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Nonlinearity between the Loss of Employment and Lockdown Measures in Malaysia

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Abstract

Motivation and aim: Relating the loss of employment and various lockdown measures in Malaysia is an important endeavour to uncover the magnitude of the impact of these measures on the number of job losses during the COVID-19 pandemic between 1 January 2020 to 31 December 2020. We investigate the nonlinear impact of lockdown measures on the loss of employment, meaning that as lockdown measure intensifies, loss of employment increases, but at some turning point as lockdown measure relaxes, the loss of employment reduces. In other words, the lockdown measures exhibit an inverted U-shape curve with the loss of employment in Malaysia.

Methods and material: The AutoRegressive Distributed Lag (ARDL) model approach popularized by Pesaran et al. (2001) were used to estimate the relationships between the loss of employment and lockdown measures. Daily data on the loss of employment was compiled by the Employment Insurance System (EIS) Centre, PERKESO, Malaysia; while daily data on stringency index, school closures, workplace closures, public event cancellations, gathering restrictions, stay at home policies, internal movement restrictions and international travel controls was taken from the Covid-19 Government Response Tracker (OxCGRT) database compiled by Hale et al. (2020) on a daily basis (which is available at https://covidtracker.bsg.ox.ac.uk/).

Key findings: The Bounds F-test results for cointegration suggest that there is long-run relationship between the loss of employment and lockdown measures (both linear and non-linear) undertaken by the Malaysian government. The positive relationship between loss of employment and lockdown measure suggests that as the lockdown intensify, the number of people lost their jobs also increase. However, as time goes by and coupled with government stimulus package programmes, the loss of employment dwindled.

Policy implications: The linear relationship implies that lockdown measures have increased job loss; however, the non-linear relationship suggests that job loss increases at first, but when lockdown measures are implemented, the number of job losses lowers after it reaches an optimal turning point. It is believed that the cause for this phenomenon is the Malaysian government's fast move to mitigate the negative impacts of the Covid-19 outbreak on the Malaysian economy. The RM290 billion fiscal stimulus package along with the health measures such as public campaigns, testing policies, contact tracing, emergency health care investments, vaccine investments and facial coverings, among others, have contributed in boosting the economy and reducing job losses in the first half of 2020.

JEL Classifications
I18, H30; J64

Keywords
Loss of employment; Lockdowns; Nonlinear; ARDL; Malaysia

Nonlinearity between the Loss of Employment and Lockdown Measures in Malaysia

1. INTRODUCTION

The Covid-19 pandemic has not only caused a global health disaster but also an economic and labour market crisis. Many countries around the world have implemented lockdown measures to slow down the spread of coronavirus, but this has come at the expense of economic growth (World Bank, 2020). The global economic growth is expected to contract by more than 4% in 2020 (Cotofan et al., 2021). The tourism and hospitality industries, which include hotels, restaurants, wholesales and retails, crafts and shopping malls, movie theatres, cafes, airlines, and other land and sea modes of transportation, are the most affected sectors of the economy. According to studies by ILO-OECD (2020) and OECD (2021), the impact of the unprecedented Covid-19 crisis on the economy is many times bigger than the impact of the 2008 Global Financial Crisis.

The global unforeseen economic downturns have had a significant impact on the worldwide labour market (Cotofan et al., 2021). Some of the negative effects of the pandemic and the containment measures enforced by governments around the world include business closures, loss of employment, higher unemployment rates, lower labour participation rates, and reduced hours worked (OECD, 2021). Furthermore, online job posting has decreased dramatically since the beginning of the Covid-19 pandemic. For example, internet job postings in Australia, Canada, New Zealand, the United Kingdom, and the United States have decreased by more than half. Indeed, in Continental Europe, the decrease in hiring rates outnumbers the rise in dismissal rates. Unfortunately, the young labour market entrants were the ones who bore the brunt of the large reductions in openings and hiring rates (Eichhorst et al., 2020).

According to the International Labour Organization (ILO, 2020b), lockdowns and related economic interruptions, travel restrictions, school closures, and other containment measures have had a quick and significant impact on workers and businesses. Preliminary estimates from the International Labour Organization (ILO) (2020a) suggested that worldwide unemployment could reach 24.7 million in 2020, up from a base of 188 million in 2019. Besides that, projections of labour income losses imply a global fall of 10.7% in the first three quarters of 2020 (compared to the same time in 2019), amounting to US$3.5 trillion, or 5.5% of global GDP (ILO, 2020c). Because the informal economy employs 62% of the world's workforce, the crisis is expected to affect 1.6 billion of these workers, pushing them into poverty at rates ranging from 26% in 2019, to between 59 and 80% in 2020, depending on the geographical location (Lee et al., 2020). Among the G20 countries, the number of people who lost their jobs, went on furlough, or lost their work contract climbed by 40% in Mexico, and by roughly 8% - 9% in Japan and Korea in the first quarter of 2020. To add to the pain and misery, most G20 countries have lowered the number of total hours worked, with a shocking 46% in Mexico and a major decline of roughly 10% in Australia. Earnings in Australia have fallen by 3.2% while wages in the United Kingdom have fallen by 1.2% (ILO-OECD, 2020).

A study by Jingyi et al. (2021) on the ASEAN countries found that vulnerable workers in the informal sector, self-employed workers, gig workers, migrant workers, and micro, small, and medium enterprises workers were most affected by the Covid-19 pandemic crisis and the lockdown measures taken by their respective governments. In Malaysia, the government imposed nationwide lockdown measures on March 18, 2020 in order to slow down the spread of the Covid-19 pandemic among the public. Due to the economy and labour market disturbances, the unemployment rate increased to 3.5% in the first quarter of 2020, up from 3.2% in the fourth quarter of 2019 (DOSM, 2021). The number of unemployed persons increased from 512.2 thousand in the fourth quarter of 2019 to 546.6 thousand in the first quarter of 2020, with the unemployment rate reaching 4.8% and 760.7 thousand people were unemployed by the fourth quarter of 2020. Young people aged 15-24 years were particularly hard hit by the Covid-19 pandemic with unemployment rates rising from 9.9% in the fourth quarter of 2019 to 12.8% in the fourth quarter of 2020. Between the fourth quarter of 2019 and the fourth quarter of 2020, Bumiputra unemployment increased from 3.7% to 4.0%, and Chinese unemployment increased from 2.3 % to 4.3%, while Indian unemployment remained at 6.0% (DOSM, 2021). Furthermore, according to the survey conducted in March 2020 by DOSM (2020), the agriculture sector lost 21.9% of jobs followed by the service (15.0%) and industry (6.7%) sectors. Agriculture leads the way in terms of reduced working hours with 33.3%, followed by service (16.9%) and industry (12.8%).

In general, the increase in the unemployment rate in Malaysia from the pre-lockdown period in January and February 2020 to the lockdown period in March and beyond is unavoidable and unusual. The goal of this study is to lead research into the impact of lockdown measures on the Malaysian labour market and to determine the size of the impact of the lockdown measures on job losses in Malaysia during the Covid-19 pandemic in 2020.

This study contributes significantly to the literature in two aspects. First, it uses a unique dataset of administrative daily statistics on the number of job losses from January 1 to December 31, 2020, received from the Social Security Organization's Office of Employment Insurance System (SOCSO). Using the data, we use the AutoRegressive Distributed Lag (ARDL) modelling approach to examine the relationship between job loss and a variety of lockdown measures, both in the long and short run. Second, we examine the effectiveness of government responses to the Covid-19 crisis during the lockdown to include policy responses in the model. In other words, we want to identify the optimal time at which the loss of employment begins to decline as a result of the different efforts taken by the Malaysian government to contain the spread of the Covid-19 outbreak. Therefore, the findings of this paper will not only benefit the scholarly community, but also the Malaysian and other governments in determining the level of economic containment, particularly in the labour market.

