



The Nexus Between COVID-19 and Digital Gig Economy in Malaysia: An Empirical Investigation Using Vector Autoregression (VAR) Model

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ABSTRACT

This paper aims to investigate potential causal relationships between the digital gig economy, COVID-19, and unemployment in Malaysia. The initial part of the study consisted of determining whether the variables were stationary. The ADF findings indicated that all variables are stationary at the level and first difference. Because series are integrated with different orders, this study employs the Vector Autoregression (VAR) model to investigate the impact of the pandemic and unemployment on the digital gig economy. A variance decomposition or forecast error variance decomposition (FEVD) is employed as additional evidence presenting more detailed information regarding the variance relations between the selected variables. The evidence points to the fact that COVID-19 has a significant negative short-run impact on the digital gig economy. The Granger causality test shows a unidirectional relationship between COVID-19 and the gig economy. Variance decomposition results found that the digital gig economy is explained by itself in the short run, so other variables in the model do not strongly influence the variable. However, COVID-19 cases, death, and unemployment can strongly predict the gig economy. The results suggest that COVID-19 instances impact online occupations since a health crisis may harm the main factor of production, which is labour, thus directly impacting labour productivity, even when the task may be

completed from home. Besides that, the study suggests that that Malaysian adaptability, which refers to a worker's capacity to successfully manage psychosocial functions in response to new, changing, and unexpected events, settings, and situations, may be delayed.

Keywords: COVID-19, Gig Economy, Labour Market, Unemployment, VAR Model.

INTRODUCTION

Throughout human history, several pandemics have been defined as widespread epidemics of infectious illnesses, such as the Plague of Athens (430-426 BC), Antonine Plague (165-180 AD), Plague of Justinian (541-542 AD), Black Death (1347-1351), Spanish Flu (1918-1919), HIV/AIDS pandemic (1981 to present), and the latest one, the COVID-19 pandemic. This continuing pandemic, caused by the SARS-CoV-2 virus, has infected over 400 million people globally and caused over 6 million fatalities. Compared to the SARS outbreak, the effects of the COVID-19 pandemic were significantly underestimated [1]. In December 2019, in Wuhan, China, this COVID-19 outbreak began. The virus is spread mainly by respiratory droplets and causes sickness. The World Health Organization (WHO) declared an international public health emergency on January 30, 2020, as more countries reported instances of the virus spreading out further. Consequently, the WHO declared COVID-19 a pandemic in March 2020.

As of December 2022, the Health Ministry (MOH) of Malaysia recorded a total of 5,026,164 cases of COVID-19 infections throughout the country, and Malaysia documented 36,852 Coronavirus-Related Deaths since the outbreak began (Figure 1). The response from governments worldwide, including Malaysia, consisted of several different measures, such as lockdowns, limits on travel, extensive testing, and contact tracking. The pandemic significantly affected day-to-day life, as seen by the closure of many companies and schools, as well as the Movement Control Order (MCO) for individuals to remain inside their homes. Although vaccinations have been made available, new virus strains keep appearing, and problems persist in guaranteeing that all people have fair access to healthcare. The pandemic has also had profound social, economic, and political repercussions, the entire extent of which may not be known for quite some time.

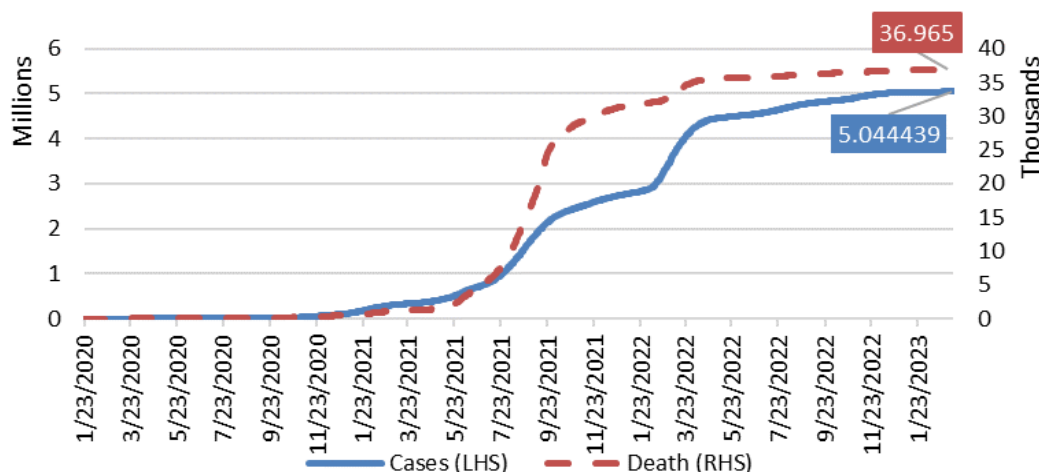


Figure 1. Total Confirmed COVID-19 Cases, and Death in Malaysia

Source: World Health Organization (WHO)

As COVID-19 emerged in Malaysia, unemployment was significantly affected by the MCO. According to the Department of Statistics Malaysia (DOSM), the unemployment rate jumped from 3.3% in the first quarter of 2020 to 5.3% in the second quarter of 2020. It was the highest level since the global financial crisis of 2009. The MCO was especially harsh on workers in the informal sector, those with low-wage jobs, and those with inadequate job security.

