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# Long-Run and Short-Run Relationships Between Covid-19 and the Loss of Employment in Malaysia: Evidence Using GARCH-M, EGARCH-M and PGARCH-M Models

# Relações de Longo e Curto Prazo Entre Covid-19 e Perda de Empregos na Malásia: Evidência Usando Modelos *GARCH-M, EGARCH-M* e *PGARCH-M*

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## Abstract

The purpose of the present paper is to investigate the long-run and short-run relationships between the loss of employment and the Covid-19 pandemic in Malaysia's labour market. The Covid-19 measures include the number of Covid-19 new cases, the number of Covid-19 new deaths, the number of total Covid-19 cases and the Covid-19 fear index. Using cointegration analysis, we found that the loss of employment exhibit long-run relationships with the four Covid-19 measures. Our short-run analysis using the PGARCH-M model able to captures the volatility and clustering of the variability in the loss of employment. The PGARCH-M model shows evidence of the leverage effects or asymmetric effects which suggest that the positive shocks (good news) increase volatility in the loss of employment, more than the negative shocks (bad news) in a crisis situation.

*Keywords*: Covid-19, Loss of employment, Cointegration, PGARCH-M, Malaysia

*JEL Classification*: I15, I18, C50, J68

## Resumo

O objetivo do presente artigo é investigar as relações de longo e curto prazo entre a perda de emprego e a pandemia de Covid-19 no mercado de trabalho da Malásia. As variáveis usadas para medir a expressão da Covid-19 incluem o número de novos casos de Covid-19, o número de novas mortes de Covid-19, o número total de casos de Covid-19 e o índice de medo da Covid-19. Usando a análise de cointegração, descobrimos que a perda de emprego exibe relações de longo prazo com as quatro medidas de Covid-19. A nossa análise de curto prazo recorreu ao modelo *PGARCH-M*, capaz de capturar a volatilidade e a variabilidade na perda de emprego. O modelo *PGARCH-M* mostra evidências de efeitos de alavancagem ou efeitos assimétricos, o que sugere que os choques positivos (boas notícias) aumentam a volatilidade na perda de empregos mais do que os choques negativos (más notícias) numa situação de crise.

*Palavras-chave*: Covid-19, Perda de emprego, Cointegração, PGARCH-M, Malásia

*Códigos JEL*: I15, I18, C50, J68

## 1. INTRODUCTION

One of the dampening effects inflicted by the Covid-19 pandemic is on the economy and the labour markets (Kong & Prinz, 2020; Deady et al., 2020; Almeida & Santos, 2020). As pointed out by Zimmermann et al. (2020) that in a globalised world, the outbreak of the Covid-19 can spread very fast with more globalised countries being affected faster and with a larger impact. Furthermore, the situation can be worst in democratic countries as the impact of the Covid-19 could be higher in terms of health effects. According to Karabulut et al. (2021), most democratic countries are not fast enough to react and are less effective in responding to such crisis. On the contrary, an autocratic government that usually will not consider any electoral consequences will act faster, stronger and mobilize more effective resources to curtail the spread of Covid-19.

In Malaysia, the threat of Covid-19 becomes a reality when the first Covid-19 positive case was reported on 25 January 2020. Studies have shown that the news about the Covid-19 pandemic caused fear, anxiety and certain level of uncertainty among the people (Ozdurak et al., 2020; Blustein & Guarino, 2020). Phan and Narayan (2020) have considered Covid-19 as the father of all fears. The fear of the unknown leads the public, the government and businesses to react and this reaction will have devastating impact on the economy.

The Malaysian population is not spared from this fear, anxiety and confusion created by the Covid-19 outbreak; and it has been argued that the fear of Covid-19 and the lockdown measures adopted by the government of Malaysia have caused job losses among the population (Shah et al., 2020). The Malaysian government enforces its lockdown measures, the so-called Movement Control Order (MCO) on 18 March 2020; in which some of the measures include the closure of non-essential businesses, schools and workplace are closed, stay at home order, mass gathering are prohibited, public events are banned, and domestic and international travelling was restricted. Since March 2020 the Department of Statistics Malaysia (DOSM) report that the unemployment rate immediately increases to 3.9% compared to the earlier rate of 3.3% in February and 3.2% in January 2020 (DOSM, 2020a). The unemployment rate peak to 5.3% in May and then starts to decline to 4.7% in August 2020.

Like many other countries, the impact of Covid-19 on the Malaysian labour market has been disproportionate. Rahman et al. (2020) point out that the workers that are most at risk and vulnerable to the Covid-19 are those were already considered vulnerable before the crisis. They are overly exposed to the pandemic due to their relatively low education, low level of income, and they are young workers. For example, in the second quarter 2020, among the unemployed people, female unemployed (5.5%) is greater than the male unemployed (4.7%); young workers aged 15-24 years (12.5%) is greater than the older workers of 25-34 years (5.2%) (DOSM, 2020b).

During the Covid-19 pandemic, the young people aged 15-24 years was greatly affected with unemployment rate increased from 9.9% in the fourth quarter 2019 to 12.8% in the fourth quarter 2020. By ethnic groups, unemployment rates increase for Bumiputra from 3.7% to 4.7%; and Chinese from 2.3% to 4.3% between the fourth quarter 2019 to the fourth quarter 2020; while the Indians maintained its unemployment rate at 6.0% during the two periods (DOSM, 2021). Furthermore, the findings from a survey conducted in March 2020, DOSM (2020c) reported that 21.9% of job lost was from the agriculture sector followed by the service (15.0%) and industry (6.7%) sectors. In terms of reduced working hours, the agriculture sector leads with 33.3%, followed by service (16.9%) and industry (12.8) sectors.

The purpose of the present study is to investigate the long-run and short-run relationships between the daily loss of employment and the Covid-19 pandemic in Malaysia for the period 25 January 2020 to 10 September 2020. To assess the reaction of the labour market to the Covid-19 pandemic, we are using daily data on the number of loss of employment. The novelty of the present study is the use of daily administrative data compiled by the Employment Insurance System (EIS) at PERKESO, Putrajaya. The unemployed workers who are members of the Social Security Organization (SOCSO) are required to register with the EIS in order to make their claims for the loss of employment. The EIS centre reports these statistics daily and weekly. Su et al. (2021) admitted that study linking Covid-19 and the labour market is uncommon. To the best of our knowledge, this paper is the first to estimate the volatility of job losses and its relationships with Covid-19 variables.

The paper is organized as follows. In the next section we discuss the literature review, follow by discussions on the methods and data used in the analysis in Section 3. We present the empirical results in Section 4, and the last section is our conclusion.

## 2. LITERATURE REVIEW

According to Davidescu et al. (2021) the study on the impact of Covid-19 on the labour market is of paramount important due to several reasons. First, the increase in the number of job losses will lead to an increase in unemployment that will reduce productivity and slowing economic growth. Second, slow economic growth and coupled with low productivity will ultimate reduce wages. Lower or reduced income or wages will deny workers and family's access to good quality or nutritious food. Thus, during the Covid-19 pandemic, food insecurity could be one important issue to be address by the government. Third, the heterogenous effects of the Covid-19 pandemic will lead to widening income disparity, increase income inequality and poverty among the population; and the vulnerable people will be the worst impacted.

The facts and similar scenario can be seen from other countries. In the United Kingdom female, young and low-paid and certain ethnic minority groups were among the workers that lost their job as a result of the shut-down order by the UK government to prevent the spread of the coronavirus (Blundell et al., 2020). The lockdown on 23 March, over 8 million employees have lost their job by the end of May 2020 (Dias et al., 2020). Study by Powell and Francis-Devine (2021) reported that unemployment rates for minority ethnic groups in the United Kingdom were higher than average before the Covid-19 pandemic and experience a larger increase than average from the first quarter 2020 to the first quarter 2021.

In the US, Couch et al. (2020) found that the African-American experienced an increase in unemployment to 16.6%, while the Latinx registered an unemployment rate of 18.2%. They argue that the unfavourable occupational distribution and lower skills contributed to why Latinx experienced much higher unemployment rates than whites. Beland et al. (2020) also found that the adverse effects of the Covid-19 on the US labour market are larger for men, young workers, Hispanic and less educated workers. In another study on the US, Falk et al. (2020) report that young workers, women, workers with low educational attainment, part-time workers and racial and ethnic minorities experienced high unemployment rates due to Covid-19 pandemic. On the other hand, the uncertainty shocks due to the unprecedented Covid-19 pandemic lead to a decrease in labour force participation rate (Fontaine, 2020).

For the European countries, a study by van der Wielen and Barrios (2020) show that there was a significant slowdown in the labour market and consumption in the European Union countries as a result of an increase in people's economic anxiety during the Covid-19 pandemic. The fact is that the Covid-19 pandemic has fundamentally shattered the illusion of security at work which is now reeling with unprecedented job losses (International Labor Organization, 2020). On the other hand, a causality test conducted by Su et al. (2021) indicate that Covid-19 cases cause unemployment for Germany, Italy and the UK; while Covid-19 new deaths cause unemployment in Italy and UK. Nevertheless, they conclude that the Covid-19 pandemic increases the unemployment rate robustly in most of the European economies.

