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Volatility in Loss of Employment in Malaysia during the Covid-19 Pandemic: Evidence using GARCH-M, EGARCH-M, TGARCH-M and PGARCH-M Models

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Abstract

Motivation and aim: The purpose of the present study is to investigate whether the news on Covid-19 new cases and new deaths are drivers in the volatile movements in the daily loss of employment in the Malaysian labour market. This paper provides a novel evidence using real time administrative data on the loss of employment in Malaysia for the period 1 January 2020 to 31 December 2020.

Methods and material: In this study we test the above contention by employing both the AutoRegressive Distributed Lag (ARDL) and Generalised AutoRegressive Conditional Heteroscedasticity (GARCH) models. Apart from using the standard symmetry GARCH-M, we also employed three versions of asymmetric GARCH-M, namely EGARCH-M, TGARCH-M and PGARCH-M. Daily data on the loss of employment was compiled by the Employment Insurance System (EIS) Centre, PERKESO, Malaysia; while daily data for the number of confirmed new cases and confirmed 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/).

Key findings: Our analysis from estimating the various versionS of the ARDL(p,q1,q2)-(E,T,P)GARCH(1,1)-M suggest that the ARDL-EGARCH-M model able to capture the volatility and clustering of the variability in the loss of employment. The ARDL-EGARCH-M model shows evidence of the leverage effects or asymmetric effects which suggest that the negative shocks (bad news) increase volatility in the loss of employment, more than the positive shocks (good news) in a crisis situation.

Policy implications: The present study suggest that the EGARCH-M model is the best model that can explain the volatility and clustering in the loss of employment in Malaysia during the 2020 pandemic period. The short-run and long-run information on the loss of employment and the number of new cases, and new deaths, as well as the conditional variance affect the variability in the loss of employment in Malaysia. For forecasting purposes, 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, thus, more accurate policy can be design to address unemployment in the future.

JEL Classifications
E20, I10; J64

Keywords
Covid-19; Loss of employment; ARDL; GARCH-M; Malaysia

Volatility in Loss of Employment in Malaysia during the Covid-19 Pandemic: Evidence using GARCH-M, EGARCH-M, TGARCH-M and PGARCH-M Models

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). In the labour market, this kind of shock leads to a decrease in labour force participation rate (Fontaine, 2020). According to van der Wielen and Barrios (2020) there was a significant slowdown in the labour markets 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).

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). 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.

The Malaysian population is not spared from the shock created by the Covid-19 outbreak. In Malaysia the threat of Covid-19 becomes a reality when the first Covid-19 positive cases were reported on 25 January 2020. It has been argued that 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 increase 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, and slightly increase to 4.8% in December 2020.

Nonetheless, the impact of Covid-19 on the Malaysian labour market has been disproportionate like many other countries. The labour force participation rate has reduced from 69.1% in quarter four 2019 to 68.1% in quarter two in 2020. 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). In the fourth quarter of 2020, the unemployment rate equals for both female and male with 4.8% each; while young workers aged 15-24 years unemployment rate increase to 12.7% compared to a lower unemployment rate of 4.8% for older workers of 25-34 years (DOSM, 2020c).

The time plots of loss of employment, number of Covid-19 new cases and number of new deaths are presented in Figure 1 and Figure 2. On the daily basis, as Figure 1 shows, the number of people who lost their jobs fluctuates from day to day. In the first wave of the Covid-19, the number of loss of employment culminated its peak in July 2, 2020 registering 1,540 number of job losses. We can clearly observe that the movements of loss of employment and the Covid-19 new cases and new deaths are volatile throughout the year 2020. For the Covid-19 new cases series, after the Sabah state election in 26 September 2020, we notice an upward surge in the number of Covid-19 new cases until the end of 2020. On the other hand, the volatility of the Covid-19 new deaths can be observed clustered between two time periods – first, between mid-March 2020 to mid-May 2020, and second, between mid-September until end of 2020. More Covid-19 new deaths were recorded after September 2020 which has direct relation with the upward surge in the Covid-19 new cases after the Sabah state election in 2020.

Nevertheless, the purpose of the present study is to investigate whether Covid-19 new cases and new deaths drives daily loss of employment volatility in Malaysia for the period January to December 2020. Since the daily unemployment rate is not available, in this study we use daily data on loss of employment to proxy for the labour market reactions to the pandemic in Malaysia. Since daily macroeconomic time series are characterize by volatility and clustering, in this study we employ the Generalized Autoregressive Heteroscedasticity (GARCH) to deal with volatility in modeling loss of employment in Malaysia for the period January to December 2020.

2. DATA AND BASIC STATISTICS

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 1 January 2020 to 31 December 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 recorded number of Covid-19 new cases, and the number of Covid-19 new deaths. Daily data for the number of confirmed new cases and confirmed 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/).

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

Data Descriptions and Preliminary Analysis

Standard econometric text book suggests that one of the assumptions in estimating a regression model requires that all variables are stationary. Studies have indicated that most macroeconomic time series variables are stationary in their levels or first-differences (Nelson & Plosser, 1982; Perron, 1988). In first-differences, for a variable $\log x_t$, its changes is computed as $\Delta \log x_t = \log x_t / \log x_{t-1}$. Figure 3 illustrates the volatile movements in the logarithm of all three series – loss of employment, new cases and new deaths in levels, as well as log changes (differences) in loss of employment, new cases and new deaths. The clustering and volatility in log changes of the loss of employment, new cases and new deaths are shown in Figures 3 - (b), (c) and (d) respectively, are quite apparent. For Covid-19 new cases, clustering is obvious in the late first quarter and third quarter of 2020; while for Covid-19 new deaths, clustering occurs in the second and fourth quarters of 2020.

Table 1 reports the summary statistics of the three variables – levels and first-differences. For the level series, the mean for the loss of employment is 6.11, and the maximum and minimum values are 8.03 and 2.64, and the standard deviation is 0.80. On the other hand, the mean, maximum and minimum for the new cases are 4.30, 8.53 and 0.0 respectively; while for the new deaths the mean, maximum and minimum for the new deaths are respectively, 0.69, 3.18 and 0.0. The mean of all series are positive, thus indicating that on average the series has increased over time. The standard deviations for both new cases and new deaths are 2.55 and 0.92 respectively. The standard deviation shows that news on Covid-19 new cases is the most volatile. The negative skewness showed by loss of employment, new cases and log changes in new deaths indicate that these series show longer or fatter tail on the left side of the distribution. It implies that the series drops more than it rises. The positive skewness showed by new deaths, log changes in loss of employment and new cases suggest these series show longer or fatter tail on the right side of the distribution and implies that the series increases more than it drops. On the other hand, all series have high kurtosis of greater than 3.0 (except for new cases and new deaths in level) which indicate the presence of fat tails and a leptokurtic series. Nonetheless, all variables show non-normality in the series as indicated by the Jarque-Bera (Jarque & Bera, 1980) and Anderson-Darling

(Anderson & Darling, 1952) tests. In all cases the null hypothesis of normality in the residuals can be rejected at the 1% significant level; implying that all three series (both levels and first-differences) are not normally distributed. The quantile-quantile (Q-Q) plots of each of the series presented in Figure 4 clearly support the non-normality of the series in levels as well as in log changes, which is in line with daily data that characterize with skewness and kurtosis in the series.