2. CONTRIBUTION TO THE LITERATURE

According to studies on the impact of lockdown measures on the labour market in the United States, business closure or bankruptcy prompted enterprises to downsize their labour force, reduce working hours, or in the worst-case situation, terminate jobs entirely (Beland et al. 2020; Brodeur et al., 2020; Coibion et al., 2020; Gupta et al., 2020). Fairlie et al. (2020) reported that unemployment rate rises to 14.7% in less than two months after state governments implemented lockdown measures. Unfortunately, workers in low-wage jobs, Hispanics, younger workers, people with a lesser level of education, and women were the most affected (Cortes & Forsythe, 2020). In fact, Karabarbounis et al. (2020) demonstrated the positive association between unemployment rate and lockdown measures in the United States. Dreger and Gros (2021) discovered that when the lockdown measures are implemented, the jobless rate rises within 2-4 weeks and unemployment claims rise virtually immediately. Furthermore, the impact of lockdown measures is not symmetrical, with tightening measures having a 50% greater impact than relaxing actions.

Nearly 8 million employees in the UK lost their jobs by the end of May 2020 as a result of the shutdown on March 23 (Dias et al., 2020). According to a study by Powell and Francis-Devine (2021), unemployment rates for minority ethnic groups in the United Kingdom were higher than the national average before the Covid-19 pandemic and increased faster than the national average from the first quarter of 2020 to the first quarter of 2021. For example, Pakistani unemployment increased from 6.1% in January-March 2020 to 8.6% in January-March 2021; Chinese unemployment increased from 4.0% to 6.9%, Indian unemployment increased from 3.8% to 6.5%, and White unemployment increased from 3.6% to 4.1% during the same period. Unfortunately, young people were the most affected, with 70% of employment losses occurring between March 2020 and March 2021 among those under the age of 25. Cortes et al. (2020) reported that people working in the tourism, hospitality, food, and retail sectors in Ireland lost the most jobs. Furthermore, lower-income persons, younger workers, and migratory workers were disproportionately affected by job losses.

According to Bauer and Weber (2020), shutdown measures accounted for 60% of the number of persons who lost their jobs in Germany. Spain and Greece were particularly hard hit by the Covid-19 pandemic, with double-digit unemployment rates (15% in Spain and 17% in Greece in the second quarter of 2020) compared to single-digit jobless rates in other European countries (Gomez & Montero, 2020; Dolado et al., 2021). Guven et al. (2020) stated that Australia's national lockdown measures lowered labour force participation by 3.3%, increased unemployment by 1.7%, and cut weekly working hours by 2.5%. Australia's lockdown measures have also resulted in the greatest increase in unemployment rates on record, rising from 5.2% in March to 7.1% in September 2020, with Treasury expecting an 8% rate by September 2020 (Deadly et al., 2020). However, among the Scandinavian countries, Denmark and Norway's labour markets have suffered the most with dramatic increases in newly unemployed people beginning in week 11 of 2020, followed by Finland and Sweden (Juranek et al., 2020).

Ranchhod and Daniels (2021) used the first wave of the NIDSCRAM (2020) survey data for a sample of over 6,000 persons aged 18 to 59 in South Africa to assess the impact of lockdown measures. Their research discovered a significant drop in employment from 57% in February to 48% in April. According to the report, approximately one out of every three employed adults in the sample lost their job and earned no earnings in April 2020. Additionally, Bassier et al. (2020) stated that informal workers and their families in South Africa are particularly vulnerable to the pandemic's negative economic impacts and accompanying lockdown measures. During a pandemic, their situation deteriorates because their informality makes it impossible for the government to deliver targeted economic help swiftly. Similarly, Schotte et al. (2021) found that the Ghanaian government's rigorous three-week lockdown restrictions had a huge and considerable immediate negative impact on employment in the Greater Accra and Greater Kumasi Metropolitan Areas and contiguous regions. They discovered that workers in informal self-employment were most affected by the lockdown's short-term employment effects, and self-employed people and women's incomes were negatively affected in the medium run across the country.

According to Al-Masri et al. (2021), the construction, domestic services, and hospitality sectors in Brazil were the most vulnerable to the pandemic crisis with huge job losses and reduced hours worked. Low-wage workers were hit the hardest, with their salaries plummeting the greatest. Extreme poverty and income inequality grew during the Covid-19 crisis, with the Gini coefficient increasing by 5% and extreme poverty rising to 9.2%. Similarly, in some Asian countries, such as India, Vyas (2020) examined a sample of households from the Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy Private Limited and found that unemployment rates spiked sharply after a nationwide lockdown was imposed. The unemployment rate soared to 23.8% in the week ending March 29, 2020, and then rose to 26.2% in April 2020. Lee at al. (2020) analysed microeconomic survey data from Delhi and showed that the lockdown in India reduced income and days worked by 57% and 73%, respectively. Bhatt et al. (2021) suggested that the social distancing shutdown in India between March 2020 and May 2020 resulted in the closure of several enterprises, either temporarily or permanently, putting many workers out of work. Indeed, between March and May 2020, unemployment rose from 8 to 24.3% due to the lockdown. According to de Mel and Perera (2020), once the first incidence of Covid-19 was discovered on March 11, 2020, the country was placed under the most extreme curfew-level lockdown for a period of 52 days. As a result, in the immediate aftermath of the lockdown, 160,996 employees lost their employment.

4. METHODOLOGY

To relate the loss of employment to lockdown, we estimate the following simple model, based on the work of Dreger and Gros (2021), Bauer and Weber (2020), Guven et al. (2020), and Juranek et al. (2020).

$$\mathrm{loe}_t = \theta_0 + \theta_1 \mathrm{lockdown}_t + \varepsilon_t \quad (1)$$

where loe_t is the loss of employment, and $\mathrm{lockdown}_t$ is the stringency index. The stringency index is the sum of multiple ordinal values of restrictions on domestic and international travels, mass gathering limitations, public event cancellations, school and workplace closures, stay-at-home mandates, and public transportation closures. The error term, ε_t is assumed to have constant variance and a zero mean. All variables are converted to logarithms, resulting in parameter estimates that are considered as elasticities.

We use Pesaran et al.'s (2001) AutoRegressive Distributed Lag (ARDL) technique to estimate Equation (1). In small samples and with sufficient lag structure to deal with endogeneity in the model, the ARDL approach is efficient and robust to a mixture of I(0) and I(1) variables. Pesaran et al. (2001) have shown that both long-run and short-run models can be estimated simultaneously using the ARDL approach. According to Pesaran et al. (2001), the following ARDL model in levels can be used to derive a long-run model as shown in Equation (1).

$$\mathrm{loe}_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \mathrm{loe}_{t-i} + \sum_{i=0}^{q} \beta_{2i} \mathrm{lockdown}_{t-i} + \eta_t \quad (2)$$

where Equation (1) (as shown in Equation (3) below) can be derived from Equation (2) when we have, $\theta_0 = \frac{\beta_0}{1-\sum\beta_{1i}}$, $\theta_1 = \frac{\sum\beta_{2i}}{1-\sum\beta_{1i}}$, and $\epsilon_t = \frac{1}{1-\sum\beta_{1i}}\eta_t$. As such we have the following equation,

$$\text{loe}_t = \frac{\beta_0}{1-\sum\beta_{1i}} + \frac{\sum\beta_{2i}}{1-\sum\beta_{1i}}\text{lockdown}_t + \frac{1}{1-\sum\beta_{1i}}\eta_t \quad (3)$$

or as in Equation (1), $\text{loe}_t = \theta_0 + \theta_1\text{lockdown}_t + \varepsilon_t$; with Equation (2) must pass the non-serial correlation test with an optimum lag lengthusing the Schwarz criterion.