Numerous small and medium-sized firms (SMEs) were forced to close or restrict operations during the MCO, resulting in substantial employment losses. Table 2 shows the job retrenchment in Malaysia during the COVID-19 pandemic, where the highest number mainly was high-skilled labour such as professionals, Technicians & Associates Professionals and Managers.

As unemployment increases, the gig economy is expanding in Malaysia—the majority of people participate in it due to its low entry barriers. The COVID-19 pandemic has accelerated the gig economy's growth as people stayed home to minimise contact. Gig economies and freelances work has transformed the Malaysian employment landscape by creating new opportunities and increasing flexibility.

Technology advancements and a rise in digital platforms have made working remotely from home or other locations easier. In order to bring up the country's level of preparedness to dominate the digital economy, the government has drawn up the Malaysian Digital Economy Blueprint that outlines targets in terms of the contributions of the digital economy to the Malaysian economy. This initiative intends to encourage firms that employ gig workers, including technology companies, startups, and even bigger businesses, to engage in gig worker training.

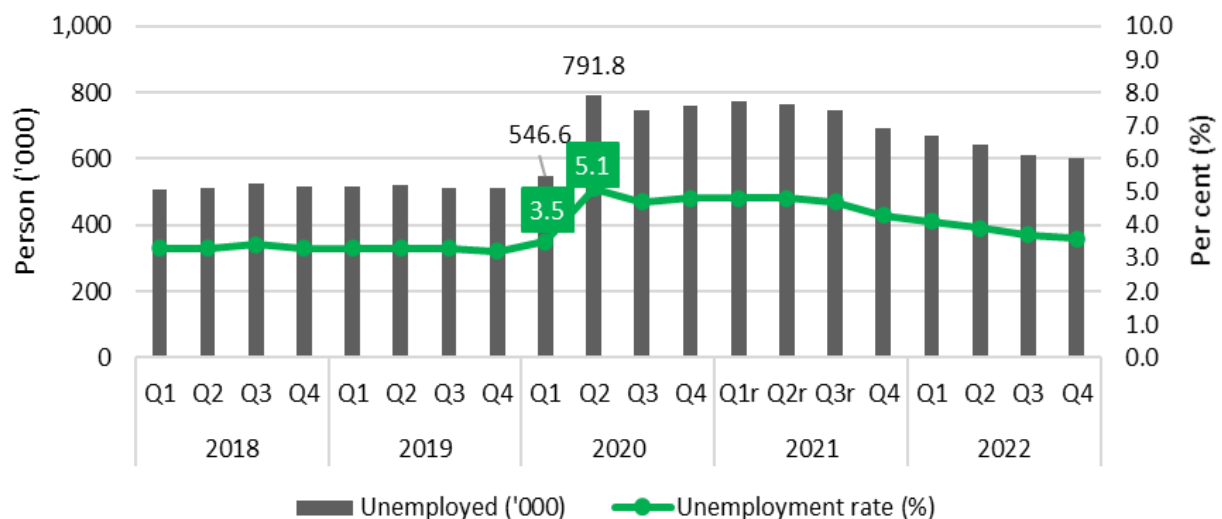


Figure 2. Unemployed persons and unemployment rate, Q1 2018 - Q4 2022 in Malaysia

Source: Labour Force Survey Report, Malaysia, Q4 2022, DOSM

Table 2: Job retrenchment by occupation 2020 and 2021

Types of skills	Occupation	2020	2021
High-skilled	Managers	14,176	9,617
	Professionals	28,116	17,051
	Technicians & Associate Professionals	20,548	12,187
Middle-skilled	Clerical Support Workers	9,249	5,690
	Service & Sales Workers	11,885	4,319
	Skilled Agricultural, Forestry, Livestock & Fisheries Workers	73	51
	Craft & Related Trades Workers	2,321	1,105
	Plant & Machine Operators and Assemblers	11,826	6,643
Low-skilled	Elementary Occupations	7,009	3,934
	Undefined	1,821	763
	Total	107,024	61,360

Sources: Perkeso & MOHR

The disadvantage of this sort of labour is the absence of a social safety net, despite its many advantages. With improved legislation and employment protections for gig workers, gig work can attract highly skilled workers and become a viable and profitable option in the future. The development of the gig economy has reached Asia, and its market size is expanding exponentially. Oxford Internet Institute, University of Oxford's Online Labour Index (OLI) provides an online gig economy index equivalent to standard labour market economic statistics. Table 3 displays the online labour demand for six areas of the digital gig economy in Emerging Asian nations. According to this data, the gig economy is prominent in several Asian nations, including Malaysia, ranging from the populous giants India and China to other developing countries. Malaysia has a 0.2% online labour demand in Software Development and Technology. Meanwhile, Creative and Multimedia, Writing and Translation, and Clerical and Data Entry have each a 0.1% contribution to the labour demand of the online gig economy.