In Table 2 we present the results of estimating two regressions for loss of employment with new cases and new deaths as regressors. In column 2 we estimate the regression in level, while in column 3 we present the regression results in first-differences. The quantile-quantile (Q-Q) plots of the residuals from estimating regressions in level and first-differences are shown in Figure 5 (a) and (b) respectively. The estimated regression results suggest that both new cases and new deaths are significant; but regression in log changes suggest that both regressors have no impact on loss of employment. While both regressions showing very small R-squared, however, regression in changes show smaller standard error of regression. On the other hand, the diagnostic test statistics show some interesting results. While regression in levels failed both the no autocorrelation and homoscedastic tests; the regression in changes failed the homoscedastic test (at 10% level). Furthermore, as shown by the Q-Q plots for both residuals clearly suggest non-normality of the residuals in both regressions. The above results clearly suggest that a more appropriate models are needed that can deal with kurtosis and excess volatility in the variables, such as the Generalised Autoregressiove Conditional Heteroscedasticity (GARCH) model suggested by Engle (1982); and its various family of GARCH models.

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 correlogram Q-statistics (Ljung & Box, 1978) and ARCH LM test (Engle, 1982) for the residuals. The Q-statistics (Ljung and Box, 1978) is used to test for serial correlation in the mean equation while 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.

Forecasting Performance Measures

In this study 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,

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

where T is the number of observation; while σ^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. METHODS OF ESTIMATIONS

The main purpose of the present study is to estimate the relationship between the loss of employment and its regressors - Covid-19 new cases and new deaths. As presented in Table 2, the estimated regression results suggest that the relationships are spurious. The level regression probably consists of non-stationary variables which upon estimation will give spurious results since regressing non-stationary variables violate the assumption of stationarity of the ordinary least squares estimator (Granger & Newbold, 1974). On the other hand, regressing variables in changes will also result in spurious regression problem. In this case, the long-run information with respect to the variables involve are missing in this short-run model. More importantly, the residuals of both estimated regressions are not normally distributed implying that the regression is mis-specified with non-constant variance.

In view of the above problems, we endeavour to investigate the relationship between the daily loss of employment and daily news on Covid-19 new cases and new deaths by employing the GARCH model. In a GARCH model we are required to model two equations, namely; the mean equation and the variance equation, and both are short-run equations.

In order to model the mean equation for loss of employment, we start by establishing the long-run relationship between the variables. We estimate the following long-run regression in level, say

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

where loe_t is logarithm of loss of employment, covid_{jt} is logarithm of Covid-19 measures with j equals number of new cases, and number of new deaths; and the error term ε_t is assumed to be white noise.

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 estimating Equation (1). Regressing non-stationarity variables will results in spurious regression results. Taking this into consideration, in this study the conventional augmented Dickey-Fuller unit root test proposed by Dickey and Fuller (1981) is employed to determine the order of integration of the series involved. The null hypothesis of a unit root will be tested, first on the level of the series (including the deterministic term – intercept or/and trend) and then on their first-differences. If the null hypothesis cannot be rejected at level, but unit root can be rejected in first-difference, we can then conclude that the series y_t is non-stationary in levels but achieve stationarity after first-differences. In other words, $\text{y}_t \sim \text{I}(1)$ and $\Delta\text{y}_t \sim \text{I}(0)$.

Having determine that say, the loss of employment, number of new cases and number of new deaths are I(1) in levels, we can proceed with the testing for cointegration test. The main purpose to conduct cointegration between the three variables is to determine the validity of the long-run model as per Equation (1). Cointegrability of the variables will ensure that the estimated regression is non-spurious. For a cointegrated model all statistical properties are valid and inferences can be made using the usual statistical indicators.

In this study, 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 the long-run and short-run (our mean equation) models can be estimated simultaneously. Furthermore, the Bound-F test for cointegration can be conducted within this framework. According to Pesaran et al. (2001), a long-run model as per

Equation (1) can be derived from the following say, ARDL(1,1) model in levels,

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

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

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

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 Equation (1) by using the ARDL approach, Pesaran et al. (2001) proposed the Bounds F-test on the following conditional ARDL-error-correction model (ARDL-ECM);

$$\begin{aligned}\Delta \mathrm{loe}_t = \rho_0 + \rho_1 \mathrm{loe}_{t-1} + \rho_2 \mathrm{covid}_{jt-1} + \textstyle\sum_{i=1}^{p} \vartheta_{1i} \Delta \mathrm{loe}_{t-i} \\ + \textstyle\sum_{i=0}^{q} \vartheta_{2i} \Delta \mathrm{covid}_{jt-i} + \epsilon_t\end{aligned} \tag{4}$$

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 Equation (1) is valid non-spurious long-run model.

Having estimate the long-run cointegrating regression, the short-run model (our mean equation), i.e. the error-correction model can be specify as,

$$\Delta \mathrm{loe}_t = \delta_0 + \pi \mathrm{ECM}_{t-1} + \sum_{i=1}^{p} \delta_{1i} \Delta \mathrm{loe}_{t-i} + \sum_{i=0}^{q} \delta_{2i} \Delta \mathrm{covid}_{jt-i} + \mu_t \qquad (5)$$

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 π would also indicate cointegration (Engle & Granger, 1987). The estimated parameter π, would lies between 0 and -2 (Loayza & Rancière, 2006; Blanco, 2013; Fromentina & Leon, 2019). The novelty of the error-correction short-run model is that the long-run information regarding both loe_t and covid_{jt} has been incorporated in the short-run model, which is I(0) as represented by the ECM_{t-1} term.

Having determine our mean equation (i.e. the error-correction model) next we can specify the variance equation. In this study, as shown in Figures (3), (4) and (5) and empirical evidences described in Table 1, to take into account the volatility of the series, we employ the GARCH) and exponential GARCH model and its variants which can accommodate for non-constant variance over time. There are two types of GARCH models: (1) The symmetric GARCH model, and (2) The Asymmetric GARCH model.

The Symmetric GARCH Model

Much work 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). The GARCH(1,1) with conditional mean equation according results in Table 3 can be expressed as

$$\Delta loe_t = \delta_0 + \pi ECM_{t-1} + \delta_1 \Delta loe_{t-1} + \delta_2 \Delta loe_{t-2} + \delta_3 \Delta newcases_t + \delta_4 \Delta newcases_{t-1} + \delta_5 \Delta newcases_{t-2} + \epsilon_t, \qquad \epsilon_t \sim (0, \sigma_t^2) \tag{6}$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{7}$$

Nevertheless, as shown in Table 3, the error correction model or our mean equation is not free from heteroscedasticity problem. To address this problem, Engle et al. (1987) proposed the conditional mean to be a function of conditional variance as follows,

$$\Delta loe_t = \delta_0 + \pi ECM_{t-1} + \delta_1 \Delta loe_{t-1} + \delta_2 \Delta loe_{t-2} + \delta_3 \Delta newcases_t + \delta_4 \Delta newcases_{t-1} + \delta_5 \Delta newcases_{t-2} + \lambda \sigma_t^2 + \epsilon_t, \qquad \epsilon_t \sim (0, \sigma_t^2) \tag{8}$$

Equation (8) is what we called the GARCH-in-Mean (GARCH-M).