The short-run model, i.e. the error-correction model (ECM), can be specified as,

$$\Delta\text{loe}_t = \varphi_0 + \pi_0\text{ect}_{t-1} + \sum_{i=1}^{p}\varphi_{1i}\Delta\text{loe}_{t-i} + \sum_{i=0}^{q}\varphi_{2i}\Delta\text{lockdown}_{t-i} + \mu_t \quad (4)$$

where $\text{ect}_{t-1} = \varepsilon_{t-1} = \text{loe}_{t-1} - [\theta_0 + \theta_1\text{lockdown}_{t-1}]$. Cointegration would also be shown by the significant and negative value of the estimated coefficient π_0. (Engle & Granger, 1987). The estimated parameter π_0, would lie between 0 and -2 (Loayza & Ranciere, 2006; Samargandi et al., 2015; Fromentin & Leon, 2019).

The Office of Employment Insurance System, SOCSO, provides daily administrative data of job losses. Loss of employment refers to employees in the formal sector who have lost their jobs in the private sector (excluding voluntary resignation, expiry of a fixed-term contract and retrenchment due to misconduct). It is a subset of unemployment that provides a good indicator for monitoring the labour market. The Covid-19 Government Response Tracker (OxCGRT) database, built by Hale and colleagues (2020), was used to generate daily data for lockdown measures. The stringency index in the

OxCGRT database ranges from 0 to 100, with ordinal values for school closures (0 to 3), workplace closures (0 to 3), public event cancellations (0 to 2), gathering restrictions (0 to 4), public transportation closures (0 to 2), stay at home policies (0 to 3), internal movement restrictions (0 to 2), and international travel controls (0 to 4) (for details see Hale et al., 2020). To convert all series into logarithms, we utilize the formula $\log y_t = \log [x_t + \sqrt{(x_t^2 + 1)})]$ in this study (Busse & Hefeker, 2007). For the analysis, apart from the stringency index, we test all lockdown measures on the loss of employment in Malaysia.

5. EMPIRICAL RESULTS

Although the ARDL technique does not need unit root testing for all series in the model, we proceed to test the order of integration for all series to guarantee that none of them is I(2). Elliot et al. (1996) presented a more efficient unit root test which we have adapted in our work. According to Elliott et al. (1996), their modified Dickey-Fuller (DF) test statistic, which employs a Generalised Least Squares (GLS) method, outperforms the standard Dickey-Fuller test in terms of small-sample size and power. When an uncertain mean or trend is present, Elliott et al. (1996: pp 813) discovered that their "DF-GLS test had dramatically improved power." Table 1 shows the results of the unit root test for the series' order of integration using the DF-GLS process. The results of the unit root test clearly show that all variables are I(1), indicating that the series become stationary after differencing once. All variables are non-stationary in levels, but their first-differences are stationary, implying that all series are I(1) in levels.

The long-run model (Equation 1) is then estimated and derived by estimating Equation (2) using the Ordinary Least Square with robust standard error due to Newey-West (Newey & West, 1987) heteroscedasticity and autocorrelation consistent (HAC) standard error estimates. The ARDL model's lag structure was chosen using the Schwarz criterion. The results of estimating Equation (2) are shown in Panel A of Table 2. The estimated parameters of Equation (2) show that all lagged variables are significant at the 1% level. Nonetheless, most importantly, all estimated lockdown regressions passed the non-serial correlation property. Panel B depicts the long-term relationship between job loss and lockdown measures. The other lockdown measures, with the exception of "domestic travel" and "remain at home," demonstrate a positive impact of the lockdown policy on the number of job losses. The findings reveal that overseas' travel restrictions have the greatest influence on job losses whereas public gathering restrictions and school closures have the least impact on the number of jobs lost. Nevertheless, our findings suggest that the lockdown policy in Malaysia had direct influence on job losses.

However, are the foregoing findings valid? The validity of the long-run model in Equation (1) can be verified using the cointegration Bounds F-test, according to Pesaran et al. (2001). The long-run model is non-spurious if Equation (1) shows cointegration. The unit root tests confirm that none of the variables are I(2); therefore, using the Bounds F-test is a viable option. Pesaran et al. (2001) propose estimating the Bounds F-test statistics by running the following conditional error-correction model (CECM) to test for cointegration:

$$\Delta loe_t = \alpha_0 + \alpha_1 loe_{t-1} + \alpha_2 lockdown_{t-1} + \sum_{i=1}^{p} \gamma_{1i} \Delta loe_{t-i} + \sum_{i=0}^{q} \gamma_{2i} \Delta lockdown_{t-i} + \epsilon_t \quad (5)$$

The Bounds-F tests were used to evaluate on whether the null hypothesis, $\alpha_1 = \alpha_2 = 0$ is against the alternative hypothesis that $\alpha_1 \neq \alpha_2 \neq 0$. When the obtained F-statistic is compared to the Bounds critical values tabulated by Narayan (2005) for small sample size, the long-run cointegrating relationship is identified. When the estimated F-statistic surpasses the upper Bounds of critical value that the variables are cointegrated, the null hypothesis of no cointegration is rejected. The variables, on the other hand, are not cointegrated if the null hypothesis of no cointegration is not rejected and the computed F-statistic falls below the critical value's lower bounds. The conclusion is inconclusive if the estimated F-statistic falls between the upper and lower bounds of critical values. The null hypothesis is rejected, indicating that there is cointegration and that the long-run model in Equation (1) is valid. In Table 2, Panel C, the outcome of the Bounds F-test on estimating Equation (5) is shown. The findings of the Bounds F-test clearly show that for all lockdown measures, the null hypothesis of no cointegration can be rejected at the 1% level. This indicates that the long-run model is valid, and the results are non-spurious, implying a long-term relationship between job loss and containment policy variables.

Finally, the outcomes of the short-run model or the error-correction model for the loss of employment are presented in Panel D of Table 2 by estimating Equation (4). The significance of the error-correction term, ect_{t-1}, is the major variable of interest. All lockdown measures – restrictions on domestic travel, restrictions on gathering, restrictions on international travel, cancellation of public events, school closures, stay at home, workplace closures, and stringency index – have negative error-correction terms that are statistically significant at the 1% level. The significance of the error-correction term confirms that there is a cointegration or long-run relationship between job losses and the lockdown policy, as determined by the Bounds F-test. Other lockdown measures, aside from domestic travel limitations and the stay-at-home policy, have positive impact on the amount of job losses in Malaysia.

Further Analysis: Non-linear Effects of Lockdown on Job Losses

The findings in Table 2 clearly show that the linear association between job losses and lockdown measures is indefinite. In other words, increasing the intensity of the lockdown will eventually result in an ever increase in the number of people losing their jobs. However, this is not exclusive in Malaysia. We have watched the number of people losing their jobs decreasing over time between July to December 2020. The Malaysian government has responded positively to the many lockdown measures imposed to mitigate the severity of the economic disruption by introducing multiple fiscal stimulus package programmes which total up to RM290 billion in 2020. The stimulus package included provisions to assist small and medium enterprises, and unemployed workers.Salary subsidies were also provided to assist employers in keepingtheir workers. After reaching a peak in June 2020, Figure 1 shows a noticeable decline in the number of job losses beginning in July 2020. As a result, we hypothesise in this study that the relationship between job losses and lockdown may be non-linear. To put this conjecture to test, we proceed to estimate the following:

$$\mathrm{loe}_t = \theta_0 + \theta_1 \mathrm{lockdown}_t + \theta_2 \mathrm{lockdown}_t^2 + \omega_t \qquad (6)$$

When the a *priori* expected sign $\theta_1 > 0$ and $\theta_2 < 0$ are present, a non-linear relationship is proven.