Table 3 Online Labour Demand of the Digital Gig Economy in Emerging Asia in 2020

Country	Online Labour Demand in Six Online Gig Economy Sectors (%)						
	Clerical and Data Entry	Creative and Multimedia	Professional Services	Sales and Marketing Support	Software Development and Technology	Writing and Translation	Total
China	0.1	0.1	0	0.1	0.2	0.2	0.7
India	0.5	0.9	0.1	0.6	3.5	0.7	6.3
Indonesia	0	0	0	0	0.1	0	0.1
Malaysia	0.1	0.1	0	0	0.2	0.1	0.5
Philippines	0.2	0.1	0	0.1	0.2	0.2	0.8
Thailand	0	0.1	0	0	0.1	0.1	0.3
Vietnam	0	0	0	0	0.1	0.1	0.2

Source: Online labour Index, by The iLabour Project

A relatively recent phenomenon, especially in the case of Malaysia, the gig economy is often regarded as the most important economic shift of the past decade. As a result of the MCO, many companies have requested their staff to work remotely if at all feasible. It begs the question, then, of whether or not the pandemic has had a positive effect on the gig economy. Other than that, it is also interesting to know the impact of unemployment during the COVID-19 pandemic on the gig economy. The gig economy is typically conceptualised along two types: the physical gig economy and the digital gig economy. This study aims to focus on the latter category. Therefore, this study aims to investigate the influence of COVID-19 on the digital gig economy in Malaysia.

The rest of the paper is structured as follows. The second part discusses the literature, while the third section addresses the data and methodology. The fourth section presents the findings and discussion, while the fifth section concludes the paper with recommendations.

LITERATURE REVIEW

The Gig Economy

Recent years have seen significant strides in studying the gig economy. The most outstanding amount of research has been done on the socioeconomic effects of the gig economy. These studies have demonstrated the many positive effects that digital platforms for the gig economy have had on society [2, 3, 4]. Others have investigated consumer behaviour as well as issues concerning market design [5, 6, 7, 8, 9, 10]. Some research examines the ethical and moral issues of working in the gig economy, where these studies point out that these business models have drawbacks like social protection [11, 12].

Emerging research has begun to examine the demand and supply of employees in the online labour market, including their origins and potential motivations. Research on labour supply in the gig economy is significant and essential because worker characteristics and motivations can directly affect these platforms' long-term growth and sustainability. Combining the definitions, online labour is defined as contingent (task- or project-based) intangible work delivered digitally and done for money, organised via online outsourcing platforms that are marketplaces bringing together buyers and sellers [13, 14, 15]. Figure 3 shows an exhaustive taxonomy of online labour in the digital gig economy, dividing it into two categories which are (1) crowd work and (2) online freelancing [16].

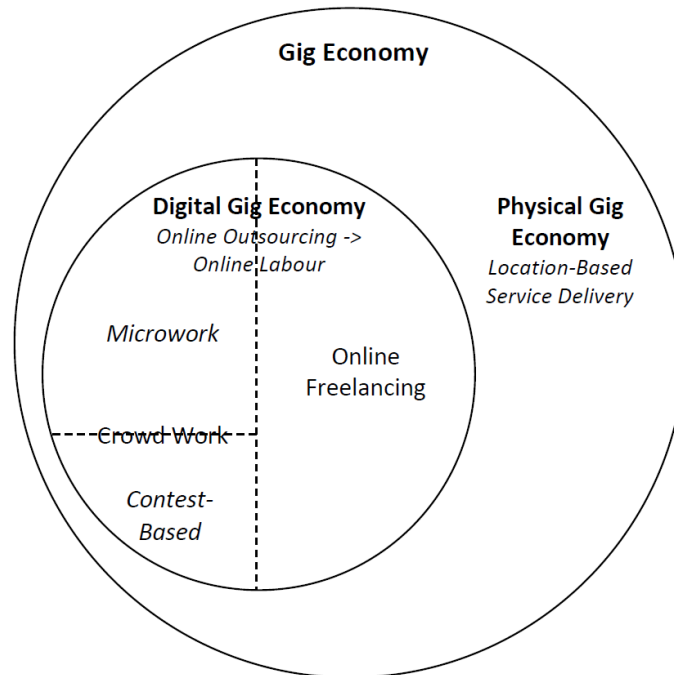


Figure 3: The Conceptual Framework of the Gig Economy Terminologies

Source: Adapted from Heeks (2017).

Crowd work is where tasks are not given to a specific individual and are further subdivided into microwork (i.e., data entry, interpretation of content) and contest-based (i.e. design creation). Online freelancing refers to the practise of assigning a more substantial assignment to a specific individual such as software development, web development, translation, transcription, data analytics, design, administrative support, and sales and marketing [17, 18].

It is important to note that online labour signifies the digitisation of tasks and work organisation [19]. It is distinguished from other gig economy jobs in which only the work organisation is digitised: in these circumstances, the service is assigned via a platform, but the delivery of tasks to a client in a physical location. This type of gig work is referred to as the “physical gig economy” or is often used as the “on-demand” economy or labour. This term encompasses well-known platforms such as Grab and Food Panda.