Another study on the European countries, the work by Katris (2021) by employing a Vector Autoregression (VAR) model approach indicates that the impact of Covid-19 on the total unemployment, female and youth unemployment in Greece has been less severe compared to higher impact on the other EU27 countries. Nevertheless, Ahmad et al. (2020) argued that Covid-19 is not going to go away very soon in selected European countries. They have forecasted that the unemployment rate is expected to increase in the next 5 years for Belgium, France, Germany, Italy, Spain and. Turkey.

## 3. METHODOLOGY

### 3.1 The Long-run Model

The main purpose of the present study is to estimate the long-run and short-run relationships between the loss of employment and the Covid-19 pandemic, measure by the number of new cases, the number of new deaths, total number of Covid-19 cases and Covid-19 fear index. To establish the long-run relationship between two series, we estimate the following long-run regression,

$$\mathrm{loe}_t = \psi_0 + \psi_1 \mathrm{covid}_{jt} + \varepsilon_t \tag{1}$$

where $\mathrm{loe}_t$ is logarithm of loss of employment, $\mathrm{covid}_{jt}$ is logarithm of Covid-19 measures with j equals the number of Covid-19 new cases, the number of Covid-19 new deaths, the number of total Covid-19 cases and Covid-19 fear index; and the error term $\varepsilon_t$ is assumed to be white noise.

To determine the long-run relationship between $\mathrm{loe}_t$ and $\mathrm{covid}_{jt}$ we conduct cointegration test on Equation (1) by employing three estimators. First, by using the Ordinary Least Square (OLS) with robust standard error, corrected for both autocorrelation and heteroskedasticity due to Newey and West (1987) approach. The residual from the estimated regression is then tested for unit root by using the conventional Dickey and Fuller (1981) and Phillips and Ouliaris (1990) unit root tests. Rejection of the null hypothesis of unit root implies cointegration, thus, exhibiting long-run relationship between $\mathrm{loe}_t$ and $\mathrm{covid}_{jt}$.

A cointegrated regression is a valid long-run equation or model, in other words, it is non-spurious (Granger & Newbold, 1974). For the second estimator, we employ the dynamic OLS (DOLS) proposed by Stock and Watson (1993). According to Stock and Watson (1993) DOLS is robust and efficient in small sample, simultaneity bias, and can accommodate higher orders of integration of a series. In estimating Equation (1) using DOLS, an I(1) variable is regress on other I(1) variables, the I(0) variables, and lags and leads of the first-difference of the I(1) variables. To test for cointegration when using the DOLS estimator, we employ the Hansen (1992) instability test. According to Hansen (1992), the $\mathrm{L}_c$ statistic is a LM test statistic and can be used to test for the null hypothesis of cointegration against the alternative of no cointegration.

Finally, we employ the autoregressive distributed lag (ARDL) procedure proposed by Pesaran et al. (2001). The ARDL procedure is efficient and robust to a mixed of I(0) and I(1) variables, in small sample and endogeneity with good enough lag structure in the model. Furthermore, by using the ARDL approach, Pesaran et al. (2001) show that both long-run and short-run models can be estimated simultaneously. According to Pesaran et al. (2001), a long-run model as per Equation (1) can be derived from the following ARDL(1,1) model in levels,

$$\mathrm{loe}_t = \chi_0 + \chi_1 \mathrm{loe}_{t-1} + \chi_2 \mathrm{covid}_{jt} + \chi_3 \mathrm{covid}_{jt-1} + \eta_t \qquad (2)$$

where Equation (1) can be derived from Equation (2) when we have,

$$\mathrm{loe}_t = \frac{\chi_0}{1-\chi_1} + \frac{\chi_2+\chi_3}{1-\chi_1} \mathrm{covid}_{jt} + \frac{1}{1-\chi_1} \eta_t \qquad (3)$$

or as in Equation (1), $\mathrm{loe}_t = \psi_0 + \psi_1 \mathrm{covid}_{jt} + \varepsilon_t$; with$\psi_0 = \frac{\chi_0}{1-\chi_1}$, $\psi_1 = \frac{\chi_2+\chi_3}{1-\chi_1}$, and $\epsilon_t = \frac{1}{1-\chi_1}\eta_t$. Equation (2) must pass the non-serial correlation test with optimum lag length.

Nevertheless, to test for cointegration on Equations (1) or (3) by using the ARDL approach, Pesaran et al. (2001) proposed the Bounds F-test on the following conditional ARDL-error-correction model (ARDL-ECM);

$$\Delta \mathrm{loe}_t = \rho_0 + \rho_1 \mathrm{loe}_{t-1} + \rho_2 \mathrm{covid}_{jt-1} + \sum_{i=1}^{p} \delta_i \Delta \mathrm{loe}_{t-i} + \sum_{i=0}^{q} \vartheta_i \Delta \mathrm{covid}_{jt-i} + \epsilon_t \qquad (4)$$

The bound-F tests were tested on whether $\rho_1 = \rho_2 = 0$ (null hypothesis) versus $\rho_1 \neq \rho_2 \neq 0$ (alternative hypothesis). The long-run cointegrating relationship is identified when the computed F-statistic is compared with the bound critical values tabulated by Narayan (2005) for small sample size. The null hypothesis of no cointegration is rejected when the computed F-statistic exceeds the upper bounds of critical value that the variables are cointegrated.

On the other hand, the variables are not cointegrated if the null hypothesis of no cointegration is not rejected where the estimated F-statistic falls below the lower bounds of critical value. If the calculated F-statistic falls between the upper and lower bounds of critical values, the decision is inconclusive. Rejection of the null hypothesis of non-cointegration meaning that there is cointegration and Equations (1) or (2) are valid non-spurious long-run model.

After estimating the long-run cointegrating regression, the short-run model, i.e. the error-correction model can be derived as,

$$\Delta \mathrm{loe}_t = \delta_0 + \pi \mathrm{ECM}_{t-1} + \sum_{i=1}^{p} \delta_i \Delta \mathrm{loe}_{t-i} + \sum_{i=0}^{q} \vartheta_i \Delta \mathrm{covid}_{jt-i} + \mu_t \qquad (5)$$

where $\mathrm{ECM}_{t-1} = \varepsilon_{t-1} = \mathrm{loe}_{t-1} - [\psi_0 + \psi_1 \mathrm{covid}_{jt-1}]$. The significance and negative values of the estimated coefficient $\pi$ would also indicate cointegration (Engle & Granger, 1987). The estimated parameter $\pi$, would lies between 0 and -2 (Loayza & Ranciere, 2006; Samargandi et al., 2015; Fromentin & Leon, 2019).

The novelty of the error-correction short-run model is that the long-run information regarding both $\mathrm{loe}_t$ and $\mathrm{covid}_{jt}$ has been incorporated in the short-run model, which is I(0) as represented by the $\mathrm{ecm}_{t-1}$term. Similarly, we can also estimate the short-run model after estimating Equation (1) using OLS and DOLS by savings the residuals, and incorporate the lagged one period residuals (i.e., $\mathrm{ECM}_{t-1}$) into Equation (5) after estimating their respective cointegrating regressions. The error-correction models derived from OLS and DOLS is then estimated using OLS with robust standard error.

## 3.2 Volatility and GARCH Models

Numerous works on modeling volatility has been mostly focused on financial time series. Autoregressive conditional heteroscedasticity (ARCH) and its generalization (GARCH) models represent the main methodologies that have been applied in modeling and forecasting stock market volatility. The GARCH model which is able to capture volatility clustering was proposed by Bollerslev (1986). The GARCH model allows the conditional variance to be dependent upon its own previous lags.

In every GARCH family model requires two distinct specifications: the mean and variance equations. In general a GARCH(1,1) was sufficient to capture the volatility clustering in the data (Engle, 2004). In this study, as shown by the volatility in the series in Figure (1) and the descriptive statistics in Table 1 that indicate non-normality of all the series (except number of total Covid-19 cases in level), we employ the GARCH model and its variants which can accommodate for non-constant variance over time.

### 3.3 The GARCH-M Model

The GARCH model which is able to capture volatility clustering was proposed by Bollerslev (1986). The GARCH model allows the conditional variance to be dependent upon its own previous lags. In this study we specify the mean equation with the inclusion of volatility in the loss of employment ($\log\sigma_t^2$), and therefore, our GARCH(1,1)-M can be expressed as follows,

$$\Delta loe_t = \delta_0 + \pi ECM_{t-1} + \sum_{i=1}^{p} \delta_i \Delta loe_{t-i} + \sum_{i=0}^{q} \vartheta_i \Delta covid_{jt-i} + \lambda \log\sigma_t^2 + \epsilon_t, \quad \epsilon_t \sim (0, \sigma_t^2) \qquad (6)$$

$$\sigma_t^2 = c + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (7)$$

The mean Equation (6) is in fact the error-correction discussed above, but with the inclusion of volatility in loss of employment. The variance Equation (7) states that the conditional variance of $\log\sigma_t^2$ depends on the squared error lagged one period ($\epsilon_{t-1}^2$) as well as on its conditional variance lagged one period ($\sigma_{t-1}^2$). The constant $c$ is the long-term average volatility; while α and β represent how the volatility is affecting by current news and past information regarding volatility, respectively. The parameters $c$, α and β are assumed to be non-negative to guarantee that volatility is always positive. Furthermore, the stationary condition for GARCH(1,1) is $\alpha + \beta < 1$; and the speed for which the shock to volatility decays becomes slower as $\alpha + \beta$ approaches 1.