Similarly, we begin our investigation by looking for a unit root on the square term, $\mathrm{lockdown}_t^2$. The unit root test findings are presented in Table 3, and we may deduce that the lockdown measures are non-stationary at their levels, but they become stationary after first-differencing. By estimating Equation (6), the long-run model, on the other hand, is shown in Table 4. The estimated ARDL regressions for all lockdown measures are shown in Panel A. At the 1% level, the lagged variables of both dependent and independent variables are generally significant. Furthermore, there is no evidence of serial correlation in any of the estimated regressions. The long-run model can be obtained from the ARDL model, as explained above, and this long-run model is represented in

Panel B of Table 4. As evidenced by models with gathering restrictions, school closures, workplace closures, and the stringency index as lockdown measures, our findings show a non-linear association between loss of employment and lockdown. We can see that $\theta_1 > 0$ and $\theta_2 < 0$ are significant at the 1% level in these four cases. Nevertheless, the parameters θ_1 and θ_2 are not significant in other lockdown measures.

The non-linear inverted U-shape curve between loss of employment and lockdown suggests that while loss of employment increases early in the lockdown measures, it reduces at some optimal point as the lockdown measures continue. The reasons could be the government's relaxation of the lockdown measures that allows firms to operate as well as the government's fiscal stimulus packages that are designed to mitigate the impact of Covid-19 on the economy. We estimate the fitted regression (6) for gathering restrictions, school closures, workplace closures, and stringency index with Time and Time-squared to determine the optimal point for lockdown measures that reduce the loss of employment as a result of government initiatives as presented below.

$$\overline{\mathrm{loe}}_t = \delta_0 + \delta_1 \mathrm{time}_t + \delta_2 \mathrm{time}_t^2 + \tau_t \qquad (7)$$

where $\overline{\mathrm{loe}}_t$ is the fitted regression Equation (6), and for an inverted U-shape curve, the predicted sign of the parameters is $\delta_1 > 0$ and $\delta_2 < 0$. Table 5 shows the evidence for the inverted U-shape curve. The estimated parameters δ_1 and δ_2 in all estimated regression equations are significant at the 1% level and have the expected signs, resulting in an inverted U-shape curve. The ideal turnaround points in the loss of employment that corresponds to each lockdown measure is computed in the last row. For example, the enforcement of public gathering restrictions, job losses began to decline on July 13th, 2020; similarly, with school closures, job losses began to decline on August 23rd, 2020; workplace closures on July 9th, 2020; and stringency index on September 10th, 2020.

On the other hand, we estimate Equation (6) with the Government Response Index as the regressor to explore the consequences of government actions on the Covid-19 outbreak. The government response index, according to Hale et al. (2020), consists of 16 different measures, including school closures, workplace closures, public event cancellations, gathering restrictions, public transportation closures, stay-at-home policies, internal movement restrictions, international travel controls, income support, household debt or contract relief, public information campaigns, and testing. The null hypothesis of a unit root cannot be rejected at the level of the series, according to our unit root test results for government response index; however, the null hypothesis of a unit root can be rejected at the 1 % level in first-differences (see Notes in Table 6). After determining that the government response index and its square term are both I(1) in level, we may use the ARDL technique to estimate Equation (6).

Table 6 shows the results of the effects of the government response index on the loss of jobs. As demonstrated in Panel A of Table 6, the estimated ARDL parameters are significant at the 10% level, and the estimated regression is free of serial correlation. Cointegration is established when the Bounds F-statistics are significant at the 1% level, as shown in Panel C. The negative sign and significance of the error-correction term, as shown in Panel D, also indicate cointegration. The long-run model shown in Panel B exhibits expected results and is statistically significant at the 10% level. The non-linear U-shape curve between job loss and the government response index is readily seen when the parametersθ_1 and $\theta_2$are statistically significant and show the correct sign. We computed the optimal turnaround point in Panel E, when job losses begin to reduce as a result of the government's continued reaction to the Covid-19 pandemic. According to this measure, job losses began to diminish on July 16, 2020. Figure 2 and Figure 3 show the quadratic relationship between the loss of employment and each of the four lockdown measures as well as the government response index. The graphs show a non-linear link between job loss and lockdown measures as well as the government response index, in the form of an inverted U-shape curve.

Finally, we use Equation (6) to re-estimate the effectiveness of the Malaysian government's four fiscal stimulus packages by introducing dummy variables for the fiscal stimulus packages. We assigned a value of 1 to each dummy variables on the day the stimulus package was revealed and assigned a value of zero otherwise. The four fiscal stimulus packages were launched on different dates in 2020 and the order of announcements is as follows:

1. February 27, 2020, the First Economic Stimulus Package was announced;
2. March 27, 2020, the Prihatin Economic Stimulus Package was announced;
3. April 4, 2020, the Prihatin Economic Stimulus Package for SMEs was announced; and
4. June 5, 2020, the Penjana Economic Stimulus Package was announced.

To exemplify our point, we estimate Equation (6) for the lockdown measure using the stringency index. The dummy variable was used in the short-run models (ARDL, CECM, and ECM) but not in the long-run model in this exercise. Table 7 shows the findings of ARDL, the long-run model, and the Bounds F-statistics. In fact, all of the fiscal dummy variables in the ARDL calculated equations are statistically significant at the 1% level. We calculated the anticipated loss of employment at their mean (absolute), which is equivalent to 459 individuals, using the estimated regression equation for stringency index shown in Table 4 as the benchmark. Similarly, the mean (absolute) number of people who lost their job is equal to 458 for the first stimulus package 1, 460 for Prihatin 1, 458 for Prihatin 2, 457 for Penjana, and 456 for all four fiscal stimulus packages when using the estimated regression equation for each of the fiscal dummy variables as shown in Table 7. The benchmark mean value is clearly greater than the predicted regressions with fiscal dummies. Therefore, we may conclude that fiscal stimulus measures will, on average, reduce the number of job losses during the Covid-19 pandemic in 2020.

6. CONCLUSION

In general, it is evident that Malaysia's lockdown policies have resulted in an increase of employment losses. During Malaysia's lockdown series, we have noticed that the closure of some industries or economic activities in the agriculture, manufacturing, and services sectors has a significant impact on the labour market, with firms downsizing their workforce, putting their employees on reduced working hours or partial pay, or, in the worst-case scenario, losing their jobs entirely. The cost of the choice between public health and economic health is not insignificant. However, the severity of economic consequences in terms of reduced income and increased unemployment can be mitigated by economic stimulus initiatives that provide cash and liquidity to help firms and employees survive the Covid-19 pandemic.

In this study, we used the ARDL approach to determine the linear and non-linear relationship between job losses and lockdown measures between January to December 2020. The linear relationship implies that lockdown measures have increased job loss; however, the non-linear relationship suggests that job loss increases at first, but when lockdown measures are implemented, the number of job losses lowers until it reaches an optimal turning point. It is believed that the cause for this phenomenon is the Malaysian government's fast move to mitigate the negative impacts of the Covid-19 outbreak on the Malaysian economy. The RM290 billion fiscal stimulus package along with the health measures such as public campaigns, testing policies, contact tracing, emergency health care investments, vaccine investments and facial coverings, among others, have contributed in boosting the economy and reducing job losses in the first half of 2020.