Empirical Review

The labour market landscape has changed recently because COVID-19 hit the economy. Several studies have been done to see these changes. COVID-19 affected small American companies in the US [19]. The study found that the pandemic had significantly reduced the number of jobs in small enterprises, with more than 40% of them temporarily closing, and many of them probably will not reopen. Also, they revealed that companies in low-income neighbourhoods were highly affected by the pandemic. In addition, in the United States, they discovered that the pandemic had a significant influence on unemployment, resulting in a rapid increase in job losses and a decrease in labour force participation [20].

Furthermore, the United Kingdom discovered that during the early phases of the pandemic, unemployment surged dramatically, particularly among workers in sectors most affected by

lockdown measures [21]. Meanwhile, a study in the Netherlands found that the pandemic had a significant effect on unemployment, leading to a sharp rise in people losing their jobs, especially the less educated young workers [22]. The World Bank stated that not only those working in formal but those working in informal labour markets also had been significantly impacted by the pandemic, with many workers facing decreased hours, pay, and job security. In addition, certain industries, including tourism, hospitality, and retail, were forced by many enterprises to close because of lockdowns and restrictions.

There are several studies discussing the impact of the gig economy on unemployment. In the case of the European Union, they discovered that while the gig economy reduced unemployment rates in some nations, including Spain and Portugal, it increased unemployment rates in other nations, including Italy and France [23]. In a recent study, the relationship between the gig economy and daily records of new cases and deaths of COVID-19 patients as proxies for COVID-19 has been employed by using GARCH and VAR models. The result of volatility clustering demonstrates that the volatility of the gig economy increased with the news of COVID-19 [24]. The results of VAR demonstrate that COVID-19 significantly increases the number of new job vacancies.

DATA AND METHODOLOGY

This study focuses on the influence of the COVID-19 health crisis and unemployment in connection to the gig economy in Malaysia. Data has been collected from three distinct sources. The iLabour Project at Oxford University provided the gig economy statistics, known as the Online Labor Index (OLI). It assesses the supply and demand of online freelance labour across nations and occupations by analysing the number of projects and tasks across platforms in real time. As this study focuses on Malaysia, only Malaysia OLI data is used.

The latest information on new cases and fatalities from COVID-19 have been used as proxies for COVID-19 disease. The data has been collected from the World Health Organization (WHO) websites. The log transformation was applied to the raw series to normalise them for the same rates and numerical structure. Meanwhile, the data for the unemployment rate has been obtained from the Department of Statistics Malaysia (DOSM). The time series have been interpolated to monthly data from January 2020 to September 2022. Eviews statistics program was used for analysis.

In short, we estimated the following model:

$$OLI_t = \beta_0 + \beta_1 Cases_t + \beta_2 Death_t + \beta_3 Unemp_t + \varepsilon_t \quad (1)$$

This study employed non-stationarity tests before testing the VAR/VECM models to explore the dynamic interdependencies between the Gig Economy, COVID-19, and unemployment. In the first step, the study will use the Augmented Dickey-Fuller Test (ADF) in order to establish the order of integration of the variables [25]. After performing the stationarity test, there are three (3) likely outcomes:

1. Series are integrated of order 0. In other words, the series is stationary in level $I(0)$, requiring no differencing. It is not necessary to perform a cointegration test.

2. Series are integrated of order 1. In other words, the series is stationary after the first difference $I(1)$. It is necessary to perform a cointegration test to establish a long-run relationship.
3. Series are integrated of different orders. In other words, the series combines $I(0)$ and $I(1)$.

In order to determine the short- and long-term relationship between COVID-19 and the Gig economy, this study either employs the Vector Autoregression (VAR) or Vector Error Correcting Mechanism (VECM) approach. If time series are non-stationary but cointegrated, the VECM can examine long- and short-term dynamics. In this regard, if all variables are stationary in the first differences $I(1)$, the lag length criteria for the Johansen Cointegration Test must be specified. Cointegration analysis is essential to avoid the risk of spurious regression because if two non-stationary variables are cointegrated, a VAR model in the first difference is misspecified due to the effect of a common trend [26].

The lag length for VAR will be decided based on AIC, FPE and HQIC criteria. A VAR model, representing a dynamic multivariate time series, is utilised to forecast numerous time series variables using a single model. VAR model is often used to predict interrelationship time series, in which there are no exogenous variables, and all variables in the model are explained by their own lagged terms and the lagged terms of other endogenous variables and random errors. The following describes the general structure of a VAR model:

$$X_t = A_1 X_{t-1} + \dots + A_p X_{t-p} + \mu + \varepsilon_t \quad (2)$$

where: $X_t, X_{t-1}, \dots, X_{t-p}$ are $(n \times 1)$ vectors $(x_{1t}, x_{2t}, \dots, x_{nt})$ of current and lagged values of n variables which are $I(1)$ in the model; $A_1, \dots, A_p$ are matrices of coefficients with $(n \times n)$ dimensions; μ is an intercept vector; ε_t is an independently and identically distributed vector with zero mean and variance matrix $\sum_{\varepsilon}$.