The mean Equation (8) says that changes in loss of employment depends on a constant δ_0; the linear combination between loss of employment, Covid-19 new cases and new deaths (i.e. the residuals of long-run model lagged one period); lagged one and two periods changes in loss of employment; the current changes in Covid-19 new cases, lagged one and two period changes in new cases; and the conditional variance (volatility or shock). On the other hand, the variance Equation (7) states that the conditional variance of σ_t^2 depends on the squared error lagged one period (ϵ_{t-1}^2) as well as on its conditional variance lagged one period (σ_{t-1}^2). The constant ω 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 ω, α, β and λ 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. When the sum of the ARCH and GARCH term is closed to one, the volatility is persistent, meaning that the volatility may take longer time to return to a quieter phase. Furthermore, for $\alpha + \beta > 1$, the unconditional variance of ϵ_t is undefined, and this would be termed 'non-stationarity in variance', while $\alpha + \beta = 1$ is known as a 'unit root in variance'. On the other hand, a positive and significant λ implies that increased volatility given by an increase in conditional variance represented by σ_t^2 leads an increase in changes in loss of employment or *vice versa*.

The Asymmetric GARCH Models:

The EGARCH 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 σ_t^2 to respond asymmetrically to positive and negative values of loe_t. To overcome the symmetrical GARCH, Nelson (1991) proposes the EGARCH model that can captures 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,

$$\log(\sigma_t^2) = \omega + \alpha \left| \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \gamma \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \log(\sigma_{t-1}^2) \quad (9)$$

where the left-hand side of Equation (9) 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 ω, α, γ and β. However, to maintain covariance stationary, β must be positive and less than 1. The parameter α and γ represent the magnitude (or size) effect and the symmetric effect of the model, the GARCH effects respectively; while β measures the persistence in conditional volatility. This implies that when β 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 asymmetric effects of the shocks of volatility is measured by parameter γ. Leverage effect is presents when $\gamma \neq 0$; whereas when $\gamma = 0$, the model is symmetric. A zero γ would imply that positive and negative shocks of the same magnitude have the same effect on volatility in loss of employment. If $\gamma < 0$, it implies that the negative shocks (bad news) increase volatility more than the positive shocks (good news); while if the coefficient of γ is positive, then positive shocks tend to produce higher volatility in the immediate future than negative shocks. Furthermore, when ϵ_{t-1} is good or positive news the total effect is measured by $(1+\gamma)/|\epsilon_{t-1}|$ and when ϵ_{t-1} is bad or negative news the total effect is measured by $(1-\gamma)/|\epsilon_{t-1}|$. The parameters of the EGARCH are not restricted to ensure that the conditional variance is always positive while the log form of conditional variance can be negative.

The TGARCH model

The Threshold GARCH (TGARCH) model is another model proposed by Glosten et al. (1993) and Zokian (1994) used to handle leverage effects in financial time series. For a TGACRH(1,1) model, the specification of the conditional variance is as follows,

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma d_{t-1}\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{10}$$

where ω, α, β and γ are volatility long-run average, the previous forecast, symmetric news and negative news respectively. d is the indicator function and d_{t-1} is a dummy variable, defined as,

$$d_{t-1} = \begin{cases} 1 & \text{if } \epsilon_{t-1}<0, \text{ bad news} \\ 0 & \text{if } \epsilon_{t-1}>0, \text{ good news} \end{cases} \tag{11}$$

The coefficient γ is the asymmetry or the leverage term. When $\gamma = 0$, the TGARCH model collapses to the standard GARCH model; while if $\gamma \neq 0$ indicates the presence of asymmetric shocks. When the shock is positive, $\epsilon_{t-1} > 0$ (i.e. good news) the effect on volatility is α, but when the news is negative, $\epsilon_{t-1} < 0$ (i.e. bad news) the effect on volatility is $\alpha + \gamma$. An intuitive measure of the degree of symmetry is $(\alpha+\gamma)/\alpha$. Thus, if γ is significant and positive, negative shocks have a larger effect on volatility, than positive shock. The opposite might be true if γ were negative. On the other hand, β measures clustering in the conditional variance and $(\alpha+\beta+\gamma)/2$ measures persistence of shocks on volatility. According to Ling and McAleer (2002) the parameters

$\left(\frac{\alpha+\beta+\gamma}{2}\right) < 1$ formed a regularity condition for the existence of the second moment of TGARCH(1,1) model. Nevertheless, for the TGARCH model, the following parameter restrictions $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \gamma \geq 0$ must hold to ensure positive conditional variance.

The PGARCH 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

$$\sigma_t^d = \omega + \alpha(|\epsilon_{t-1}| + \gamma\epsilon_{t-1})^d + \beta\sigma_{t-1}^d \qquad (12)$$

where d is the power term, with $d > 0$ and $|\gamma| \leq 1$. The parameter γ 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. The impact of news on volatility in PGARCH model is similar to that of TGARCH when $d = 1$.

Distribution Assumption of the Error (ϵ_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. 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, TGARCH and PGARCH models by assuming ϵ_t follows a normal, 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. More specifically, the sensitivity and appropriateness of the assumption results were observed by changing the distribution assumption from normal to Student's t-distribution to generalized error distribution.

4. THE EMPIRICAL RESULTS

The results of the ARDL(3,3,0)-GARCH(1,1)-M and ARDL(3,3,0)-EGARCH(1,1)-M models for the loss of employment in Malaysia for the period January to December 2020 is presented in Table 5. The conditional mean equation is in the form of the error-correction model which was derived from the ARDL(3,3,0) as presented in Table 4. Our results in Table 4 clearly indicate that the residuals of the ECM model is not free from the presence of heteroscedasticity; and in view of this situation we have included the conditional variance σ_t^2, as additional regressor in the conditional mean equation. Thus, we specify a GARCH-M model for our analysis for the volatility of the loss of employment in this study. Similar approach to specify an ECM model for the conditional mean equation was undertaken by Holmes and Maghrebi (2016) and Haughton and Iglesias (2017). Study by Holmes and Maghrebi (2016) on unemployment rate and the stock market in the US, however, failed to find any cointegration relationship between the stock market and unemployment rate and left them with estimating a short-run mean equation without the ECM_{t-1} term. On the other hand, Haughton and Iglesias (2017) 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.

In Table 5, we present both the GARCH-M (columns 2-4) and EGARCH-M (columns 5-7) models with three types of error distributions, namely; normal, Student's t- and generalized error distributions. In the table, we display the mean and the variance equations, the goodness of fit (R-squared), the standard error of regression (SER), the Q-statistics for serial correlation test, ARCH test for the presence of heteroscedatic in the error, and also three model section criteria – AIC, SC and HQC. For our GARCH-M model, the mean equation suggests that mostly all estimated parameters are significant. The estimated coefficients of the error-correction term π, is negative and significant at the 1% level. The significant of π suggests cointegration or long-run relationships between the loss of employment and new cases and new deaths of Covid-19. The short-run variables – changes in lagged (one and two periods) of loss of employment and current and lagged (one and two periods) new cases of Covid-19 also impacted the current changes in the loss of employment. However, the conditional variance or volatility in the loss of employment affects the current changes in the loss of employment only in the case of normal error distribution. On the other hand, in the variance equation, the ARCH effect is only positive and significant in the normal error distribution model; while the GARCH effect is positive and significant in the Student's t- and generalized error distributions' models. The persistence of the volatility in the loss of employment is shown by the sum of the ARCH and GARCH effect which is less than 1, ranging from 0.40 to 0.52, thus, suggesting that the volatility in the loss of employment is moderately persistence. Furthermore, the ARDL(3,3,0)-GARCH(1,1)-M models are free from serial correction and heteroscedasticity.