### 3.4 The EGARCH-M Model

The disadvantage of GARCH model is that the conditional variance is unable to respond asymmetrically to the rise and fall in the volatile series. The so-called leverage effects enable the conditional variance $\sigma_t^2$ to respond asymmetrically to positive and negative values of $loe_t$. To overcome the symmetrical GARCH, Nelson (1991) proposes the Exponential GARCH (EGARCH) model that can capture asymmetric responses of the time-varying variance to shocks and at the same time, ensures that the variance is always positive. An EGARCH(1,1) model can be defined as follows,

$$\log(\sigma_t^2) = c + \alpha \left| \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \gamma \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \log(\sigma_{t-1}^2) \qquad (8)$$

where the left hand side of Equation (8) is the logarithm of the conditional variance. This implies that the leverage effect is exponential rather than quadratic and that the forecasts of the conditional variance are guaranteed to be non-negative, thus, EGARCH does not impose any non-negative constraints on the model parameters $c, \alpha, \gamma$ and $\beta$.

However, to maintain stationarity, $\beta$ must be positive and less than 1. The parameter $\beta$ represents a magnitude effect or the symmetric effect of the model, the GARCH effects; while $\beta$ measures the persistence in conditional volatility. This implies that when $\beta$ is relatively large, and then volatility takes a long time to die out following a "crisis in the market" (Alexander, 2009). The leverage effect or asymmetry is measured by parameter $\gamma$. Leverage effect is presents when $\gamma \neq 0$; whereas when $\gamma = 0$, the model is symmetric. If $\gamma < 0$, it implies that the negative shocks (bad news) increase volatility more than the positive shocks (good news).

### 3.5 The PGARCH-M model

Ding et al. (1993) proposed the Power GARCH (PGARCH) model to deal with asymmetry. For a PGARCH(1,1) model, the conditional variance is expressed as

$$\sigma_t^d = c + \alpha(|\epsilon_{t-1}| + \gamma\epsilon_{t-1})^d + \beta\sigma_{t-1}^d \qquad (9)$$

where d is the power term, with $d > 0$ and $|\gamma\,| \leq 1$. The parameter $\gamma$ is the leverage effect, and when $d > 0$ and $\gamma \neq 0$ and significant we established the existence of asymmetry or leverage effect. For the power term, when d equals 2 and $\gamma = 0$, the PGARCH(1,1) replicate a GARCH(1,1) model. If d equals 1 the conditional standard deviation will be estimated.

### 3.6 Distribution Assumption of the Error ($\epsilon_t$)

It is recognized that volatile and clustered time series data are not normally distributed. There is the presence of excess kurtosis and heavy tails in the distribution of the residuals of the estimated regression (see Table 1). To account for the excess kurtosis and fat tails that is present in the residuals of the time series, in this study we estimate all GARCH, EGARCH and PGARCH models by assuming $\epsilon_t$ follows a Student's t- and generalized error distribution (G.E.D) (see Bollerslev, 1987; Nelson, 1991). These distributions are appropriate to capture the excess kurtosis and the skewness in the residuals series.

### 3.7 Model Selection Criteria

In this study the best fitting model will be chosen on the basis of: (a) diagnostic checks, (b) model selection criteria, and (c) evaluation on in-sample and out-of-sample forecasting performances. For the diagnostic checks we employ the ARCH LM test (Engle, 1982) for the residuals. The ARCH LM test is to determine whether the residuals of the variance equation exhibit heteroskedasticity.

On the other hand, in selecting the best model, we use three model selection criterion namely, Akaike information (Akaike, 1974), Schwarz criterion (Schwarz, 1978) and Hannan-Quinn criterion (Hannan & Quinn, 1979). All criteria are based on likelihood functions and all are closely related to each other and can be used alternately. The one that gives the smallest value will be chosen as the best fitting model.

To evaluate the forecast performance of the model, we use three different criteria, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Theil Inequality Coefficient (Theil, 1967) to compare the performance accuracy of several competing models. The model with a smaller forecast error would be considered as a better and more appropriate model.

The RMSE, MAE and Theil inequality coefficient are calculated as follows,

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{T}(\sigma^2-\hat{\sigma}^2)^2}{T}},\ \text{MAE} = \frac{\sum_{t=1}^{T}|\sigma^2-\hat{\sigma}^2|}{T} \text{ and Theil} = \frac{\sqrt{\frac{\sum_{t=1}^{T}(\sigma^2-\hat{\sigma}^2)^2}{T}}}{\sqrt{\frac{\sum_{t=1}^{T}\sigma^2}{T}} + \sqrt{\frac{\sum_{t=1}^{T}\hat{\sigma}^2}{T}}} \qquad (10)$$

where T is the number of observation; while $\sigma^2$ and $\hat{\sigma}^2$ are the actual variance (volatility) and forecasted volatility, respectively. The RMSE measures the difference between the true values and the estimated values, and accumulates all these difference together as a standard for the predictive ability of a model. The criterion is the smaller value of the RMSE, the better the predicting ability of the model. MAE criterion measures deviation from the series in absolute terms, and measure how much the forecast is biased. The RMSE assigns greater weights to large forecast errors, while MAE gives equal weights to both over and under predictions of the variance. Lastly, the Theil inequality coefficient is a scale invariant measure that always lies between zero and one, where zero indicates a perfect fit. That in turn occurs only exact or gives zero errors.

### 3.8 Sources of Data

In this study we are using real time administrative data on the loss of employment compiled by the Employment Insurance System (EIS) centre, PERKESO, Malaysia for the period 25 January 2020 to 10 September 2020. The loss of employment used in this study is to proxy for the labour market reactions (since daily unemployment rate is not available) to the Covid-19 pandemic. To represent the coronavirus outbreak we used the number of Covid-19 new cases, the number of Covid-19 new deaths and the number of total Covid-19 cases (i.e., sum of Covid-19 new cases and Covid-19 new deaths). Daily data for the number of confirmed Covid-19 new cases and confirmed Covid-19 new deaths 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/).

Apart from the number of Covid-19 new cases, the number of Covid-19 new deaths and the number of total Covid-19 cases, we employ another measure of Covid-19 that is the Covid-19 fear index. The Covid-19 fear index is constructed using the approach proposed by Salisu and Akanni (2020) as follows,

$$\mathrm{Covid} - 19\ \mathrm{Fear\ Index}_\mathrm{t} = 0.5\left[\left(\frac{\mathrm{newcases}_\mathrm{t}}{\mathrm{newcases}_\mathrm{t}+\mathrm{newcases}_{\mathrm{t}-14}}\right) + \left(\frac{\mathrm{newdeaths}_\mathrm{t}}{\mathrm{newdeaths}_\mathrm{t}+\mathrm{newdeaths}_{\mathrm{t}-14}}\right)\right] \quad (11)$$

where $\mathrm{newcases}_{\mathrm{t}-14}$ and $\mathrm{newdeaths}_{\mathrm{t}-14}$ are the number of Covid-19 new cases and number of Covid-19 new deaths, respectively reported at the beginning of the incubation period, $\mathrm{t} - 14$.

All five series used in the study were transformed into logarithm for further analysis. In this study we use the formula, $\log \mathrm{y}_\mathrm{t} = \log\,[\mathrm{x}_\mathrm{t} + \sqrt{(\mathrm{x}_\mathrm{t}^2 + 1)})]$ to transform all the series into logarithm (Busse & Hefeker, 2007). By employing this method, we maintain the sign of $\mathrm{x}_\mathrm{t}$.

## 4. THE EMPIRICAL RESULTS

### 4.1 Descriptive Statistics

The plots of the loss of employment, the number of Covid-19 new cases, the number of Covid-19 new deaths, the number of total Covid-19 cases and Covid-19 fear index are presented in Figure 1. The ten graphs clearly depicted the ups and downs movement in the daily series, giving evidence of volatilities and clustering of the five series in their logarithm (levels) and log-differences (first-differences). Thus, by specifying a GARCH type model is most suitable to model volatilities in loss of employment. Table 1 describes the mean, maximum, minimum, skewness, kurtosis and Jacque-Bera tests for the five series. The mean of all series are positive, indicating that the series has increased over time.

The five series in their level indicate that there were few extreme points; for the loss of employment ranging from 2.6 min to 8.0 max; while from 0.0 min to 6.3, 2.6, 3.8 and 0.8 max for Covid-19 new cases, Covid-19 new deaths, total Covid-19 cases and Covid-19 fear index, respectively. This implies that each series has been fluctuating and varies over time, thus, giving large standard of deviation. In their first-differences, the variability of the series is shown by the positive max and negative min for all series. The loss of employment and new cases in levels have negative skewness; while the rest of the series in levels and first-differences have positive skewness; and all series have high kurtosis of greater than 3.0 (except for new cases, total cases and fear index in level) which indicate the presence of fat tails and a leptokurtic series. Moreover, the Jacque-Bera test statistics for all series in both levels and first-differences reject the null hypothesis of normality in the series.