Subsequently, in light of these findings, the following VAR models have OLI as the main dependent variable and others as the independent variables.

$$OLI_t = \beta_0 + OLI_{t-2} + Cases_{t-2} + Death_{t-2} + Unemp_{t-2} + \varepsilon \quad (3)$$

$$Cases_t = \beta_0 + OLI_{t-2} + Cases_{t-2} + Death_{t-2} + Unemp_{t-2} + \varepsilon \quad (4)$$

$$Death_t = \beta_0 + OLI_{t-2} + Cases_{t-2} + Death_{t-2} + Unemp_{t-2} + \varepsilon \quad (5)$$

$$Unemp_t = \beta_0 + OLI_{t-2} + Cases_{t-2} + Death_{t-2} + Unemp_{t-2} + \varepsilon \quad (6)$$

The equation has self-explanatory symbols. β_0 represent the constant, and ε stands for the error term. The subscripts t and $t-2$ denote monthly and two months' previous values, respectively. The results calculated based on above mentioned models have been discussed in the following sub-section of this paper.

The Granger causality test is then used to determine whether the incidence of COVID-19 and the gig economy exhibit bidirectional or unidirectional causality. According to Granger, Y is said to "Granger-cause" X if and only if X is better predicted by using the past values of Y than by not doing so with the past values of X being used in either case [27]. In short, if a scalar Y can help to forecast another scalar X , then we say that Y Granger causes X . If Y causes X and X does not

cause Y, it is said that unidirectional causality exists from Y to X. If Y does not cause X and X does not cause Y, then X and Y are statistically independent. If Y causes X and X causes Y, it is said that feedback exists between X and Y. Essentially, Granger's definition of causality is framed in terms of predictability [26]. If the gig economy shares a long-run relationship with other variables under study, the subsequent step is to investigate causality, as if two or more variables are cointegrated, there is causality in at least one direction.

The VECM confines the long-run behaviour of endogenous variables to converge to their cointegrating relationships while permitting short-term adjustment dynamics. It is a restricted VAR designed for use with non-stationary series known to be cointegrated. According to Engle and Granger, since the deviation from long-run equilibrium is progressively corrected by a series of partial short-run adjustments, the cointegration term is known as the correction term [28]. The estimated VECM is described as follows:

$$\Delta X_t = \mu + \theta_1 \Delta X_{t-1} + \dots + \theta_{p-1} \Delta X_{t-p+1} + \Pi X_{t-1} + \varepsilon_t \quad (7)$$

Where: ΔX_t is the first difference of endogenous variables, θ denotes short-run coefficients and contains information regarding the short-run relationships among the variables. Π is an $(n \times n)$ coefficient matrix decomposed as $\Pi = \gamma \times \beta$, in which γ represents the adjustment coefficients β and the cointegrating vectors. It is essential to evaluate the model's validity by doing diagnostic checks to verify if its residuals match white noise [29].

In econometrics and other applications of multivariate time series analysis, a variance decomposition or forecast error variance decomposition (FEVD) is used to aid in interpreting a VAR model once it has been fitted. The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. It determines how much of the forecast error variance of each variable can be explained by exogenous shocks to the other variables. Thus, this study will also employ variance decompositions estimates.

FINDINGS AND DISCUSSIONS

As this study aims to see the nature of the relationship between the online gig economy (OLI), COVID-19 (Cases & Death) and unemployment (Unemp), this study uses monthly data from January 2020 to September 2022. Figure 4 shows the graph of all the series used for the analysis. The x-axis shows the monthly series in the quarterly overview. The y-axis (RHS) shows the OLI and the y-axis (LHS) depicts the logged transformation of COVID-19 monthly cases, deaths, and unemployment rate. OLI data shows the ups and downs trend with a downward movement, while COVID-19 new cases and deaths show an increasing trend. The unemployment rate indicates a sudden increase in the first quarter of 2020 and goes almost static trend onward with slow downward movement afterwards starting from the third quarter of 2021.

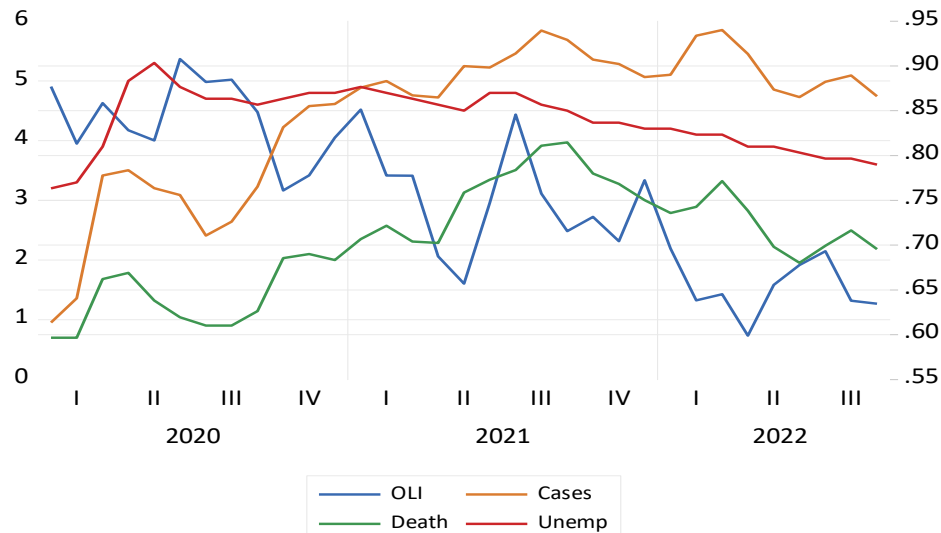


Figure 4. Comprehensive graph depicting all the variables of the study

Source: the authors based on the data sources mentioned in the methodology section