This study offers the government three crucial policy answers in terms of economic management during the pandemic crisis. First, it is shown in this analysis that using daily administrative data on job losses increases the monitoring capacities of government interventions in the labour market. This emphasises the need of having timely disaggregated labour market information (LMI) to monitor current and future economic crises effectively.

Such information is crucial for understanding, tracking, managing, and minimising the effects of pandemic and non-pandemic consequences on the labour market. As a result, it is critical to enhance and expand employment in the collection of daily data.

Second, our model and studies offer the government with useful policy responses in terms of lockdown measures and sectoral intervention. Various lockdown measures have varied effects on job losses, with restrictions on overseas travel having the greatest impact. The reality that international travel restrictions are linked to the tourism industry's survival (e.g. air transport, accommodation and restaurants as well as wholesale and retail trade) suggest that for as long as the international travel restrictions are in place, tourism and allied industries will require continued government support and help.

Third, our computation of the optimal turning point for the loss of employment informs policy responses to the government's various stimulus programmes. This ideal turning point provides an estimated date or duration for stimulus package effectiveness, and this information removes some of the "black-box" for most policies. This study not only reveals the stimulus packages' efficacy period, but also provides a comparative assessment of several stimulus packages. For example, in terms of mitigating job losses, the Penjana stimulus package outperforms the other three fiscal stimulus packages. As a result, there will be a better understanding of why different stimulus packages have varying effects on job loss.

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Table 1 Results of Dickey-Fuller GLS unit root tests on the series

Series	Level		First-difference	
	Intercept	Intercept + trend	Intercept	Intercept + trend
$\text{Loss of employment}_t$	-1.1165 (13)	-1.8181 (13)	-2.6189***(13)	-4.8077***(13)
$\text{Restrictions on domestic travel}_t$	-1.1226 (0)	-1.9195 (0)	-18.467***(0)	-18.473***(0)
$\text{Restrictions on gathering}_t$	0.1655 (0)	-1.7056 (0)	-18.485***(0)	-18.514***(0)
$\text{Restrictions on international travel}_t$	-0.2719 (0)	-1.1365 (0)	-18.476***(0)	-18.503***(0)
$\text{Restrictions on public events}_t$	-0.3391 (0)	-0.5028 (0)	-18.473***(0)	-18.539***(0)
School closure_t	-0.4420 (0)	-1.6828 (0)	-18.474***(0)	-18.484***(0)
Stay at home_t	-0.6315 (0)	-1.7119 (0)	-18.473***(0)	-18.501***(0)
$\text{Workplace closure}_t$	-0.5173 (0)	-1.6153 (0)	-19.087***(0)	-19.101***(0)
$\text{Stringency index}_t$	0.2956 (12)	-1.6446 (12)	-5.0544***(11)	-5.0857***(11)

Notes: Asterisks *** denotes statistically significant at 1% level. Figures in round brackets (…) are truncated lag length. Critical values for unit root with intercept refer to MacKinnon (1996); while critical values for unit root with intercept and trend refer to Elliot et al. (1996, Table 1).

Table 2 Results of lockdown effects on the loss of employment

Independent variables	Independent variable, lockdown measures:							
	Restrictions on domestic travel	Restrictions on gathering	Restrictions on international travel	Restrictions on public events	School closure	Stay at home	Workplace closure	Stringency index
A. ARDL(p,q)	ARDL(2,0)	ARDL(2,0)	ARDL(2,0)	ARDL(2,1)	ARDL(2,1)	ARDL(2,0)	ARDL(2,0)	ARDL(2,0)
Constant	2.8875***	2.8966***	2.5101***	2.9603***	2.9404***	2.8866***	2.9121***	2.0695***
	(11.458)	(10.358)	(8.2315)	(10.726)	(10.529)	(11.442)	(9.9953)	(6.6891)
loe_{t-1}	0.7526***	0.7319***	0.7328***	0.7156***	0.7221***	0.7523***	0.7313***	0.7314***
	(12.221)	(12.303)	(12.990)	(12.937)	(12.639)	(12.254)	(12.730)	(12.814)
loe_{t-2}	-0.2209***	-0.2430***	-0.2425***	-0.2566***	-0.2416***	-0.2208***	-0.2439***	-0.2429***
	(-4.7327)	(-4.6638)	(-4.5760)	(-4.6910)	(-4.6261)	(-4.6929)	(-4.4291)	(-4.3884)
$lockdown_t$	-0.0188	0.1710***	0.3415***	-1.0347***	-0.5782**	-0.0282	0.1716***	0.2281***
	(-0.3102)	(3.5103)	(2.6673)	(-4.1322)	(-2.2134)	(-0.5877)	(3.3934)	(3.2012)
$lockdown_{t-1}$				1.3315***	0.7581***			
				(5.7568)	(2.8914)			
R^2	0.4119	0.4269	0.4248	0.4512	0.4420	0.4121	0.4265	0.4272
SER	0.6130	0.6051	0.6063	0.5930	0.5980	0.6129	0.6054	0.6050
$LM\chi^2(1)$	[0.3418]	[0.3474]	[0.1382]	[0.9252]	[0.5220]	[0.3359]	[0.3412]	[0.2694]
B. Long-run model								
Constant	6.1664***	5.6669***	4.9256***	5.4717***	5.6594***	6.1613***	5.6813***	4.0457***
	(36.158)	(44.720)	(11.503)	(42.198)	(50.023)	(56.233)	(45.502)	(7.2341)
$lockdown_t$	-0.0402	0.3347***	0.6701***	0.5486***	0.3463***	-0.0603	0.3348***	0.4460***
	(-0.3079)	(3.9194)	(2.8017)	(5.1024)	(4.2159)	(-0.5790)	(3.8105)	(3.7011)
C. Conditional ECM								
Bounds F-stat	33.959***	37.800***	37.251***	41.129***	40.360***	34.015***	37.692***	37.891***
D. Short-run model								
ect_{t-1}	-0.4682***	-0.5111***	-0.5096***	-0.5410***	-0.5195***	-0.4685***	-0.5125***	-0.5115***
	(-10.123)	(-10.680)	(-10.602)	(-11.140)	(-11.036)	(-10.131)	(-10.665)	(-10.693)
Δloe_{t-1}	0.2209***	0.2430***	0.2425***	0.2566***	0.2416***	0.2208***	0.2439***	0.2429***
	(4.1839)	(4.6171)	(4.5950)	(4.9347)	(4.6602)	(4.1842)	(4.6281)	(4.6184)
$\Delta lockdown_t$				-1.0347**	-0.5782**			
				(-2.0679)	(-2.2260)			
R^2	0.2317	0.2513	0.2486	0.2831	0.2711	0.2320	0.2508	0.2518
SER	0.6112	0.6034	0.6045	0.5913	0.5962	0.6111	0.6036	0.6032

Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10%, respectively. Figures in round brackets (…) are t-statistics while figures in square brackets […] are p-values. R^2 and SER denote R-squared and standard error of regression, respectively. LM $\chi^2(1)$ denotes the Lagrange multiplier test for serial correlation of order one in the ARDL equations. $loe_t$and $lockdown_t$ denote loss of employment and lockdown measures, respectively. Lockdown measures include, namely, restrictions on domestic travel, banned on gatherings, restrictions on international travel, banned of public events, school closure, stay at home requirement, workplace closure, and the stringency index. Δ denotes first-difference operator. For Bounds F-test critical values refer to Narayan (2005).