The estimated EGARCH-M model, on the other hand, show that the error-correction model fit the data very well in which the parameter of the ECM_{t-1} term is negative and significant at the 1% level. The short-run variables – changes in lagged one and two periods loss of employment, and changes in current, lagged one and two periods in new cases Covid-19 are significant and in most cases show negative signs. Nevertheless, the volatility in the loss of employment are significant and show negative sign in the normal error distribution model; while showing positive impact on the changes in loss of employment in both the Student's t- and generalized error distributions' models. For the normal error distribution, the negative volatility suggest that increase in the volatility in the loss of employment will reduce the current changes in the loss of employment; while the positive volatility in the loss of employment suggest that higher volatility will increase the current changes in the loss of employment. As for the variance equation, except for the constant term, both the ARCH and GARCH effects are positive and significant in the Student's t error distribution model. The sum of the ARCH and GARCH effect is less than 1 for both Student's t- and generalized error distributions' models; in particular equals to 0.5 for the Student's t-error distribution's model; this suggest that the persistency of volatility is moderate. The leverage (or asymmetry) effects in the changes in the loss of employment are shown by the estimated parameter γ that is negative and significant at the 1% level. The negative leverage effect suggests that the negative shocks (bad news) generate more volatility than the positive shocks (good news). The diagnostic tests suggest that the ARDL(3,3,0)-EGARCH(1,1)-M model is free from serial correlation and heteroscedasticity except for the generalized error distribution's model.

Similar to the EGARCH-M model, the TGARCH-M and PGARCH-M models are able to test for the asymmetry in the volatility of the loss of employment. Results of estimating both this models are presented in Table 6. For each model, we have estimated with three error distributions – the normal, Student's t- and generalized error distributions. The estimated conditional mean equation for both TGARCH-M and PGARCH-M indicate that the data fit the ECM estimated equations very well. The ECM_{t-1} term is negative and significant at the 1% level, suggesting that there is cointegration between the loss of employment and new cases and new deaths Covid-19. In the short-run, the lagged one and two periods in the loss of employment as well as the current and lagged one and two periods in new cases Covid-19 affect the current changes in the loss of employment. The mean equation also disclosed that the volatility in the loss of employment affect the current changes in the loss of employment.

Results from the TGARCH-M model suggest that the ARCH effects is negative while the GARCH effects is positive, nevertheless, the leverage effect which is positive and significant clearly suggest the presence of asymmetry effect of the volatility on the loss of employment. The significance of the leverage effect suggests that the negative shocks (bad news) exhibit larger effect on the conditional variance (volatility) than the positive shocks (good news) of the same magnitude. The TGARCH-M model also cannot reject the null hypothesis of non-serial correlation in the mean equation and homoscedastic of the residuals in the variance equation. On the other hand, the results of the PGARCH-M model indicate that both the ARCH effects and GARCH effects are positive and significant. The sum of the ARCH and GARCH effects is less than 1. The leverage effect is significant and positive in the normal and generalized error distributions' models. The positive leverage suggests that positive shocks are associated with higher volatility than negative shocks. The power term d, is positive and significant in the normal and generalized error distributions' models. Since d is clearly not equal

2, thus establishing that it is not a standard GARCH model. The Q-statistic test for serial correlation suggest that only model estimates using normal and Student's t-error distribution are free from serial correlation, nonetheless, the ARCH test for heteroscedasticity indicate that all three estimated variance equations do not exhibit heteroscedastic error.

Model Forecast Accuracy

We have estimated four different versions of the GARCH-M models to capture the volatility in the loss of employment in Malaysia during the Covid-19 pandemic for the period January to December 2020. Our next task is to determine which of the four models with three different variations in the error distribution assumptions best explain the volatility in the loss of employment. In this study we will based our best choice of model on: (1) model selection criteria; (2) estimated parameters that fit the theory; (3) in-sample forecasting ability; and (4) out-of-sample forecasting ability.

Results in Tables 5 and 6 suggest that based on the three model selection criteria – AIC, SC and HQC; the error distribution models that possess the smallest AIC, SC and HQC is the generalized error distribution for GARCH-M, TGARCH-M and PGARCH-M; while the normal error distribution for EGARCH-M. Nevertheless, for the GARCH-M model only the GARCH effect is significant; while in the EGARCH-M model, the ARCH effect has a negative sign and the sum of ARCH and GRACH effects is negative, thus failed the non-negativity condition of the EGARCH model. On the other hand, the G.E.D model for the TGARCH-M model also failed the non-negativity conditions when the ARCH effect show negative sign; while the G.E.D model for the PGARCH-M model although fulfill all the conditions, but, the model exhibit the presence of heteroscedasticity in the residuals of the variance equation.

Nevertheless, in Table 7 we have presented the forecasting performance of all the models with all three variants in the residual distribution assumptions. 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 GARCH-M; Student's t- for EGARCH-M; normal error distribution for both TGARCH-M and PGARCH-M models. 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 normal error distribution for GARCH-M and TGARCH-M models; while G.E.D for both EGARCH-M and PGARCH-M models. Nonetheless, based on the failure of the non-negativity conditions by both GARCH-M and TGARCH-M models, we are left with the EGARCH-M and PGARCH-M to choose from.

How do we choose the best model out of this complex analysis? We do this by the elimination process. For example, for the EGARCH-M model, the normal error distribution model can be rejected because the ARCH effect does not meet the non-negativity condition of the EGARCH-M, and the G.E.D model, on the other hand, failed the homoscedastic error property of the variance equation. Thus, for the EGARCH-M model the Student's t-error distribution should be considered the best model. In fact, this model has the smallest RMSE, MAE and Theil inequality coefficients and the second smallest RMSE, MAE and Theil inequality coefficients compared to the G.E.D model in terms of out-of-sample forecasting accuracy. On the other hand, the choice for the best PGARCH-M model can be evaluated based on in-sample forecasting ability. On this point, we can see that the G.E.D model exhibit heteroscedastic error in the variance equation despite having the smallest RMSE, MAE and Theil inequality coefficients for the out-of-sample forecasting accuracy. But, the normal error distribution model exhibit the smallest RMSE, MAE and Theil inequality coefficients, and also the second smallest RMSE, MAE and Theil inequality coefficients in forecasting ability. In view of this information, the best model for PGARCH-M is the normal error distribution model. Nevertheless, comparing between EGARCH-M (Student's t-error distribution) and PGARCH-M (normal error distribution), it is fair to conclude that the ARDL(3,3,0)-EGARCH(1,1)-M is the best model to represent volatility in the loss of employment in Malaysia for the period January to December 2020. The in-sample and the out-of-sample forecasting accuracy as indicated by the RMSE, MAE and the Theil inequality coefficients for the EGARCH-M is smaller than the forecast performance by the PGARCH-M model.

5. CONCLUSION

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. Similarly in Malaysia, the number of people who lose their job increased 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 new cases and new deaths of the Covid-19 pandemic on the Malaysian labour market. Using daily data on the loss of employment, number of new cases, number of deaths, our cointegration analysis indicate that the loss of employment exhibit long-run relationships with the number of new cases, and the number of new deaths. In the long-run the Covid-19 pandemic measures do affect the loss of employment in Malaysia during January 2020 to September 2020 period.