## 4.2 Results of Unit Root Test

In economic time series a study involving integrated series, the testing for the order of integration of a series is an important exercise prior to further analysis. Regressing non-stationarity variables will result in spurious regression conclusion. Taking this into consideration, in this study the Dickey-Fuller Generalized Least Square (DF-GLS) unit root test proposed by Elliot et al. (1996) was employed to determine the order of integration of the series involved. Elliott et al. (1996) assert that the modified Dickey-Fuller (DF) unit root test by using a generalized least squares (GLS) approach has the best overall performance in terms of small-sample size and power, compared to the conventional Dickey-Fuller test. Further, Elliott et al. (1996: pp.813) point out that their "DF-GLS test has substantially improved power when an unknown mean or trend is present."

Table 2 demonstrates the DF-GLS unit root tests result for all five variables; tested on their levels and first-differences. We can observe that the null hypothesis of a unit root in level cannot be rejected for the loss of employment, the number of Covid-19 new cases, the number of Covid-19 new deaths and total Covid-19 cases except for the Covid-19 fear index in which the null hypothesis of a unit root in its level can be rejected at the 1% level. However, in their first-differences, all four variables – loss of employment, number of Covid-19 new cases, the number of Covid-19 new deaths and total Covid-19 cases that the null hypothesis of a unit root can be rejected at the 1% level. Thus, we can conclude that the four series - loss of employment, number of Covid-19 new cases, number of Covid-19 new deaths and total Covid-19 cases are I(1) variables, while Covid-19 fear index is I(0) in levels. An I(1) variable in level suggest that this series in first-difference is stationary.

## 4.3 Results of Cointegration Tests

Having determine that the loss of employment, number of Covid-19 new cases, number of Covid-19 new deaths and total Covid-19 cases are I(1), and Covid-19 fear index is I(0) in levels, we can proceed with the testing for cointegration test. In our case, the three estimators – OLS, DOLS and ARDL can be applied for the testing of cointegration between the loss of employment and Covid-19 cases; while the relationship between the loss of employment and Covid-19 fear index can be tested for cointegration using the ARDL approach only because ARDL procedure cater for a mixed of I(1) and I(0) variables.

Results in Panels A and B portray in Table 3 suggest strong support of cointegration relationship between the loss of employment with the number of Covid-19 new cases, the number of Covid-19 new deaths and number of total Covid-19 cases as shown by the significance of Dickey-Fuller ($\mathrm{DF}_{\mathrm{t-stat}}$), Phillips-Ouliaris ($\mathrm{PO}_{\mathrm{t-stas}}$) and Hansen ($\mathrm{L}_{\mathrm{c-stat}}$) statistics. For Panel C, cointegration is also supported as shown by the significance of both the $\mathrm{ECM}_{\mathrm{t-stat}}$ and the $\mathrm{Bound}_{\mathrm{F-stat}}$ tests statistics. These results imply that there are long-run relationships between the losses of employment with the Covid-19 variables – number of Covid-19 new cases, number of Covid-19 new deaths, number of total Covid-19 cases and the Covid-19 fear index, irrespective of the estimators used, and thus suggest that Equation (1) is a valid non-spurious long-run model.

The existence of cointegration suggests that there is an error-correction model between the variables. The error-correction or the short-run model would be the mean equation in the GARCH model. For consistency, we report the results of estimating the error-correction model from the ARDL approach as per Equation (5) in Table 4. Results in Table 4 indicate that the estimated coefficients of the $\mathrm{ECM}_{\mathrm{t-1}}$ terms are negative and statistically significant at the 1% level; therefore giving us further evidence to support for cointegration or the existence of long-run relationships between the loss of employment and the number of Covid-19 new cases, number of Covid-19 new deaths, number of total Covid-19 cases and the Covid-19 fear index. The speed of adjustment of 0.40 suggests that 40% of the disequilibrium in the loss of employment will be corrected each year. The error-correction models suggest that the number of Covid-19 new cases and the number of total Covid-19 cases affect the loss of employment in the short-run, but not for the number of Covid-19 new deaths and Covid-19 fear index. Nonetheless, in the short-run the variability in the loss of employment is also affected by its own lagged period.

### 4.4 Results for GARCH-M, EGARCH-M and PGARCH-M models

Next we turn to our main results of interest – the GARCH-M, EGARCH-M and PGARCH-M models. Tables 5, 6, 7 and 8 present the results of estimating the GARCH-M, EGARCH-M and PGARCH-M models for the number of Covid-19 new cases, the number of Covid-19 new deaths, total Covid-19 cases and Covid-19 fear index, respectively. For each estimated GARCH-M, EGARCH-M and PGARCH-M models, we have presented both the Student's t- and generalized error distribution (GED). In this study, we have specified our mean equation in the form of the error-correction model as per Equation (5), with the inclusion of an additional variable – volatility in loss of employment. The novelty of this equation is that it includes both the short-run as well as the long-run relation or information between the losses of employment with the Covid-19 variables. Similar approach was undertaken by Haughton and Iglesias (2017). They employed the ARDL-GARCH(1,1) model to determine the relationships between exchange and the stock market in the Caribbean and Latin America. For the mean equation they employed the unrestricted error-correction model to represent the conditional mean equation.

Table 5 presents the results of the ARDL(3,2)-(E,P)GARCH(1,1)-M model for the loss of employment with respect to the number of Covid-19 new cases. Columns 2 and 3 show the result for GARCH-M; columns 4 and 5 for EGARCH-M; while columns 6 and 7 for PGARCH-M. Results for the mean equations suggest that the $\mathrm{ECM}_{t-1}$ term is significant in the GARCH-M and PGARCH-M (in GED only) models. This implies that news on the number of Covid-19 new cases affect changes in the loss of employment; and the short-run effects of changes in Covid-19 new cases affect changes in loss of employment in the EGARCH-M and PGARCH-M models. But, more importantly the volatility of loss of employment in the mean equation is significant only in the PGARCH-M model with positive sign. This signifies that an increase in the volatility of loss of employment will increase the current changes in the loss of employment. Thus, the daily data fits very well for the PGARCH-M model.

On the other hand, results for the estimated variance equations suggest that the ARCH effects are not significant in the GARCH-M and EGARCH-M models, but it is significant in the PGARCH-M model. However, the GARCH effects are significant in all models (except for Student's t- in EGARCH-M). In the PGARCH-M model, all variable in the variance equations are significant and show positive signs. The ARCH effect, GARCH effect, leverage effect, and the power term d, is positive and significant in both the student's t and GED models. The sum of the ARCH and GARCH effects is less than 1. The positive leverage effect suggests that positive shocks are associated with higher volatility than negative shocks supporting the asymmetry effects of the news on Covid-19. Also, as shown by the power term d, which is not equal 2, thus, establishing that it is not a standard GARCH model. Furthermore, the ARCH test for heteroscedasticity indicates that the estimated variance equations in the PGARCH-M model do not exhibit heteroscedastic error.

Results for the number of Covid-19 new deaths, the number of total Covid-19 cases and Covid-19 fear index are depicted in Table 6, Table 7 and Table 8, respectively. Generally, the outcomes of the results are similar to the findings in Table 5. In all three tables, the PGARCH-M model performs better than both the GARCH-M and EGARCH-M models in terms of the significant and the correct sign of the variables. The estimated parameter of the $\mathrm{ECM}_{t-1}$ term is negative and significant at the 1% level. This implies that there is cointegration or long-run relationships between the loss of employment and the news in Covid-19 cases. The speeds of adjustment of between 0.06 to 0.12 suggest that 6% to 12% of the disequilibrium will be corrected within a year. Furthermore, the variable, $\log\sigma_t^2$ is positive and significant in the mean equations, thus, implies that the volatility in the loss of employment is an important factor affecting the current changes in the loss of employment.

For the variance equations, all variables exhibit positive sign and were significant at the 1% level, particularly in the GED specification for the number of Covid-19 new deaths and the number of total Covid-19 cases; while in the Student's t- specification for the Covid-19 fear index. In these three cases, the sum of the ARCH and GARCH effects is less than 1. The power term d is positive, significant and less than 2. The leverage effect variable is positive and significant, thus suggest that the effects of Covid-19 news (either news on new death, total Covid-19 case or Covid-19 fear index) are not symmetrical. The positive leverage indicates that positive shocks exhibit larger volatility effect than the negative shocks. Lastly, the ARCH test for heteroscedasticity indicates that the estimated variance equations in the PGARCH-M model do not exhibit heteroscedastic error.

### 4.5 Results of Best Model Performance and Forecast Accuracy

Our next task is to determine which of the three models – GARCH-M, EGARCH-M and PGARCH-M with two different variations in the error distribution assumptions (Student's t- and GED) best explain the volatility in the loss of employment. In this study we based our best choice of model on: (1) model selection criteria; and (2) in-sample forecasting ability and out-of-sample forecasting ability. Looking through Tables 5 to 8, between Student's t- and GED specifications for the PGARCH-M model, the smallest value for AIC, SC and HQC is shown by the Student's t- specification for all four measures of Covid-19 -the number of Covid-19 new cases, number of Covid-19 new deaths, number of total Covid-19 cases and Covid-19 fear index.