To understand the impact of COVID-19 incidence and unemployment on the gig economy, we have performed a series of steps which detail already discussed in the previous part. First, this study ran the Augmented Dickey-Fuller (ADF) test to know about the stationarity of the series. The test results are given in Table 4. The outcome demonstrated that OLI and Unemp were stationary at level $I(0)$ while cases and death were stationary at the first difference $I(1)$, making cointegration impossible. It shows that the gig economy, COVID-19 and unemployment are integrated at different levels; therefore, no long-run relationship exists between the variables. Thus, this study used only the VAR model to see the short-run relationship between the gig economy, COVID-19 and unemployment.

Table 4. Augmented Dickey-Fuller test.

Variables	ADF testing statistics			
	Level		1 st difference	
	t-stat	Prob.*	t-stat	Prob.*
OLI	-4.556158	0.0052*	-5.495461	0.0006 *
Test critical values:	1%: -4.284580		-1%: -4.323979	
	5%: -3.562882		5%: -3.580622	
	10%: -3.215267		10%: -3.225334	
COVID-19 Cases	-0.732755	0.9610	-6.063063	0.0001 *
Test critical values:	1%: -3.670170		1%: -4.296729	
	5%: -2.963972		5%: - 3.568379	
	10%: -2.621007		10%: -3.218382	
COVID-19 Death	-1.215873	0.8901	-5.332212	0.0008 *
Test critical values:	1%: -4.273277		1%: -4.296729	
	5%: -3.557759		5%: -3.568379	
	10%: -3.212361		10%: -3.218382	
Unemp	-3.655839	0.0406*	-8.019536	0.0000 *

Test critical values:	1%: -4.273277 5%: -3.557759 10%: -3.212361		1%: -4.323979 5%: -3.580622 10%: -3.225334	
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Note. Values show results of Augmented Dickey-Fuller test; * shows significance p-value. Source: the authors based on the data sources mentioned in the methodology section.

The lag length of 2 was decided based on the general-to-specific sequential Likelihood Ratio test (LR), the Final Prediction Error (FPE), the Akaike Information Criterion (AIC) and the Hannan–Quinn (HQ) Criterion (Table 5). These results simultaneously validate the stability condition that all absolute eigenvalues of the system matrix are within the unit circle and the hypothesis on residuals (non-autocorrelation, homoscedasticity and normality).

Table 5. Appropriate Lag Length

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-11.94273	NA	3.29e-05	1.028563	1.213594	1.088879
1	55.40587	112.9718	1.21e-06	-2.284250	-1.359097*	-1.982673
2	80.26512	35.28410*	7.24e-07*	-2.855814*	-1.190539	-2.312976*

Note. *Indicates the appropriate lag length for the relevant test. As a result of the analysis, the most appropriate lag length was determined as two. The value with the most stars indicate the optimal lag length. Source: the authors based on the data sources mentioned in the methodology section.

The findings of a VAR analysis using OLI as the dependent variable are displayed in Table 6. The results indicate that the incidence of COVID-19 cases has a significant negative impact on OLI in the short run. This unique outcome implies that increased COVID-19 cases reduce online jobs significantly. Thus, this result suggests that online jobs are affected by COVID-19 cases as a health crisis might impact labour productivity even though the work can be done at home. This result also parallels Malaysia's digital economy's contribution to GDP, which is said to reduce from 19.1% in 2019 to 18.5% in 2020. However, this study has a contrasting finding with previous studies in which the global COVID-19 pandemic positively impacts the overall gig economy [24].

It is important to note that the data in this study exclude platforms for local services, such as Grab and Foodpanda, as these platforms are categorised as the physical gig economy. During the COVID-19 crisis in Malaysia, these workers were considered front liners, in which the participation rate in this physical gig economy was high. Even though the gig economy landscape is growing in Malaysia, especially during the pandemic, this study only focuses on online labour platforms, which are understood as platforms through which demand and supply of labour or services transact entirely digitally [23]. In other words, the worker and employer are matched digitally, the payment is made via the platform, and the work is delivered digitally. The VAR results also suggest a relatively small immediate impact of COVID-19 cases on the online gig economy in which there is a slow digital adoption or transition using more advanced technologies and speed in experimenting and innovating. For companies to work well, they had to be updated with digital tools.