In the short-run we uncover the volatility and clustering in the loss of employment during the Covid-19 outbreak in Malaysia. To model the volatility and clustering in the changes in the loss of employment, we employ the symmetric GARCH-M and three variants of the asymmetric GARCH-M models, namely; EGARCH-M, TGARCH-M and PGARCH-M models. The asymmetric GARCH models will able to capture the leverage effects, which would suggest that the negative shocks (bad news) would increase volatility in the loss of employment series more than the positive shocks (good news). Using model selection criteria, in-sample and out-of-sample forecasting performances, the present study suggest that the EGARCH-M model is the best model that can explain the volatility and clustering in the loss of employment in Malaysia during the 2020 pandemic period. The short-run and long-run information on the loss of employment and the number of new cases, and new deaths, as well as the conditional variance 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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Table 1: Descriptive statistics

Series	No. obs	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Anderson-Darling
Loss of employment	363	6.11	8.03	2.64	0.80	-0.84	4.46	75.28***	3.59***
New cases	363	4.30	8.53	0.00	2.55	-0.16	2.02	16.11***	4.46***
New deaths	363	0.69	3.18	0.00	0.92	0.92	2.43	56.30***	41.63***
Δloss of employment	363	0.00	2.74	-3.09	0.72	0.15	5.14	70.35***	7.02***
Δnew cases	363	0.02	4.56	-3.69	0.84	0.51	8.98	556.0***	10.53***
Δnew deaths	363	0.01	2.31	-3.09	0.67	-0.09	6.22	157.2***	29.27***

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

Table 2: Regression estimates for loss of employment with Covid-19 new cases and new deaths

Dependent/Independent variables	loe_t	$\Delta\mathrm{loe}_t$
constant	6.0145***	0.0025
	(70.168)	(0.0688)
$\mathrm{newcases}_t$	0.0486**	
	(2.0663)	
$\Delta\mathrm{newcases}_t$		-0.0291
		(-0.6508)
$\mathrm{newdeaths}_t$	-0.1620**	
	(-2.4659)	
$\Delta\mathrm{newdeaths}_t$		-0.0469
		(-0.8325)
R^2	0.0170	0.0030
SER	0.7919	0.7181
LM$\chi^2(1)$	***[0.000]***	[0.5742]
ARCH$\chi^2(1)$	***[0.000]***	***[0.0536]***

Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% level, respectively. LM $\chi^2(1)$ and ARCH$\chi^2(1)$ denote the Lagrange multiplier test for serial correlation of order one and heteroscedasticity of order one in the OLS equations, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] are p-values. R^2 and SER denote R-squared and standard error of regression, respectively. loe_t refers to log in loss of employment; while $\Delta\mathrm{loe}_t$.denotes log changes in loss of employment. All variables are in logarithm.

Table 3: Results of unit root tests

Types	Level		First-difference	
	Intercept	Intercept+trend	Intercept	Intercept+trend
Loss of employment	-2.1006 (12)	-3.0452 (12)	-9.0972 (12)***	-9.1143 (12)***
New cases	-1.1899 (4)	-1.7475 (4)	-14.398 (3)***	-14.378 (3)***
New deaths	-2.2756 (4)	-2.9340 (4)	-21.935 (1)***	-21.910 (1)***

Notes: Asterisks *** denotes statistically significant at 1% level. The critical values are referred to MacKinnon (1996); Figures in round bracket (…) denote optimal lag length chosen using SBC criteria.

Table 4: Results of cointegration tests

Dependent/Independent variables	ARDL(3,3,0)	Conditional ARDL-ECM model	Long-run model	Error-correction Model (short-run)
constant	2.6648***	2.6648***	5.9215***	
	(8.2453)	(8.2453)	(38.472)	
loe_{t-1}	0.7313***	-0.4500***		
	(13.875)	(-8.5025)		
loe_{t-2}	-0.2851***			
	(-4.4952)			
loe_{t-3}	0.1038**			
	(1.9793)			
Δloe_{t-1}		0.1813***		0.1813***
		(3.4176)		(3.4360)
Δloe_{t-2}		-0.1038**		-0.1038**
		(-1.9793)		(-1.9915)
$newcases_t$	-0.0780*		0.0916**	
	(-1.7348)		(2.1109)	
$newcases_{t-1}$	-0.0752	0.0412**		
	(-1.5999)	(2.0817)		
$newcases_{t-2}$	0.1248***			
	(2.6463)			
$newcases_{t-3}$	0.0698			
	(1.5328)			
$\Delta newcases_t$		-0.0780*		-0.0780*
		(-1.7348)		(-1.7527)
$\Delta newcases_{t-1}$		-0.1946***		-0.1946***
		(-3.7858)		(-3.8903)
$\Delta newcases_{t-2}$		-0.0698		-0.0698
		(-1.5328)		(-1.5474)
$newdeaths_t$	-0.1211**		-0.2692**	
	(-2.2455)		(-2.2841)	
$newdeaths_{t-1}$		-0.1211**		
		(-2.2455)		
ECM_{t-1}				-0.4500***
				(-8.5643)
R^2	0.4275	0.2847	-	0.2883
$LM\chi^2(1)$	[0.5692]	-	-	[0.7519]
$ARCH\chi^2(1)$	***[0.0335]***	-	-	***[0.0248]***
Bound F-statistic	-	18.182***	-	-

Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% level, respectively. Figures in round brackets (…) are t-statistics, while figures in square brackets […] are p-values. R^2 denotes R-squared. loe_t refers to loss of employment. LM $\chi^2(1)$ and $ARCH\chi^2(1)$ denote the Lagrange multiplier test for serial correlation of order one and heteroscedasticity of order one in the ARDL equation, respectively ARDL(p,q1,q2) denotes optimal lag length chosen using AIC criteria.

Table5: Parameter estimates of ARDL(3,3,0)-GARCH(1,1)-M and ARDL(3,3,0)-EGARCH(1,1)-M

Independent variables	ARDL(3,3,0)-GARCH(1,1)-M:			ARDL(3,3,0)-EGARCH(1,1)-M:		
	Normal	Student's t	GED	Normal	Student's t	GED
Mean equation						
δ_0 (constant)	1.0537***	1.0472	0.8440	-0.2274***	0.7190***	0.2130***
	(2.5872)	(1.5831)	(1.6096)	(-3.4730)	(3.1519)	(3.0880)
πECM_{t-1}	-0.3845***	-0.3608***	-0.2974***	-0.4035***	-0.0543**	-0.0565**
	(-5.5116)	(-6.6739)	(-7.8204)	(-8.7297)	(-2.1631)	(-2.5519)
$\delta_1 \Delta loe_{t-1}$	0.1759***	0.1153**	0.0360	-0.0934**	0.1619*	0.0900**
	(2.3363)	(2.0842)	(0.9431)	(-2.4910)	(1.7642)	(1.9750)
$\delta_2 \Delta loe_{t-2}$	-0.1364**	-0.1029**	-0.0062	-0.1001***	-0.1211**	0.0285
	(-2.2593)	(-2.1387)	(-0.2204)	(-3.8742)	(-2.5704)	(0.9398)
$\delta_3 \Delta newcases_t$	-0.0812**	-0.0680*	-0.1016***	-0.0836***	-0.0948***	-0.0937***
	(-2.0340)	(-1.8561)	(-3.6049)	(-3.5104)	(-2.7601)	(-4.8875)
$\delta_4 \Delta newcases_{t-1}$	-0.1770***	-0.1557***	-0.1595***	-0.1629***	-0.1504***	-0.1088***
	(-3.7755)	(-3.8670)	(-5.0559)	(-7.8241)	(-4.3637)	(-4.8202)
$\delta_5 \Delta newcases_{t-2}$	-0.0651	-0.0820**	-0.0682**	-0.0913***	-0.0101	-0.0301
	(-1.2857)	(-1.9703)	(-2.4835)	(-4.5609)	(-0.2516)	(-1.3809)
$\lambda log\sigma_t^2$	1.0035***	1.0438	0.8882	-0.1650***	0.5994***	0.2179***
	(2.6340)	(1.5250)	(1.6071)	(-4.2421)	(3.0789)	(3.7818)
Variance equation						
c (constant)	0.1884	0.1889**	0.2370***	-0.3508***	-0.7744***	-0.4843***
	(1.5693)	(2.0965)	(3.4193)	(-3.5821)	(-3.9977)	(-3.6169)
α (ARCH effect)	0.0542*	0.0542	0.0658	-0.6828***	0.1026*	0.0301
	(1.6501)	(1.2259)	(1.3543)	(-5.7886)	(1.7633)	(1.2895)
β (GARCH effect)	0.4153	0.4639**	0.3384**	0.3026***	0.4032***	0.5813***
	(1.1694)	(2.0538)	(2.2615)	(4.0766)	(3.0049)	(5.9841)
γ (Leverage effect)				-0.7794***	-0.4119***	-0.5990***
				(-9.3706)	(-4.2888)	(-5.2422)
$\alpha + \beta$	0.4695	0.5181	0.4042	-0.3802	0.5058	0.6114
R^2	0.2988	0.2893	0.2562	0.2702	0.2850	0.1689
SER	0.6053	0.6094	0.6234	0.6175	0.6112	0.6590
Q-stat:	[0.9480]	[0.3880]	[0.5690]	[0.0940]	[0.1810]	[0.4230]
ARCH test:	[0.6456]	[0.6914]	[0.2761]	[0.9136]	[0.1299]	***[0.0164]***
Criteria:						
AIC	1.8607	1.7768	**1.7670**	**1.6066**	1.6717	1.6412
SC	1.9792	1.9061	**1.8962**	**1.7359**	1.8118	1.7812
HQC	1.9078	1.8282	**1.8184**	**1.6580**	1.7274	1.6968