Despite the PGARCH-M model with Student's t- error distribution being the selected model, we further perform the in-sample and out-of-sample forecasting ability of the model for both Student's t- and GED. The result is presented in Table 9. Irrespective of the choice of model based on the model selection criteria above, the in-sample forecasting performance in terms of smallest RMSE, MAE and Theil inequality coefficients indicate that the best model is G.E.D for all four Covid-19 measures. On the other hand, the results of the out-of-sample forecasting accuracy indicate that the smallest RMSE, MAE and Theil inequality coefficients is shown by the generalized error distribution (GED) for the number of Covid-19 new cases and the number of Covid-19 new deaths. On the other hand, the smallest RMSE, MAE and Theil inequality coefficients for the number of total Covid-19 cases and Covid-19 fear index are shown by the Student's t- error distribution.

## 5. CONCLUSION

Ever since the start of the unprecedented Covid-19 pandemic spreading outside China, the governments in many countries affected by this pandemic have adopted the lockdown policy. This lockdown measures include the closure of non-essential businesses, stay at home order, workplace closure, restrictions on domestic and international travel and the prohibitions of mass gathering and public events which take a heavy toll on the economy. Studies have shown that the Covid-19 pandemic and the lockdown measures have resulted in the slowing down of the economic growth worldwide.

The labour market is one of the economic activities badly affected by the Covid-19 pandemic. Studies have reported that immediately after the lockdown they saw an increased in the unemployment rate in many countries. This is also evident in Malaysia where number of people who lose their job increases after the lockdown measures undertaken by the Malaysian government to mitigate the spread of the Covid-19 outbreak. In this study we have investigated the long-run and short-run effects of Covid-19 in the Malaysian labour market. Using daily data on the loss of employment, number of Covid-19 new cases, number of Covid-19 new deaths and Covid-19 fear index, our cointegration analysis indicate that the loss of employment exhibit long-run relationships with the four Covid-19 measures. In the long-run the Covid-19 pandemic measures do affect the loss of employment in Malaysia during January 2020 to September 2020 period.

To uncover the short-run relationship between loss of employment and the Covid-19 measures, we have estimated the GARCH-M, EGARCH-M and PGARCH-M models. Nevertheless, the PGARCH-M model able to captures the volatility and clustering behavior in the daily loss of employment series. The PGARCH-M model not only able to explains the volatility and clustering of the loss of employment, but also able to capture the leverage effects. In our case, the positive shocks (good news) increase volatility in the loss of employment series more than the negative shocks (bad news). In our PGARCH-M model the short-run and long-run information on the loss of employment and the number of Covid-19 new cases, the number of Covid-19 new deaths, the number of total Covid-19 cases and Covid-19 fear index, as well as the conditional variance (loss of employment volatility) affect the variability in the loss of employment in Malaysia. Therefore, it can be concluded that a short-run model that could include both the short-run as well as the long-run information can make a better model and suitable for forecasting on the loss of employment in Malaysia.

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## Attachment

### Table 1. Descriptive statistics

| Series | Mean | Max | Min | Std. Dev. | Skewness | Kurtosis | Jarque-Bera |
|---|---|---|---|---|---|---|---|
| Loss of employment | 6.2137 | 8.0327 | 2.6441 | 0.8519 | -0.8278 | 4.1660 | 36.904*** |
| New cases | 3.4613 | 6.3835 | 0.0000 | 1.6860 | -0.4701 | 2.5256 | 9.9809*** |
| Total Covid-19 cases | 3.6527 | 8.3479 | 0.0000 | 2.2091 | 0.1410 | 2.3880 | 4.3516 |
| New deaths | 0.3831 | 2.6441 | 0.0000 | 0.6644 | 1.5953 | 4.4740 | 111.17*** |
| Fear index | 0.3334 | 0.8680 | 0.0000 | 0.2202 | 0.4490 | 2.6839 | 8.1578*** |
| ΔLoss of employment | 0.0030 | 2.7431 | -3.0925 | 0.7298 | 0.2113 | 5.8788 | 76.193*** |
| ΔNew cases | 0.0112 | 6.3835 | -5.2258 | 1.1227 | 0.6238 | 10.7763 | 558.23*** |
| ΔNew deaths | 0.0000 | 1.8184 | -1.4436 | 0.5590 | 0.3061 | 4.6436 | 27.685*** |
| ΔTotal Covid-19 cases | 0.0168 | 7.2649 | -5.2258 | 1.2689 | 0.6043 | 8.4990 | 303.79*** |
| ΔFear index | 0.0009 | 0.8312 | -0.5953 | 0.2231 | 0.2372 | 4.2199 | 15.419*** |
| | | | | | | | |

*Notes*: Asterisks *** denotes statistically significant at 1% level. Series loss of employment, new cases, new deaths, and fear index are in natural logarithm.

### Table 2. Results of unit root tests

| Types | Level | | First-difference | |
|---|---|---|---|---|
| | Intercept | Intercept+trend | Intercept | Intercept+trend |
| Loss of employment | 0.2929 (6) | -1.7494 (6) | -17.297 (5)*** | -17.241 (5)*** |
| New cases | -0.4193 (4) | -1.2730 (4) | -11.551 (3)*** | -26.900 (0)*** |
| New deaths | -2.0934 (3) | -2.2081 (3) | -14.574 (2)*** | -14.580 (0)*** |
| Total Covid-19 cases | -0.5823 (4) | -1.2203 (4) | -11.443 (3)*** | -26.680 (0)*** |
| Fear index | -4.9473 (1)*** | -5.3789 (1)*** | - | - |

Notes: Asterisks *** denotes statistically significant at 1% level. The critical values for “intercept” refer to MacKinnon (1996); and for “intercept and trend” refer to Elliot et al. (1996). Figures in round bracket (…) denote optimal lag length.

**Table 3. Results of cointegration tests**

| Dependent variable/ Estimators | Independent variables: | | | | |
|---|---|---|---|---|---|
| | Constant | $\text{Covid}_t$ | $R^2$ | SER | Cointegration tests: |
| A. OLS (robust standard error) | | | | | |
| 1. $\text{loe}_t = f(\text{newcases}_t)$ | 6.1289*** | 0.0104 | 0.0004 | 0.8876 | $\text{DF}_{t-stat}$= -2.1310** |
| | (29.331) | (0.2112) | | | $\text{PO}_{\tau-stat}$= -7.1354*** |
| 2. $\text{loe}_t = f(\text{newdeaths}_t)$ | 6.2268*** | -0.1762 | 0.0167 | 0.8803 | $\text{DF}_{t-stat}$= -2.0272** |
| | (57.372) | (-1.8535) | | | $\text{PO}_{\tau-stat}$= -6.8740*** |
| 3. $\text{loe}_t = f(\text{totalcovid}_t)$ | 6.1946*** | -0.0085 | 0.0004 | 0.8876 | $\text{DF}_{t-stat}$ -2.1713** |
| | (31.492) | (-0.2134) | | | $\text{PO}_{\tau-stat}$= -7.1155*** |
| 4. $\text{loe}_t = f(\text{fear index}_t)$ | - | - | - | - | - |
| B. Dynamic OLS [lag=0, lead=2] | | | | | |
| 1. $\text{loe}_t = f(\text{newcases}_t)$ | 6.0800*** | 0.0246 | 0.0079 | 0.8933 | $\text{DF}_{t-stat}$= -2.0617** |
| | (28.701) | (0.4277) | | | $\text{L}_{c-stat}$= [0.0033] |
| 2. $\text{loe}_t = f(\text{newdeaths}_t)$ | 6.2484*** | -0.2434 | 0.0354 | 0.8809 | $\text{DF}_{t-stat}$= -2.3253** |
| | (56.883) | (-1.8535) | | | $\text{L}_{c-stat}$= [0.0028] |
| 3. $\text{loe}_t = f(\text{totalcovid}_t)$ | 6.1477*** | 0.0059 | 0.0365 | 0.8789 | $\text{DF}_{t-stat}$= -2.2624** |
| | (32.732) | (0.1332) | | | $\text{L}_{c-stat}$= [0.0032] |
| 4. $\text{loe}_t = f(\text{fear index}_t)$ | - | - | - | - | - |
| C. ARDL | | | | | |
| 1. $\text{loe}_t = f(\text{newcases}_t)$ | 6.0139*** | 0.0511 | 0.4676 | 0.6550 | $\text{ECM}_{t-stat}$= -6.2152*** |
| ARDL(3,2) | (23.618) | (0.7371) | | | $\text{Bound}_{F-stat}$= 12.762*** |
| 2. $\text{loe}_t = f(\text{newdeaths}_t)$ | 6.1979*** | -0.0754 | 0.4495 | 0.6630 | $\text{ECM}_{t-stat}$= -6.1593*** |
| ARDL(3,0) | (47.010) | (-0.4219) | | | $\text{Bound}_{F-stat}$= 12.534*** |
| 3. $\text{loe}_t = f(\text{totalcovid}_t)$ | 6.0865*** | 0.0254 | 0.4630 | 0.6578 | $\text{ECM}_{t-stat}$= -6.2096*** |
| ARDL(3,2) | (26.899) | (0.4941) | | | $\text{Bound}_{F-stat}$= 12.738*** |
| 4. $\text{loe}_t = f(\text{fear index}_t)$ | 6.3153*** | -0.3051 | 0.4246 | 0.6510 | $\text{ECM}_{t-stat}$= -5.9956*** |
| ARDL(3,0) | (30.682) | (-0.5886) | | | $\text{Bound}_{F-stat}$= 11.870*** |

Notes: Asterisks ***,** denote statistically significant at 1% and 5% level, respectively. Figures in round brackets, (…) and square brackets, […] are t-statistics and p-values, respectively. $\text{loe}_t$ refers to loss of employment. $\text{DF}_{t-stat}$ is the t-statistics of unit root test from the Engle-Granger two-steps procedure for cointegration test; while $\text{PO}_{\tau-stat}$ is the t-statistic of unit root test from the Phillips-Ouliaris cointegration test. $\text{L}_{c-stat}$ is test statistic for Hansen's cointegration test. $\text{ECM}_{t-stat}$ refers to t-statistics for the error-correction term. ARDL(p,q) denotes optimal lag length chosen using AIC.