Table 3 Further results of Dickey-Fuller GLS unit root tests on the series

Series	Level		First-difference	
	Intercept	Intercept + trend	Intercept	Intercept + trend
Restrictions on domestic travel$_t^2$	-1.2485 (0)	-1.8061 (0)	-18.412***(0)	-18.423***(0)
Restrictions on gathering$_t^2$	0.2138 (0)	-2.1428 (0)	-18.431***(0)	-18.475***(0)
Restrictions on international travel$_t^2$	-0.4977 (0)	-1.3591 (0)	-18.418***(0)	-18.437***(0)
Restrictions on public events$_t^2$	-0.5700 (0)	-0.4586 (0)	-18.413***(0)	-18.499***(0)
School closure$_t^2$	-0.6732 (0)	-1.8392 (0)	-18.417***(0)	-18.425***(0)
Stay at home$_t^2$	-0.3634 (0)	-1.6456 (0)	-18.421***(0)	-18.468***(0)
Workplace closure$_t^2$	-0.9360 (0)	-2.0483 (0)	-19.749***(0)	-19.758***(0)
Stringency index$_t^2$	0.3506 (0)	-0.7080 (0)	-7.2945***(3)	-7.3427***(3)

Notes: Asterisks *** denotes statistically significant at 1% level. Figures in round brackets (…) are truncated lag length. Critical values for unit root with intercept refer to MacKinnon (1996); while critical values for unit root with intercept and trend refer to Elliot et al. (1996, Table 1).

Table 4 Results of non-linear lockdown effects on the loss of employment

Independent variables	Independent variable, lockdown measures:							
	Restrictions on domestic travel	Restrictions on gathering	Restrictions on international travel	Restrictions on public events	School closure	Stay at home	Workplace closure	Stringency index
A. ARDL(p,q)	ARDL(2,0,0)	ARDL(2,0,0)	ARDL(2,0,0)	ARDL(2,1,0)	ARDL(2,1,0)	ARDL(2,0,0)	ARDL(2,0,0)	ARDL(2,0,0)
Constant	2.9290***	2.9413***	2.4841***	3.0155***	3.0280***	2.8867***	3.1432***	-6.8529**
	(11.557)	(10.780)	(6.7544)	(10.679)	(10.895)	(11.377)	(11.635)	(-2.1493)
loe_{t-1}	0.7504***	0.7209***	0.7327***	0.7136***	0.7074***	0.7523***	0.7048***	0.7080***
	(12.172)	(12.821)	(12.974)	(12.905)	(12.687)	(12.219)	(12.332)	(12.863)
loe_{t-2}	-0.2236***	-0.2534***	-0.2424***	-0.2596***	-0.2587***	-0.2208***	-0.2734***	-0.2644***
	(-4.8036)	(-4.7133)	(-4.5705)	(-4.6938)	(-4.8764)	(-4.6913)	(-5.1680)	(-4.8242)
$lockdown_t$	-0.3973	0.5203***	0.3964	-1.3215***	0.0022	-0.0290	1.0338***	4.5887***
	(-1.6039)	(3.7494)	(0.9763)	(-4.3703)	(0.0063)	(-0.1312)	(4.7883)	(3.0485)
$lockdown_{t-1}$				1.3129***	0.7175***			
				(6.5906)	(2.6653)			
$lockdown_t^2$	0.2609*	-0.1749***	-0.0218	0.2033	-0.2765***	0.0006	-0.4867***	-0.5072***
	(1.6689)	(-2.7051)	(-0.1614)	(1.4572)	(-2.6959)	(0.0040)	(-4.0854)	(-2.9002)
R^2	0.4136	0.4351	0.4248	0.4526	0.4524	0.4121	0.4503	0.4435
SER	0.6130	0.6016	0.6071	0.5931	0.5933	0.6138	0.5935	0.5972
$LM\chi^2(1)$	[0.4077]	[0.3985]	[0.1276]	[0.9230]	[0.6172]	[0.3357]	[0.5612]	[0.2275]
B. Long-run model								
Constant	6.1895***	5.5241***	4.8737***	5.5234***	5.4923***	6.1613***	5.5282***	-12.316**
	(35.314)	(44.965)	(7.8527)	(40.255)	(46.428)	(54.450)	(51.112)	(-2.0864)
$lockdown_t$	-0.8397	0.9772***	0.7777	-0.0158	1.3055***	-0.0620	1.8183***	8.2470***
	(-1.5741)	(3.6824)	(0.9937)	(-0.0391)	(3.6944)	(-0.1312)	(4.7948)	(2.9495)
$lockdown_t^2$	0.5515	-0.3285***	-0.0427	0.3724	-0.5016***	0.0012	-0.8561***	-0.9115***
	(1.6476)	(-2.6268)	(-0.1618)	(1.4602)	(-2.7047)	(0.0040)	(-4.0369)	(-2.8040)
C. Conditional ECM								
Bounds F-stat	25.725***	29.915***	27.864***	31.051***	32.334***	25.436***	33.073***	31.620***
D. Short-run model								
ect_{t-1}	-0.4732***	-0.5324***	-0.5096***	-0.5459***	-0.5513***	-0.4685***	-0.5685***	-0.5564***
	(-10.189)	(-10.987)	(-10.604)	(-11.194)	(-11.423)	(-10.131)	(-11.553)	(-11.296)
Δloe_{t-1}	0.2236***	0.2534***	0.2424***	0.2596***	0.2587***	0.2208***	0.2734***	0.2644***
	(4.2364)	(4.8301)	(4.5949)	(4.9898)	(4.9956)	(4.1842)	(5.2424)	(5.0560)
$\Delta lockdown_t$				-1.3215***	0.0022			
				(-2.6538)	(0.0085)			
R^2	0.2340	0.2621	0.2486	0.2850	0.2846	0.2320	0.2820	0.2730
SER	0.6103	0.5990	0.6044	0.2850	0.5907	0.6111	0.5909	0.5946

Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10%, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] are p-values. R^2 and SER denote R-squared and standard error of regression, respectively. LM $\chi^2(1)$ denotes the Lagrange multiplier test for serial correlation of order one in the ARDL equations. loe_t and $lockdown_t$ denote loss of employment and lockdown measures, respectively. Lockdown measures include, namely, restrictions on domestic travel, banned on gatherings, restrictions on international travel, banned of public events, school closure, stay at home requirement, workplace closure, and the stringency index. Δ denotes first-difference operator. For Bounds F-test critical values refer to Narayan (2005).

Table 5 Fitted loss of employment-lockdown versus time and time-squared

Independent variables	Restrictions on gathering, $\overline{\text{loe}}_t$	School closure, $\overline{\text{loe}}_t$	Workplace closure, $\overline{\text{loe}}_t$	Stringency index, $\overline{\text{loe}}_t$
Constant	-0.8034*** (-2.6183)	-0.3811 (-1.2200)	-0.2440 (-0.5447)	-2.2700*** (-7.4679)
time_t	2.6819*** (20.557)	2.4368*** (18.348)	2.3547*** (12.364)	3.2624*** (25.243)
time_t^2	-0.2548*** (-18.684)	-0.2232*** (-16.079)	-0.2128*** (-10.691)	-0.3113*** (-23.040)
R^2	0.7440	0.7763	0.6435	0.8065
Optimal point=$-\hat{\delta}_1/2\hat{\delta}_2$	5.2628	5.4588	5.5327	5.2400
Optimal point (days)=exp($-\hat{\delta}_1/2\hat{\delta}_2$)	193	234	252	189
Threshold Date	13 July 2020	23 August 2020	9 July 2020	10-September 2020

Notes: Asterisks *** denotes statistically significant at 1% level, respectively. The figures in round (…) are t-statistics. The estimated regression: $\overline{\text{loe}}_t = \delta_0 + \delta_1\text{time}_t + \delta_2\text{time}_t^2 + \tau_t$. The optimal point is calculated as $-\hat{\delta}_1/2\hat{\delta}_2$. $\overline{\text{loe}}_t$ refers to the fitted regression (Equation 6) with respect to the four lockdown measures – restrictions on gathering, school closure, workplace closure and the stringency index.