Notes: Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% 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 Q-stat and ARCH test are test for autocorrelation and heteroscedasticity, respectively. AIC, SC and HQ denote Akaike information criteria, Schwarz criteria and Hannan-Quinn criteria, respectively.

Table 6: Parameter estimates of ARDL(3,3,0)-TGARCH(1,1)-M and ARDL-PGARCH(1,1)-M

Independent variables	ARDL(3,3,0)-TGARCH(1,1)-M:			ARDL(3,3,0)-PGARCH(1,1)-M:		
	Normal	Student's t	GED	Normal	Student's t	GED
Mean equation						
δ_0 (constant)	0.0803	0.4747**	0.6918***	-0.1023**	0.6587	0.6140***
	(0.5306)	(2.4329)	(2.7632)	(-2.2053)	(1.4117)	(4.3756)
πECM_{t-1}	-0.2492***	-0.1576***	-0.1143***	-0.3901***	-0.4725***	-0.0701**
	(-4.0611)	(-3.5593)	(-3.8741)	(-9.2235)	(-6.1104)	(-2.3634)
$\delta_1 \Delta loe_{t-1}$	0.2549***	0.1811**	0.0828	0.0700***	0.1639***	-0.0253
	(3.8225)	(2.4954)	(1.4921)	(4.2602)	(3.0377)	(-0.5276)
$\delta_2 \Delta loe_{t-2}$	-0.1511***	-0.0995**	-0.0010	-0.1118***	-0.0597	-0.0374
	(-2.9828)	(-2.1611)	(-0.0414)	(-3.8089)	(-1.1557)	(-1.0865)
$\delta_3 \Delta newcases_t$	-0.0641*	-0.0564*	-0.0980***	-0.0383	-0.0645*	-0.0701***
	(-1.7951)	(-1.7217)	(-4.3801)	(-1.6435)	(-1.7730)	(-3.0091)
$\delta_4 \Delta newcases_{t-1}$	-0.1308***	-0.1128***	-0.1245***	-0.1294***	-0.1605***	-0.1030***
	(-3.2193)	(-3.1794)	(-5.3889)	(-7.7116)	(-3.9082)	(-3.7481)
$\delta_5 \Delta newcases_{t-2}$	-0.0343	-0.0177	-0.0112	-0.0372	-0.0734*	-0.0102
	(-0.7491)	(-0.4287)	(-0.4609)	(-1.2953)	(-1.8667)	(-0.3801)
$\lambda \log\sigma_t^2$	0.0811	0.4150***	0.6740***	-0.0932**	0.6917	0.4905***
	(0.6723)	(2.5804)	(2.9043)	(-2.2564)	(1.4190)	(4.4770)
Variance equation						
c (constant)	0.1548***	0.1962***	0.2038***	0.5394***	0.0984***	0.3666***
	(10.364)	(3.4248)	(4.3116)	(6.8302)	(10.169)	(8.8817)
α (ARCH effect)	-0.1452***	-0.1005**	-0.0333	0.2081***	0.0299*	0.1996***
	(-10.669)	(-2.3643)	(-1.1723)	(3.7644)	(1.7022)	(3.4812)
β (GARCH effect)	0.3899***	0.2883**	0.3453***	0.2301**	0.8529***	0.3350***
	(41.094)	(2.2572)	(3.4170)	(2.3569)	(138.43)	(3.8049)
γ (Leverage effect)	0.6966***	0.6257**	0.3066**	0.9372***	-0.3995	0.9691***
	(4.1254)	(2.4138)	(2.1725)	(12.446)	(-0.7352)	(10.677)
d (Power)				0.2343*	0.5462	0.6948***
				(1.6496)	(1.4317)	(3.8487)
$\alpha + \beta$	0.2447	0.1878	0.3120	0.4382	0.8828	0.5346
R^2	0.2563	0.2985	0.2583	0.2739	0.2832	0.2505
SER	0.6234	0.6054	0.6225	0.6160	0.6120	0.6258
Q-stat:	[0.1770]	[0.5430]	[0.4100]	[0.1110]	[0.7940]	***[0.0430]***
ARCH test:	[0.1726]	[0.1021]	[0.0634]	[0.0525]	[0.1114]	[0.1892]
Criteria:						
AIC	1.7763	1.7176	**1.6942**	1.7395	1.7987	**1.6725**
SC	1.9056	1.8576	**1.8343**	1.8796	1.9495	**1.8233**
HQC	1.8277	1.7732	**1.7499**	1.7952	1.8586	**1.7324**

Notes: Notes: Asterisks ***,**,* denote statistically significant at 1%, 5% and 10% 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 Q-stat and ARCH test are test for autocorrelation and heteroscedasticity, respectively. AIC, SC and HQ denote Akaike information criteria, Schwarz criteria and Hannan-Quinn criteria, respectively.

Table 7: Evaluation of in-sample and out-of-sample forecasting for (log) loss of employment

Models	In-sample forecasting:			Out-of-sample forecasting:		
	RMSE	MAE	Theil	RMSE	MAE	Theil
ARDL(3,3,0)-GARCH(1,1)-M:						
Normal	11.077	9.5431	0.4857	**1.5093**	**1.1759**	**0.1214**
Student-t	21.050	20.222	0.6346	2.2873	1.6472	0.1708
G.E.D.♠	**9.8860**	**9.0964**	**0.4520**	1.7008	1.2738	0.1334
ARDL(3,3,0)-EGARCH(1,1)-M:						
Normal♠	7.9783	7.2856	0.4839	1.4866	1.2614	0.1248
Student-t	**4.8027**	**4.5479**	**0.2834**	0.8902	0.6964	0.0716
G.E.D.	5.8756	4.7158	0.5713	**0.6621**	**0.5371**	**0.0551**
ARDL(3,3,0)-TGARCH(1,1)-M:						
Normal	**4.8022**	**3.5811**	**0.3064**	**1.0855**	**0.8670**	**0.0890**
Student-t	19.200	17.676	0.6164	1.8321	1.4039	0.1388
G.E.D. ♠	10.421	9.9366	0.4623	1.1710	0.9052	0.0939
ARDL(3,3,0)-PGARCH(1,1)-M:						
Normal	**7.5315**	**5.6032**	**0.4192**	1.8989	1.7559	0.1666
Student-t	22.223	21.191	0.6480	2.3617	1.6665	0.1752
G.E.D. ♠	12.288	11.314	0.5064	**1.3290**	**1.0608**	**0.1082**