**Table 4. Estimation results of the error-correction models**

| Independent variables | New cases<br>ARDL(3,2) | New deaths<br>ARDL(3,0) | Total Covid-19<br>ARDL(3,2) | Fear index<br>ARDL(3,0) |
|---|---|---|---|---|
| Constant | 0.0126 | 0.0147 | 0.0196 | 0.0017 |
| | (0.3075) | (0.3550) | (0.4803) | (0.0407) |
| $\mathrm{ECM}_{t-1}$ | -0.3914*** | -0.4013*** | -0.3953*** | -0.3839*** |
| | (-6.4846) | (-6.8260) | (-6.8542) | (-6.1723) |
| $\Delta \mathrm{loe}_{t-1}$ | 0.1426** | 0.1542*** | 0.1392** | 0.1441*** |
| | (2.5927) | (3.0376) | (2.5866) | (2.6465) |
| $\Delta \mathrm{loe}_{t-2}$ | -0.1154 | -0.1093 | -0.1166 | -0.1048 |
| | (-1.7824) | (-1.6402) | (-1.8474) | (-1.4782) |
| $\Delta \mathrm{covid}_{t}$ | -0.0998** | | -0.0846** | |
| | (-2.1314) | | (-2.2152) | |
| $\Delta \mathrm{covid}_{t-1}$ | -0.0704 | | -0.0483 | |
| | (-1.8518) | | (-1.6320) | |
| $\mathrm{R}^2$ | 0.2606 | 0.2442 | 0.2575 | 0.2103 |
| SER | 0.6391 | 0.6433 | 0.6404 | 0.6531 |

Notes: Asterisks ***,** denote statistically significant at 1% and 5% level, respectively. $\mathrm{loe}_t$ refers to loss of employment. $\mathrm{ECM}_{t-1}$ refers to lagged one period of the error-correction term.$\Delta$loe refers to first-difference in loss of employment, and $\Delta$covid refers to first-difference of the respective covid measures. The error-correction models were estimated using OLS with robust standard error due to Newey and West (1987) approach.

**Table 5. Estimation results for the number of Covid-19 new cases**

| Independent variables | ARDL(3,2)-GARCH(1,1)-M: | | ARDL(3,2)-EGARCH(1,1)-M: | | ARDL(3,2)-PGARCH(1,1)-M: | |
|---|---|---|---|---|---|---|
| | Student’s t | GED | Student’s t | GED | Student’s t | GED |
| Mean equation | | | | | | |
| $\delta_0$ (constant) | 3.4300 | 0.7197 | 19.913 | 1.1425 | 0.7541** | 0.6531*** |
| | (0.6901) | (1.5330) | (0.6884) | (1.5374) | (2.4229) | (2.7113) |
| $\pi.\mathrm{ECM}_{t-1}$ | -0.2744*** | -0.2485*** | -0.0129 | -0.0220 | -0.0673 | -0.1198** |
| | (-4.4217) | (-5.7522) | (-1.4270) | (-1.1984) | (-1.8642) | (-2.4382) |
| $\delta_1\Delta\mathrm{loe}_{t-1}$ | 0.0709 | -0.0294 | 0.5290*** | 0.1386 | -0.0322 | 0.0268 |
| | (1.0622) | (-0.5933) | (9.3254) | (1.0862) | (-0.3109) | (0.3050) |
| $\delta_2\Delta\mathrm{loe}_{t-2}$ | -0.1428*** | -0.0812** | -0.2698*** | -0.0629 | -0.1116** | -0.0603 |
| | (-2.7434) | (-2.1597) | (-5.5170) | (-1.1393) | (-2.0408) | (-1.2470) |
| $\vartheta_1\Delta\mathrm{newcases}_t$ | -0.0637 | -0.0344 | -0.0997*** | -0.0705** | -0.0581** | -0.0455** |
| | (-1.7274) | (-1.2552) | (-2.7142) | (-2.3129) | (-2.1219) | (-2.1211) |
| $\vartheta_2\Delta\mathrm{newcases}_{t-1}$ | -0.0326 | 0.0071 | -0.0058 | -0.0472 | -0.0319 | -0.0245 |
| | (-0.8708) | (0.2572) | (-0.1504) | (-1.4511) | (-0.9860) | (-0.9314) |
| $\lambda.\log\sigma_t^2$ | 3.6574 | 0.7619 | 24.405 | 1.0295 | 0.6276*** | 0.6521*** |
| | (0.7976) | (1.6988) | (0.7313) | (1.4952) | (2.9437) | (2.7089) |
| Variance equation | | | | | | |
| c (constant) | 0.2213** | 0.1989*** | -0.8063 | -0.6714*** | 0.3648*** | 0.3928*** |
| | (2.3651) | (3.5335) | (-1.9106) | (-3.7003) | (5.0182) | (5.3755) |
| $\alpha$ (ARCH effect) | 0.0214 | 0.1877 | 0.0016 | 0.0469 | 0.2196** | 0.1453*** |
| | (0.6486) | (1.3482) | (0.5951) | (1.1838) | (2.3288) | (3.6140) |
| $\beta$ (GARCH effect) | 0.4248** | 0.3845*** | 0.0123 | 0.4190** | 0.2786** | 0.3735*** |
| | (2.0453) | (3.4344) | (0.4755) | (2.5181) | (2.2484) | (3.3916) |
| $\gamma$ (Leverage effect) | | | -0.0240 | -0.2443** | 0.8846*** | 0.9403*** |
| | | | (-0.7360) | (-2.2362) | (4.0003) | (4.0346) |
| d (Power) | | | | | 0.8490*** | 0.6836*** |
| | | | | | (3.5243) | (4.5646) |
| $\alpha+\beta$ | 0.4462 | 0.5722 | 0.0139 | 0.4659 | 0.4982 | 0.5188 |
| $R^2$ | 0.3030 | 0.2909 | 0.3520 | 0.2706 | 0.2896 | 0.2724 |
| SER | 0.6219 | 0.6273 | 0.5997 | 0.6362 | 0.6279 | 0.6355 |
| ARCH test: | ***[0.0000]*** | [0.2917] | [0.7201] | [0.2952] | [0.3215] | [0.3436] |

| | | | | | | |
|---|---|---|---|---|---|---|
| Criteria: | | | | | | |
| AIC | 1.8353 | 1.8419 | 1.7029 | 1.7671 | 1.7675 | 1.7900 |
| SC | 2.0007 | 2.0074 | 1.8834 | 1.9476 | 1.9631 | 1.9855 |
| HQC | 1.9020 | 1.9087 | 1.7758 | 1.8399 | 1.8464 | 1.8689 |

Notes: Notes: Asterisks ***,** denote statistically significant at 1% and 5% level, respectively. Figures in round brackets (…) are z-statistics, while figures in square brackets […] are p-values. $R^2$ and SER denote R-squared and standard error of regression, respectively; while ARCH test is the test for heteroscedasticity. AIC, SC and HQ denote Akaike information criteria, Schwarz criteria and Hannan-Quinn criteria, respectively.