Table 6 Results of government response index effects on the loss of employment

Independent variables		t	$t-1$	$t-2$
A. ARDL(2,0,0)				
Constant	-7.5020 (-1.3807)			
Loe			0.7126*** (12.974)	-0.2610*** (-4.6509)
government response index		4.7099* (1.8394)		
government response index^2		-0.5065* (-1.7172)		
R^2	0.4416			
SER	0.5982			
$LM\chi^2(1)$	[0.2602]			
B. Long-run model				
Constant	-13.679 (-1.3809)			
government response index		8.5884* (1.8470)		
government response index^2		-0.9237* (-1.7222)		
C. Conditional ECM				
Bounds F-stat	31.226***			
D. Short-run model				
ect			-0.5484*** (-11.225)	
Δloe			0.2610*** (4.9899)	
R^2	0.2705			
SER	0.5956			
E. $\overline{\text{loe}}_t = f(\text{time}_t, \text{time}_t^2)$				
Constant	-2.1283*** (-9.2795)			
time		3.1847*** (32.659)		
time^2		-0.3016*** (-29.584)		
R^2	0.8840			
SER	0.0930			
Optimal point=$-\hat{\delta}_1/2\hat{\delta}_2$	5.2797			
Optimal point (days)=$\exp(-\hat{\delta}_1/2\hat{\delta}_2)$	196			
Threshold Date	16 July 2020			

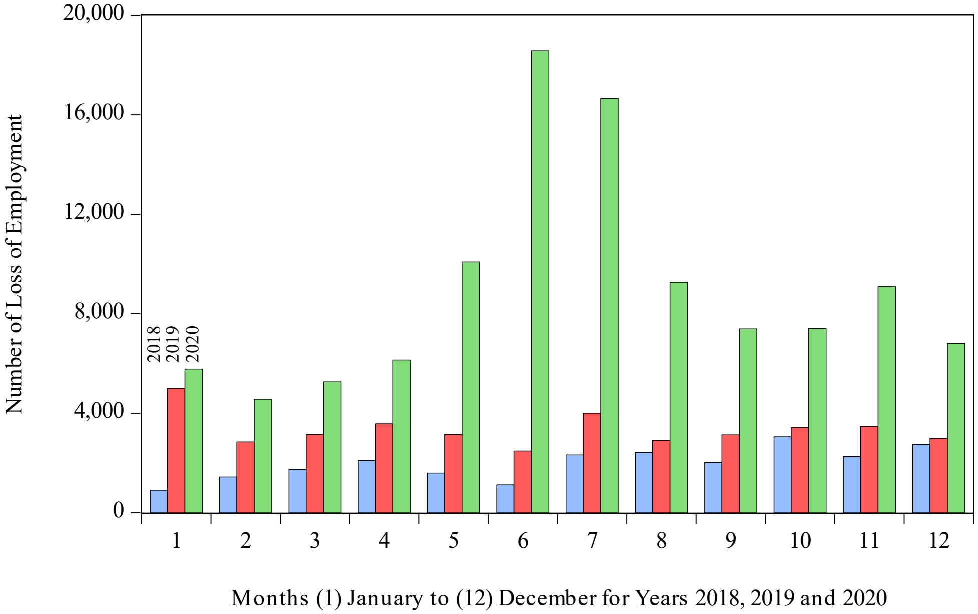
Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10%, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] are p-values. R^2 and SER denote R-squared and standard error of regression, respectively LM $\chi^2(1)$ denotes the Lagrange multiplier test for serial correlation of order one in the ARDL equations. loe and lockdown denote loss of employment and lockdown measures, respectively. Lockdown measures include, namely, restrictions on domestic travel, banned on gatherings, restrictions on international travel, banned of public events, school closure, stay at home requirement, workplace closure, and the stringency index. Δ denotes first-difference operator. For Bounds F-test critical values refer to Narayan (2005). The estimated regression: $\overline{\text{loe}}_t = \delta_0 + \delta_1 \text{time}_t + \delta_2 \text{time}_t^2 + \tau_t$. The optimal point is calculated as $-\hat{\delta}_1/2\hat{\delta}_2$. $\overline{\text{loe}}_t$ refers to the fitted regression (Equation 6) with respect to the government response index. The unit root test results for $\text{government response}_t$ is (a) level, intercept 0.45; intercept+trend -0.74' (b) first-difference, intercept -6.73; intercept+trend -6.86; while for $\text{government response}_t^2$ is (a) level, intercept 0.66; intercept+trend -0.42' (b) first-difference, intercept -18.53; intercept+trend -18.62.

Table 7 The effects of fiscal stimulus packages on the loss of employment

Independent variables	Package 1	Prihatin 2	Prihatin 2	Penjana	All fiscal stimulus packages
A. ARDL(p,q)					
Constant	-6.8713**	-6.8215**	-6.9106**	-7.0300**	-7.0758**
	(-2.1464)	(-2.1383)	(-2.1594)	(-2.2089)	(-2.2049)
loe_{t-1}	0.7078***	0.7081***	0.7091***	0.7059***	0.7067***
	(12.829)	(12.842)	(12.846)	(12.825)	(12.752)
loe_{t-2}	-0.2646***	-0.2655***	-0.2645***	-0.2673***	-0.2687***
	(-4.8178)	(-4.8312)	(-4.8227)	(-4.8780)	(-4.8762)
$lockdown_t$	4.5958***	4.5750***	4.6159***	4.6874***	4.7086***
	(3.0425)	(3.0376)	(3.0553)	(3.1291)	(3.1185)
$lockdown_t^2$	-0.5077***	-0.5053***	-0.5106***	-0.5187***	-0.5210***
	(-2.8942)	(-2.8881)	(-2.9089)	(-2.9814)	(-2.9715)
Fiscal stimulus 1	0.1419**				0.1428**
	(2.0725)				(2.0674)
Prihatin 1		-0.2974***			-0.2940***
		(-5.2098)			(-5.0850)
Prihatin 2			0.4608***		0.4608***
			(10.275)		(10.317)
Penjana				0.5808***	0.5825***
				(7.5134)	(7.4759)
R^2	0.4435	0.4439	0.4444	0.4450	0.4465
SER	0.5980	0.5979	0.5976	0.5973	0.5992
$LM\chi^2(1)$	[0.2275]	[0.3289]	[0.2094]	[0.2368]	0.3137]
B. Long-run model					
Constant	-12.340**	-12.236**	-12.440**	-12.523**	-12.592**
	(-2.0832)	(-2.0765)	(-2.0951)	(-2.1321)	(-2.1273)
$lockdown_t$	8.2537***	8.2065***	8.3098***	8.3499***	8.3793***
	(2.9427)	(2.9401)	(2.9541)	(3.0020)	(2.9899)
$lockdown_t^2$	-0.9119***	-0.9065***	-0.9193***	-0.9241***	-0.9273***
	(-2.7970)	(-2.7935)	(-2.8105)	(-2.8585)	(-2.8471)
C. Conditional ECM					
Bounds F-stat	31.541***	31.610***	31.459***	31.835***	31.584***

Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10%, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] are p-values. R^2 and SER denote R-squared and standard error of regression, respectively LM $\chi^2(1)$ denotes the Lagrange multiplier test for serial correlation of order one in the ARDL equations. loe and lockdown denote loss of employment and lockdown measures, respectively. Lockdown measure is the stringency index. Δ denotes first-difference operator. For Bounds F-test critical values refer to Narayan (2005). Mean for stringency index and stringency index-squared are 4.667545 and 21.99428, respectively. For the fiscal stimulus packages, Fiscal stimulus 1 refers to First Economic Stimulus Package announced on 27 February 2020; Prihatin 1 refers to Prihatin Economic Stimulus Package announced on 27 March 2020; Prihatin 2 refers to Prihatin Economic Stimulus Package for SMEs announced on 4 April; while Penjana refers to Penjana Economic Stimulus Package announced on 5 June 2020.

Figure 1 The number of loss of employment in 2018, 2019 and 2020 (January to December)



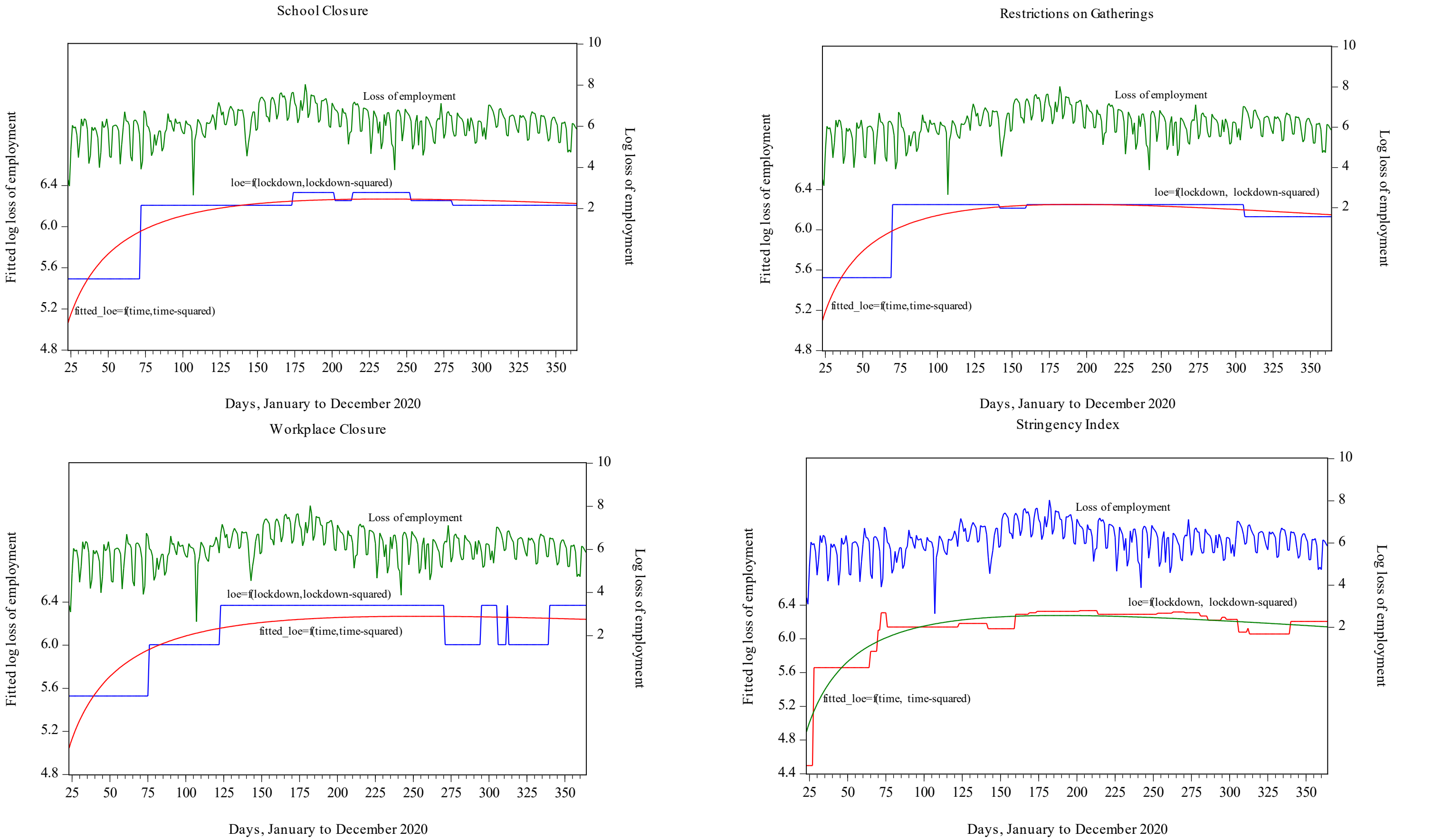


Figure 2 Non-linear relationships between the loss of employment and restrictions on gathering, workplace and school closures and stringency index

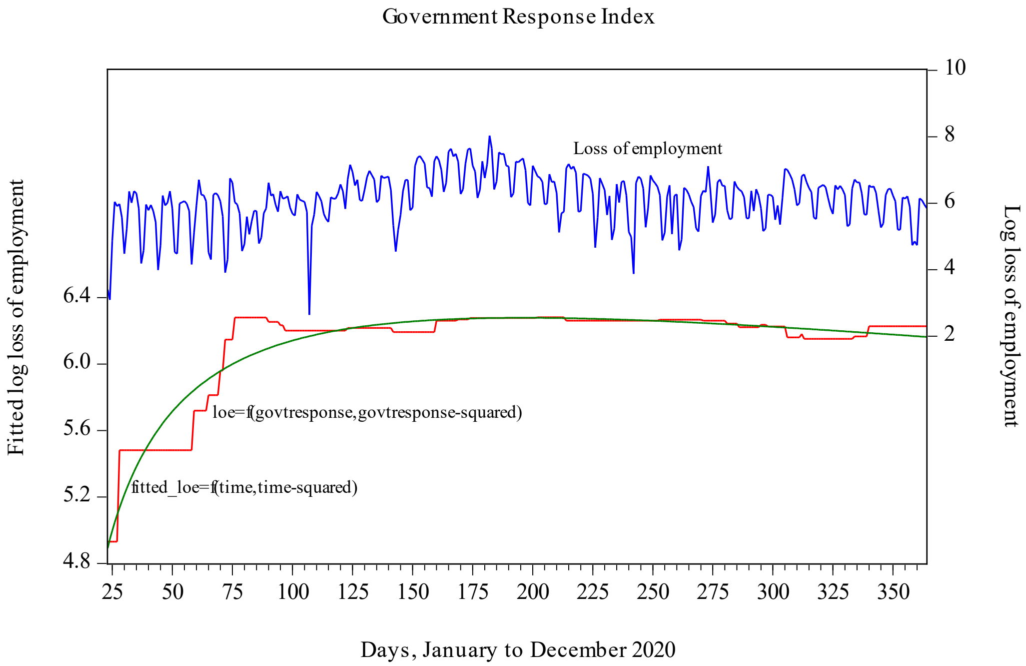


Figure 3 Non-linear relationships between the loss of employment and government response index

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