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

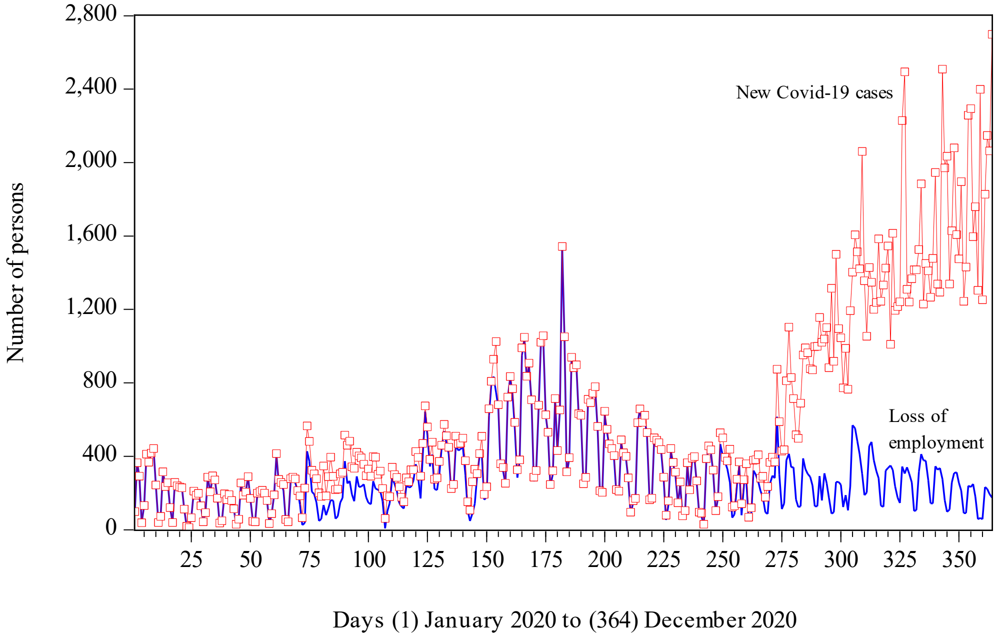

Figure 1: Daily number of loss of employment and number of Covid-19 new cases

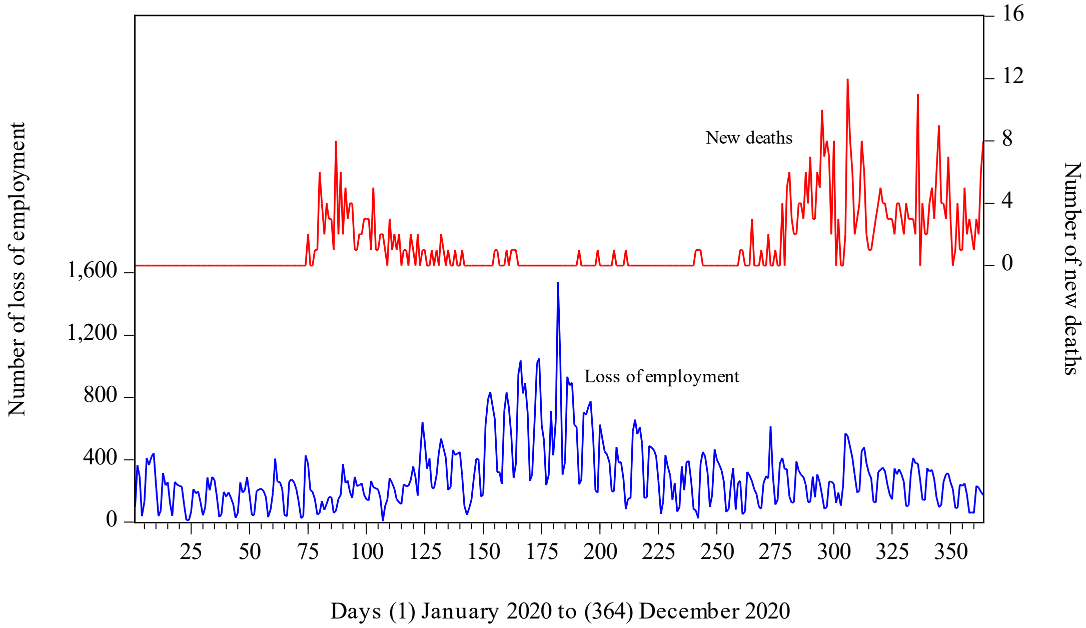

Figure 2: Daily number of loss of employment and number of Covid-19 new deaths

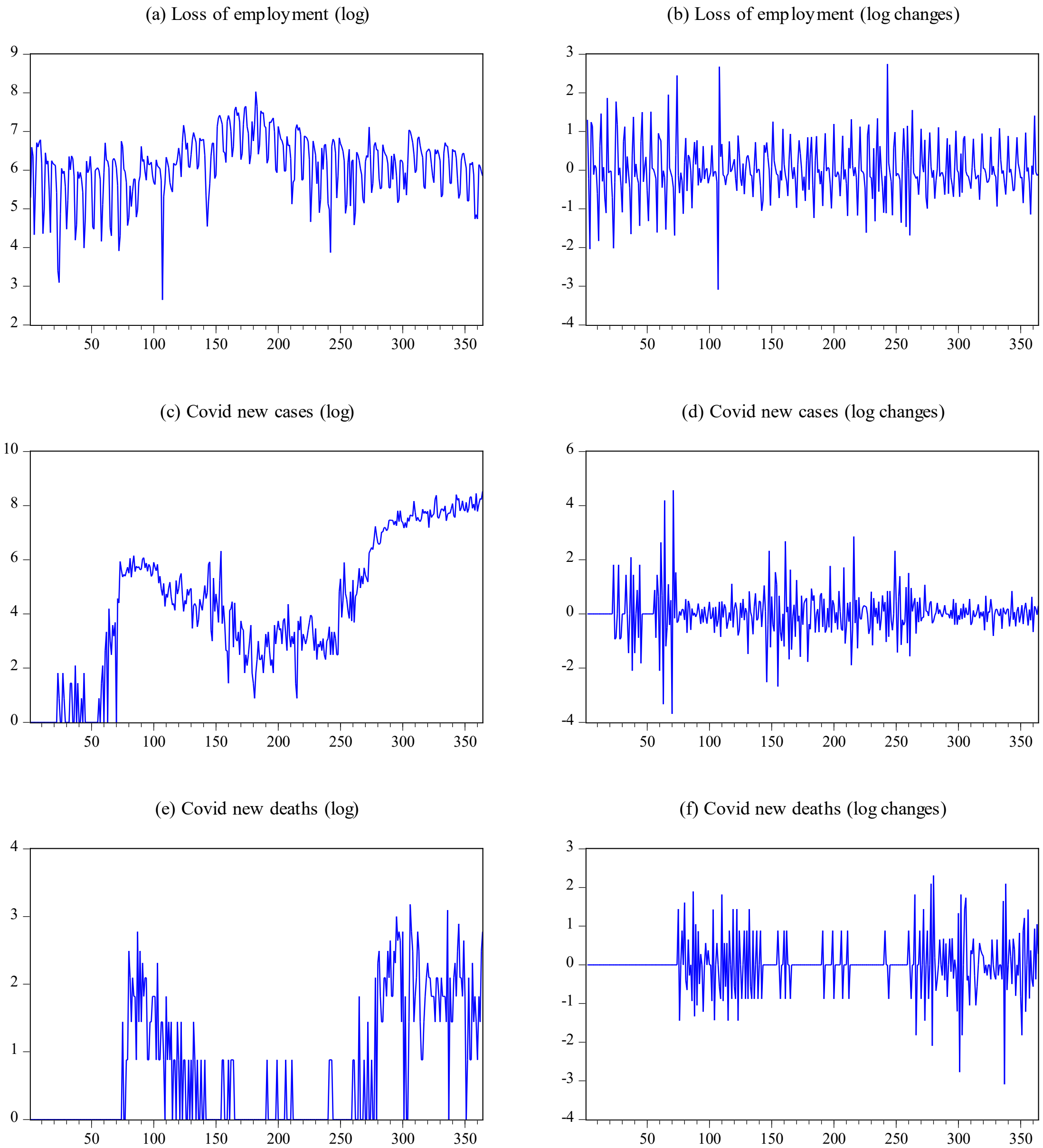

Figure 3: Daily log and log changes in number of loss of employment, number of Covid-19 new cases and new deaths