Table 6 VAR results

	Dependent variable OLI	COVID-19 cases	COVID-19 death	Unemployment
OLI _{t-1}	0.250920	-0.756732	-0.109489	0.362742
	(0.19667)	(2.07425)	(1.75965)	(0.70813)
	[1.27585]	[-0.36482]	[-0.06222]	[0.51225]
OLI _{t-2}	-0.426293*	1.526129	0.208409	-0.414497
	(0.18544)	(1.95580)	(1.65916)	(0.66769)
	[-2.29885]	[0.78031]	[0.12561]	[-0.62079]
COVID-19 cases _{t-1}	-0.072183*	0.875640*	0.280537	0.126008
	(0.03485)	(0.36758)	(0.31183)	(0.12549)
	[-2.07116]	[2.38218]	[0.89966]	[1.00415]
COVID-19 cases _{t-2}	-0.031048	-0.253694	-0.379801	0.284929*
	(0.03281)	(0.34605)	(0.29357)	(0.11814)
	[-0.94627]	[-0.73311]	[-1.29375]	[-2.41181]
COVID-19 death _{t-1}	0.050402	0.087764	0.894685*	0.121461
	(0.04069)	(0.42912)	(0.36403)	(0.14650)
	[1.23879]	[0.20452]	[2.45770]	[0.82910]
COVID-19 death _{t-2}	0.008808	0.144239	0.063378	-0.002774
	(0.03793)	(0.40004)	(0.33937)	(0.13657)
	[0.23222]	[0.36056]	[0.18675]	[-0.02031]
Unemployment _{t-1}	0.092451*	-0.525142	-0.546830	1.031537*
	(0.03587)	(0.37836)	(0.32097)	(0.12917)
	[2.57710]	[-1.38794]	[-1.70366]	[7.98597]
Unemployment _{t-2}	0.012157	0.228122	0.530153	-0.242949
	(0.03487)	(0.36779)	(0.31201)	(0.12556)
	[0.34861]	[0.62025]	[1.69917]	[-1.93492]
Cons.	0.749139*	1.971672	0.556312	1.384535
	(0.17316)	(1.82627)	(1.54927)	(0.62347)
	[4.32637]	[1.07962]	[0.35908]	[2.22069]

Note. The left column shows two lags of independent variables and a constant; Variables on the top show the dependent variables, Standard errors in () & t-statistics in [], * shows significance at a 5% level. Source: the authors based on the data sources mentioned in the methodology section.

In addition, the results show that neither lagged values of COVID-19 deaths significantly explain variation in OLI. However, unemployment shows a significant positive relationship with OLI in the short run. The result aligns with the data from Perkeso and MOHR that the most affected occupations were Professionals, and Technicians & Associate Professionals (as in Table 2). This finding suggests that the unemployment rate has risen dramatically because of retrenchment due to layoffs because of the pandemic, and the unemployed who cannot enter the formal labour market, consequently, enter the online gig economy due to low entry barriers. The low entry barriers have also been one of the critical causes of the increasing demand for gig work in every industry [30].

Regarding Cases, Death or Unemp as a dependent variable, results show that their own lags significantly positively impact the variable. In other words, for example, past COVID-19 cases

affect current cases. Another finding with unemployment as a dependent variable shows that COVID-19 cases significantly positively impact unemployment. An increase in COVID-19 cases leads to a higher unemployment rate. This finding aligns with previous studies [19, 20, 21, 22]. Furthermore, Granger analysis in Table 7 revealed that all the lagged coefficients of OLI have a short-run causal effect on OLI. As the p-value of the Granger Causality test is less than a 5% level of significance, we reject the null hypothesis in which that there is a significant short-run effect of all lags of Cases, Death and Unemp on OLI—Pairwise Granger Causality Tests indicating the direction of causality where the results show only unidirectional causality. Thus, there is no bidirectional causality between the variables.

Table 7 Granger causality test

Dependent variable: OLI			
Excluded	Chi-sq	df	Prob.
Cases	15.54231	2	0.0004*
Death	6.028594	2	0.0491*
Unemp	13.69564	2	0.0011*
All	23.19765	6	0.0007*
Dependent variable: CASES			
Excluded	Chi-sq	df	Prob.
OLI	0.666490	2	0.7166
Death	0.855084	2	0.6521
Unemp	2.062150	2	0.3566
All	4.928918	6	0.5530
Dependent variable: DEATH			
Excluded	Chi-sq	df	Prob.
OLI	0.017557	2	0.9913
Cases	1.673857	2	0.4330
Unemp	3.511231	2	0.1728
All	5.125895	6	0.5278
Dependent variable: UNEMP			
Excluded	Chi-sq	df	Prob.
OLI	0.558452	2	0.7564
Cases	6.733709	2	0.0345*
Unemp	1.937038	2	0.3796
All	31.85409	6	0.0000*

Note. Values show results of the Granger causality test; * shows significance p-value. Source: the authors based on the data sources mentioned in the methodology section.

Variance decomposition results are reported in Tables 8 to 11. This analysis is employed as additional evidence presenting more detailed information regarding the variance relations between the selected variables. Based on Table 8, in the short run, 100% forecast error variance in OLI is explained by itself, so other variables in the model do not strongly influence OLI. In other words, other variables (Cases, Death and Unemp) have a strong exogenous influence. However, forecast error variance by cases, death, and rate increases in the next months in which they can strongly predict OLI. The results suggest that unemployment may cause an increase in online labour demand and supply. People may shift to online work for possible reasons, such as the need for income to make ends meet. In some instances, gig work may be

more accessible than traditional employment. During the COVID-19 pandemic, for instance, many traditional jobs were eliminated, but the demand for delivery services and other gig work increased, making it a more accessible option for some individuals.