**Table 6. Estimation results for the number of Covid-19 new deaths**

| Independent variables | ARDL(3,0)-GARCH(1,1)-M: | | ARDL(3,0)-EGARCH(1,1)-M: | | ARDL(3,0)-PGARCH(1,1)-M: | |
|---|---|---|---|---|---|---|
| | Student’s t | GED | Student’s t | GED | Student’s t | GED |
| Mean equation | | | | | | |
| $\delta_0$ (constant) | 2.4250 | 0.6673 | 8.7438 | 1.1063*** | 0.7379*** | 0.7690*** |
| | (0.7584) | (1.3905) | (0.4723) | (3.3979) | (4.3568) | (3.3990) |
| $\pi.\mathrm{ECM}_{t-1}$ | -0.2809 | -0.2856*** | -0.0112 | -0.0141 | -0.1055*** | -0.0607*** |
| | (-4.3659) | (-6.7518) | (-0.8743) | (-0.7917) | (-2.6947) | (-2.6179) |
| $\delta_1\Delta\mathrm{loe}_{t-1}$ | 0.0695 | 0.0026 | 0.5130 | 0.0915 | 0.0885 | -0.0253 |
| | (0.9862) | (0.0747) | (6.8014) | (1.1434) | (1.1460) | (-0.5744) |
| $\delta_2\Delta\mathrm{loe}_{t-2}$ | -0.1392 | -0.0668 | -0.2637 | -0.1025 | -0.1139*** | -0.0691** |
| | (-2.6647) | (-1.8948) | (-5.3565) | (-1.9435) | (-2.7684) | (-2.4793) |
| $\lambda.\log\sigma_t^2$ | 2.8350 | 0.7637 | 16.352 | 1.0462*** | 0.6445*** | 0.6662*** |
| | (0.9704) | (1.2817) | (0.6620) | (3.3139) | (4.1007) | (4.2240) |
| Variance equation | | | | | | |
| c (constant) | 0.2456 | 0.2621** | -0.5261 | -0.5327*** | 0.4906*** | 0.3780*** |
| | (2.3271) | (2.0679) | (-0.6640) | (-4.4589) | (10.689) | (17.679) |
| $\alpha$ (ARCH effect) | 0.0386 | 0.0748 | 0.0034 | 0.0088 | 0.2548*** | 0.1612*** |
| | (0.7363) | (1.0843) | (0.5842) | (0.4437) | (3.1678) | (3.4971) |
| $\beta$ (GARCH effect) | 0.4057 | 0.3889 | 0.0179 | 0.4994*** | 0.1051 | 0.3716*** |
| | (2.1419) | (1.5150) | (0.4499) | (4.7106) | (1.3191) | (10.576) |
| $\gamma$ (Leverage effect) | | | -0.0393 | -0.2115*** | 0.8874*** | 0.9475*** |
| | | | (-0.6657) | (-4.5832) | (5.9498) | (24.793) |
| d (Power) | | | | | 0.8107*** | 0.6282*** |
| | | | | | (3.6261) | (10.331) |
| $\alpha + \beta$ | 0.4443 | 0.4637 | 0.0213 | 0.5082 | 0.3599 | 0.5328 |
| $R^2$ | 0.2951 | 0.2432 | 0.3330 | 0.2484 | 0.2656 | 0.2701 |
| SER | 0.6226 | 0.6451 | 0.6057 | 0.6430 | 0.6355 | 0.6336 |
| ARCH test: | ***[0.0000]*** | [0.6235] | [0.4464] | [0.5359] | [0.2850] | [0.3980] |
| Criteria: | | | | | | |
| AIC | 1.8275 | 1.8479 | 1.7304 | 1.7702 | 1.7589 | 1.7676 |
| SC | 1.9629 | 1.9832 | 1.8808 | 1.9206 | 1.9243 | 1.9330 |
| HQC | 1.8821 | 1.9025 | 1.7911 | 1.8309 | 1.8256 | 1.8343 |

Notes: Notes: Asterisks ***,** denote statistically significant at 1% and 5% level, respectively. Figures in round brackets (…) are z-statistics, while figures in square brackets […] are p-values. $R^2$ and SER denote R-squared and standard error of regression, respectively; while ARCH test is the test for heteroscedasticity. AIC, SC and HQ denote Akaike information criteria, Schwarz criteria and Hannan-Quinn criteria, respectively.

**Table 7. Estimation results for the number of total Covid-19 cases**

| Independent variables | ARDL(3,2)-GARCH(1,1)-M: | | ARDL(3,2)-EGARCH(1,1)-M: | | ARDL(3,2)-PGARCH(1,1)-M: | |
|---|---|---|---|---|---|---|
| | Student's t | GED | Student's t | GED | Student's t | GED |
| Mean equation | | | | | | |
| $\delta_0$ (constant) | 2.7247 | 0.5947 | 2.4137 | 1.1575 | 0.6932*** | 0.8020*** |
| | (0.7689) | (0.6732) | (0.5828) | (1.8569) | (3.0924) | (3.0769) |
| $\pi.\mathrm{ECM}_{t-1}$ | -0.2793*** | -0.2691*** | -0.0156 | -0.0186 | -0.1162*** | -0.1051*** |
| | (-4.3906) | (-5.4484) | (-1.0745) | (-1.0435) | (-3.2598) | (-6.6917) |
| $\delta_1\Delta\mathrm{loe}_{t-1}$ | 0.0665 | 0.0304 | 0.3652 | 0.1313 | 0.0296 | 0.0449 |
| | (0.9604) | (0.5957) | (1.6981) | (1.4625) | (0.3943) | (1.5413) |
| $\delta_2\Delta\mathrm{loe}_{t-2}$ | -0.1427*** | -0.0520 | -0.2097*** | -0.0680 | -0.1234*** | -0.0843*** |
| | (-2.6848) | (-1.2360) | (-3.1601) | (-1.3144) | (-2.9854) | (-2.7264) |
| $\vartheta_1\Delta\mathrm{totalcovid}_t$ | -0.0395 | -0.0425 | -0.0713** | -0.0683** | -0.0501** | -0.0360** |
| | (-1.2091) | (-1.5868) | (-2.2381) | (-2.5623) | (-2.5122) | (-2.2962) |
| $\vartheta_2\Delta\mathrm{totalcovid}_{t-1}$ | -0.0103 | -0.0299 | -0.0124 | -0.0489 | -0.0120 | -0.0301 |
| | (-0.3041) | (-1.1790) | (-0.3546) | (-1.8006) | (-0.4732) | (-1.9437) |
| $\lambda.\log\sigma_t^2$ | 3.0331 | 0.6382 | 4.2504 | 1.0523 | 0.7491*** | 0.7010*** |
| | (0.9425) | (0.6317) | (0.9596) | (1.7988) | (4.0367) | (3.2738) |
| Variance equation | | | | | | |
| c (constant) | 0.2327*** | 0.2352 | -0.4927 | -0.6798*** | 0.5259*** | 0.4721*** |
| | (2.2772) | (1.8063) | (-0.8280) | (-5.6444) | (23.638) | (26.770) |
| α (ARCH effect) | 0.0310 | 0.0764 | 0.0154 | 0.0565 | 0.2133*** | 0.1628*** |
| | (0.7317) | (0.5796) | (0.7596) | (1.2450) | (3.0676) | (6.1080) |
| β (GARCH effect) | 0.4158*** | 0.3996 | 0.1410 | 0.4118*** | 0.1785 | 0.2592*** |
| | (2.0243) | (1.3667) | (0.5872) | (3.8949) | (1.7968) | (4.7768) |
| γ (Leverage effect) | | | -0.1273 | -0.2466** | 0.8299*** | 0.8287*** |
| | | | (-1.0858) | (-2.4766) | (9.6630) | (10.932) |
| d (Power) | | | | | 0.6909*** | 0.5540*** |
| | | | | | (3.2290) | (3.5636) |
| $\alpha+\beta$ | 0.4468 | 0.4760 | 0.1564 | 0.4683 | 0.3918 | 0.4220 |
| $R^2$ | 0.3002 | 0.2567 | 0.3302 | 0.2708 | 0.2947 | 0.2787 |
| SER | 0.6232 | 0.6423 | 0.6097 | 0.6361 | 0.6256 | 0.6327 |
| ARCH test: | ***[0.0000]*** | [0.5367] | [0.9031] | [0.2811] | [0.3850] | [0.3234] |

| Criteria: | | | | | | |
|---|---|---|---|---|---|---|
| AIC | 1.8392 | 1.8647 | 1.7274 | 1.7711 | 1.7533 | 1.7756 |
| SC | 2.0047 | 2.0302 | 1.9079 | 1.9516 | 1.9489 | 1.9711 |
| HQC | 1.9060 | 1.9315 | 1.8002 | 1.8439 | 1.8322 | 1.8545 |

Notes: Notes: Asterisks ***,** denote statistically significant at 1% and 5% level, respectively. Figures in round brackets (…) are z-statistics, while figures in square brackets […] are p-values. $R^2$ and SER denote R-squared and standard error of regression, respectively; while ARCH test is the test for heteroscedasticity. AIC, SC and HQ denote Akaike information criteria, Schwarz criteria and Hannan-Quinn criteria, respectively.