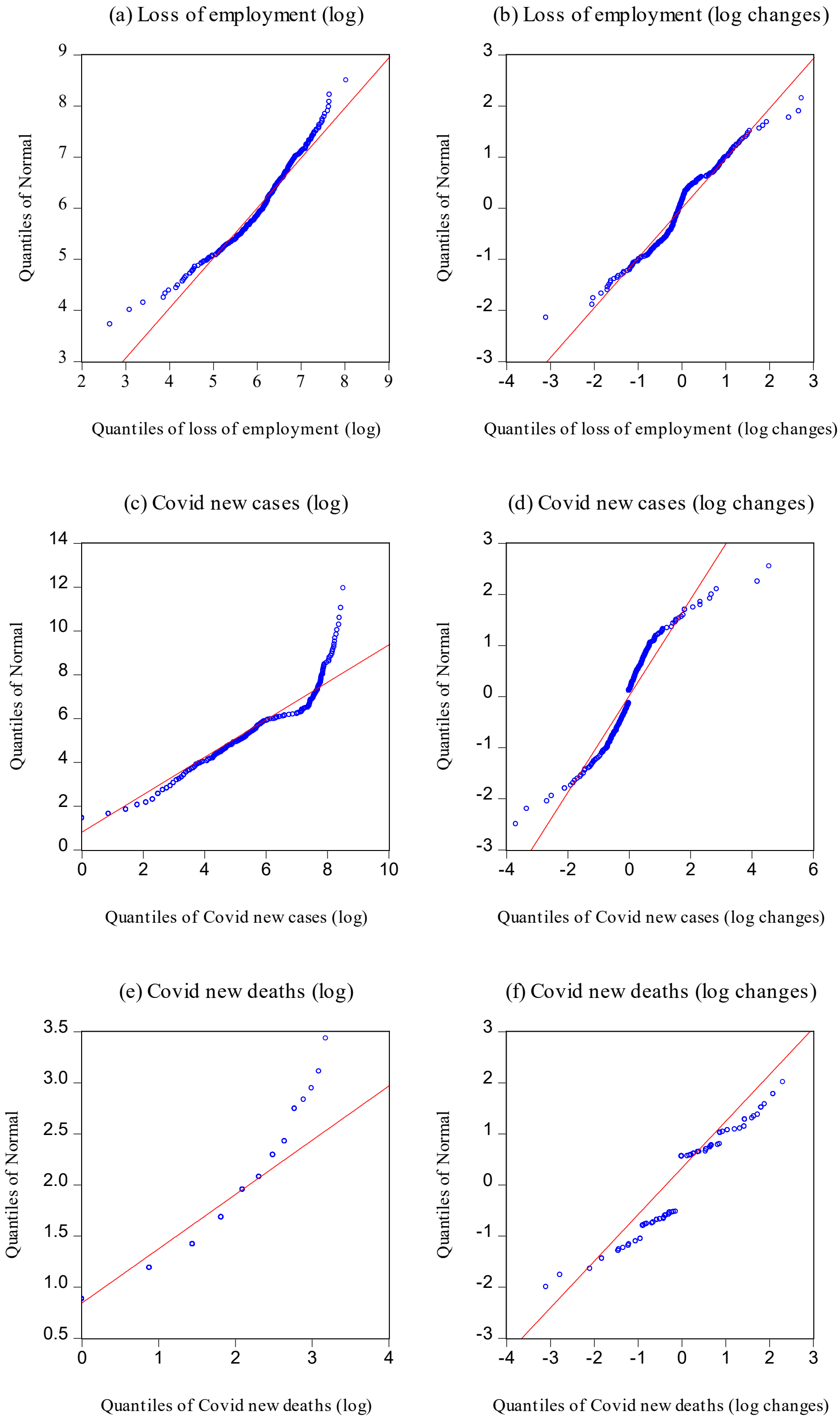

Figure 4: Q-Q plots of log loss of employment, Covid-19 new cases and new deaths, and log changes in loss of employment, Covid-19 new cases and new deaths

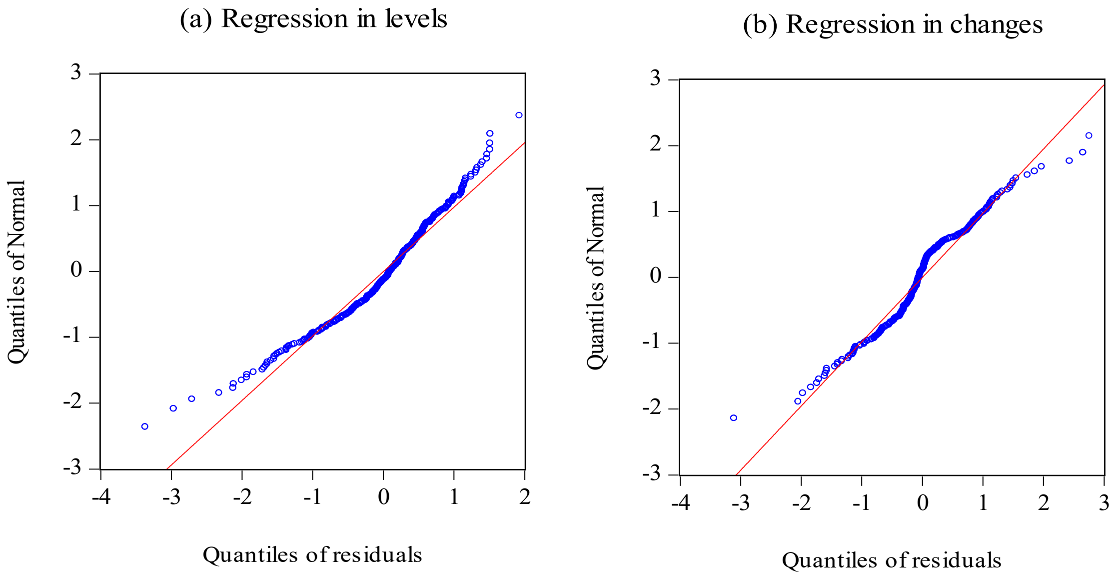

Figure 5: Q-Q plot of loss of employment regression residuals

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