
- Siregar, T.H. (2020). Impacts of minimum wages on employment and unemployment in Indonesia. *Journal of the Asia Pacific Economy*, 25(1), 62–78. <https://doi.org/10.1080/13547860.2019.1625585>
- Sturn, S. (2018). Do minimum wages lead to job losses? Evidence from OECD countries on low-skilled and youth employment. *Industrial and Labor Relations Review*, 71(3), 647–675. <https://doi.org/10.1177/0019793917741259>

- Tadjoeddin, M.Z. (2016). Productivity, wages and employment: Evidence from the Indonesia's manufacturing sector. *Journal of the Asia Pacific Economy*, 21(4), 489–512. <https://doi.org/10.1080/13547860.2016.1153227>
- Tajuddin, S.A.F., Hasan, F.A., Muhamad, S., & Sulaiman, N.F. (2021). Estimating the foreign workers' effect of minimum wage in Malaysian manufacturing sector. *Kasetsart Journal of Social Sciences*, 42, 145–150.
- Thomas, J. (2022, March 19). New minimum wage of RM1,500 from May 1. *Free Malaysia Today*. <https://www.freemalaysiatoday.com/category/nation/2022/03/19/new-minimum-wage-of-rm1500-from-may-1-says-pm/>
- Vacaflor, D.E. (2011). Was Latin America correct in relying in foreign direct investment to improve employment rates? *Applied Econometrics and International Development*, 11(2), 101–122.
- Wang, J., & Gunderson, M. (2018). Minimum wages effects on low-skilled workers in less developed regions of China. *International Journal of Manpower*, 39(3), 455–467. <https://doi.org/10.1108/IJM-10-2016-0189>
- Wye, C.K., & Bahri, E.N. (2021). How does employment respond to minimum wage adjustment in China? *Economic and Labour Relations Review*, 32(1), 90–114. <https://doi.org/10.1177/1035304620970838>
- Yamada, H. (2016). Evidence of the likely negative effect of the introduction of the minimum wage on the least skilled and poor through “labor-labor” substitution. *International Journal of Development Issues*, 15(1), 21–34. <https://doi.org/10.1108/IJDI-05-2015-0038>