### Table 8. Estimation results for Covid-19 fear index

| Independent variables | ARDL(3,0)-GARCH(1,1)-M: | | ARDL(3,0)-EGARCH(1,1)-M: | | ARDL(3,0)-PGARCH(1,1)-M: | |
|---|---|---|---|---|---|---|
| | Student’s t | GED | Student’s t | GED | Student’s t | GED |
| Mean equation | | | | | | |
| $\delta_0$ (constant) | 0.6919 | 0.6494 | 0.7352 | 1.1360 | 0.5936** | 0.6588** |
| | (0.6867) | (0.9860) | (1.8114) | (1.9538) | (2.5619) | (1.9771) |
| $\pi.\mathrm{ECM}_{t-1}$ | -0.2648*** | -0.2324*** | -0.0382 | -0.0248 | -0.0893** | -0.1245*** |
| | (-4.1039) | (-5.5043) | (-1.1389) | (-1.2102) | (-2.2248) | (-2.5551) |
| $\delta_1\Delta\mathrm{loe}_{t-1}$ | 0.0474 | -0.0326 | 0.1190 | 0.2780** | 0.0267 | -0.0153 |
| | (0.6686) | (-0.7190) | (0.9583) | (2.5672) | (0.5655) | (-0.2663) |
| $\delta_2\Delta\mathrm{loe}_{t-2}$ | -0.1312** | -0.0597 | -0.1452** | -0.1315*** | -0.0675 | -0.0187 |
| | (-2.4136) | (-1.7784) | (-2.3642) | (-2.5903) | (-1.4512) | (-0.7893) |
| $\lambda.\log\sigma_t^2$ | 1.4566 | 0.7183 | 0.7181 | 1.0509 | 0.5112*** | 0.6962 |
| | (1.1238) | (0.8984) | (1.9551) | (1.8208) | (3.8745) | (1.9345) |
| Variance equation | | | | | | |
| c (constant) | 0.3612 | 0.2392** | -0.7120** | -0.9125*** | 0.4504*** | 0.2457*** |
| | (1.5038) | (2.0216) | (-2.4750) | (-5.3623) | (6.2663) | (2.6310) |
| $\alpha$ (ARCH effect) | 0.1145 | 0.0569 | 0.1273 | 0.0401 | 0.2892*** | 0.0818 |
| | (0.8355) | (0.7998) | (1.4432) | (0.9192) | (2.6892) | (1.4131) |
| $\beta$ (GARCH effect) | 0.3858 | 0.4110 | 0.3651 | 0.1685 | 0.1816*** | 0.4058*** |
| | (1.9649) | (1.6877) | (1.9945) | (1.3965) | (3.5928) | (3.4822) |
| $\gamma$ (Leverage effect) | | | -0.3780** | -0.3396** | 0.9356*** | 0.6499 |
| | | | (-2.4614) | (-2.4185) | (10.220) | (1.0161) |
| d (Power) | | | | | 0.7362*** | 1.6438** |
| | | | | | (3.3887) | (2.4757) |
| $\alpha+\beta$ | 0.5003 | 0.4679 | 0.4924 | 0.2086 | 0.4708 | 0.4876 |

| | | | | | | |
|---|---|---|---|---|---|---|
| R² | 0.2523 | 0.1869 | 0.2475 | 0.2359 | 0.2265 | 0.2053 |
| SER | 0.6370 | 0.6643 | 0.6390 | 0.6439 | 0.6479 | 0.6567 |
| ARCH test: | [0.6720] | [0.6676] | [0.2578] | [0.3081] | [0.2913] | [0.2622] |
| Criteria: | | | | | | |
| AIC | 1.8656 | 1.8531 | 1.7656 | 1.7633 | 1.7425 | 1.8206 |
| SC | 2.0063 | 1.9937 | 1.9218 | 1.9195 | 1.9144 | 1.9925 |
| HQC | 1.9224 | 1.9099 | 1.8287 | 1.8264 | 1.8120 | 1.8900 |

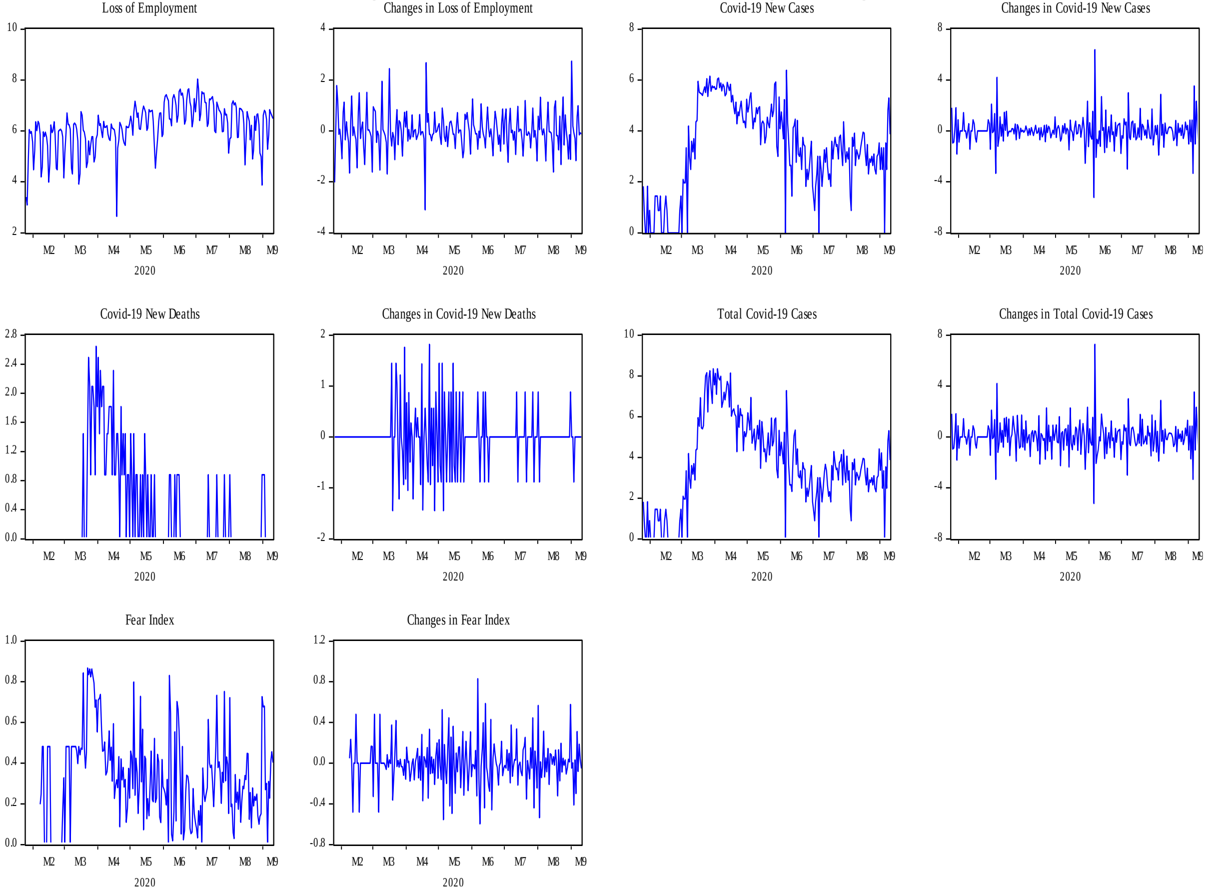
Notes: Notes: Asterisks ***,** denote statistically significant at 1% and 5% level, respectively. Figures in round brackets (…) are z-statistics, while figures in square brackets […] are p-values. R² and SER denote R-squared and standard error of regression, respectively; while ARCH test is the test for heteroscedasticity. AIC, SC and HQ denote Akaike information criteria, Schwarz criteria and Hannan-Quinn criteria, respectively.

### Table 9. Evaluation of in-sample and out-of-sample forecasting for loss of employment

| Models | In-sample forecasting: | | | Out-of-sample forecasting: | | |
|---|---|---|---|---|---|---|
| | RMSE | MAE | Theil | RMSE | MAE | Theil |
| A. New cases: | | | | | | |
| ARDL(3,2)-PGARCH(1,1)-M: | | | | | | |
| Student-t | 7.9543 | 6.9879 | 0.3981 | 2.0290 | 1.5124 | 0.1407 |
| G.E.D. | **6.7156** | **6.1228** | **0.3558** | **1.9112** | **1.3953** | **0.1341** |
| B. New deaths: | | | | | | |
| ARDL(3,0)-PGARCH(1,1)-M: | | | | | | |
| Student-t | 12.320 | 11.110 | 0.5046 | 3.1046 | 2.5490 | 0.1995 |
| G.E.D. | **5.1598** | **4.6291** | **0.2989** | **2.2318** | **1.7560** | **0.1516** |
| C. Total Covid-19 cases: | | | | | | |
| ARDL(3,2)-PGARCH(1,1)-M: | | | | | | |
| Student-t | 11.625 | 10.525 | 0.4898 | **2.8959** | **2.3170** | **0.1890** |
| G.E.D. | **6.0118** | **5.5271** | **0.3304** | 3.0672 | 2.5084 | 0.1976 |
| D. Fear index: | | | | | | |
| ARDL(3,0)-PGARCH(1,1)-M: | | | | | | |
| Student-t | 12.691 | 11.783 | 0.5085 | **3.0589** | **2.5675** | **0.1966** |
| G.E.D. | **8.0673** | **7.8216** | **0.3940** | 4.0384 | 3.3835 | 0.2454 |

Notes: RMSE, MAE and Theil refer to root mean square error, mean absolute error, mean absolute percent error and Theil inequality coefficient, respectively.

**Figure 1. Trend in loss of employment, new cases, new deaths, total Covid-19 cases and fear index in levels (logarithm) and first-difference (changes in log)**



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