Table 8 Variance Decomposition of OLI

Period	OLI	Cases	Death	Unemp
1	100.0000	0.000000	0.000000	0.000000
2	76.80486	10.40163	5.984368	6.809134
3	55.80082	14.88379	13.16704	16.14834
4	49.07102	14.08819	16.08791	20.75287
5	46.27662	14.01063	17.18802	22.52473

Source: the authors based on the data sources mentioned in the methodology section.

Table 9 shows the variance decomposition calculations for COVID-19 cases. In the short run, 97% forecast error variance in COVID-19 cases is explained by itself, so other variables in the model do not strongly influence cases. In other words, other variables (OLI, Death and Unemp) have strong exogenous influence or are weakly endogenous. In a few months, forecast error variance by cases, death and rate is increasing by an insignificant amount.

Table 9 Variance Decomposition of COVID-19 Cases

Period	OLI	Cases	Death	Unemp
1	2.338796	97.66120	0.000000	0.000000
2	4.479986	94.05567	0.000765	1.463580
3	4.120066	91.45812	0.007928	4.413882
4	3.665890	89.44147	0.066765	6.825871
5	3.482018	88.42261	0.268533	7.826838

Source: the authors based on the data sources mentioned in the methodology section.

Table 10 shows the variance decomposition calculations for COVID-19 death. In the short run, 72% forecast error variance in COVID-19 death is explained by COVID-19 cases, so other variables in the model do not strongly influence death. In short, the other variables (OLI, Death and Unemp) have exogenous influence. Forecast error variance by COVID-19 cases is increasing after a few months. As expected in this study, COVID-19 cases strongly predict COVID-19 death.

Table 10 Variance Decomposition of COVID-19 Death

Period	OLI	Cases	Death	Unemp
1	3.076397	72.84218	24.08142	0.000000
2	4.059212	78.41315	15.77241	1.755234
3	4.837864	76.64766	15.18264	3.331826
4	4.561936	75.77550	15.67606	3.986505
5	4.273533	75.41863	16.39229	3.915551

Source: the authors based on the data sources mentioned in the methodology section.

Table 11 shows the variance decomposition calculations for unemployment. In the short run, 90% forecast error variance in rate is explained by itself, so other variables in the model do not strongly influence unemployment. The forecast error variance of COVID-19 cases and death increases in a few months. It implies that COVID-19 cases and death are strong predictors of

unemployment. An extended period of the COVID-19 pandemic may lead to high unemployment.

Table 11 Variance Decomposition of Unemployment

Period	OLI	Cases	Death	Unemp
1	4.236608	0.487936	5.085561	90.18989
2	3.423972	12.56504	7.995844	76.01514
3	2.572745	14.03787	12.89964	70.48975
4	2.271739	12.32336	18.47821	66.92669
5	2.189427	13.15839	22.31392	62.33826

Source: the authors based on the data sources mentioned in the methodology section.

CONCLUSION

This study presents thorough evidence of the causal relationships between the online gig economy, COVID-19, and unemployment in Malaysia using monthly observations from January 2020 to September 2022. The COVID-19 pandemic has sent shockwaves throughout the world. Fortunately, despite lockdowns and social isolation measures, activities can go on as usual with technological advancement. However, the findings of this study indicate that COVID-19 has adversely impacted the online gig economy in Malaysia. Since the outbreak of COVID-19, there has been a decline in the number of online jobs. Furthermore, this study could not confirm the presence of a long-term association between COVID-19 and Malaysia's digital gig economy; therefore, it was only possible to establish a negative relationship between the two variables in the short run. In spite of the fact that the landscape of the gig economy in Malaysia is expanding, particularly during the pandemic, the emphasis of this study is exclusively on online labour platforms.

It implies that COVID-19 instances impact online occupations since a health crisis may harm the main factor of production, which is labour, thus directly impacting labour productivity, even when the task may be completed from home. The results also suggest that Malaysian adaptability, which refers to a worker's capability to effectively control psychosocial functions in response to new, changing, and unpredictable events, places, and circumstances, may be delayed. Even while countries such as Malaysia have already established their own digitisation blueprints, there is a pressing need to connect and streamline their efforts into a collective digital ecosystem to expedite regional recovery in the event of a pandemic. Those in low-skilled occupations will face the most significant threat. If they fail to advance, digitalisation will relegate them to non-automatable tasks, resulting in the de-skilling and devaluation of their talents. Companies that can use technology well to keep going and rethink their business model for the future by speeding up digital transformation will be ahead of their competitors.

Similar to previous research, this study concludes that COVID-19 has negatively impacted the economy. In terms of future studies, predicting pandemics and their influence on the gig economy might give vital insights to policymakers, particularly those in the physical gig economy, such as p-hailing and e-hailing, as labours tend to participate more in this type of gig economy that provides instant opportunities to earn income in times of crisis. However, the digital gig economy is an excellent opportunity and alternative to the Malaysian labour market, despite the low transition. In line with the Twelfth Malaysian Plan, the Digital Economy Blueprint, and the National 4IR (Fourth Industrial Revolution) Policy, efforts should be

intensified to change the digital skills of both companies and workers. The use of new digital technologies is crucial to attaining the Sustainable Development Goals (SDGs), given the requirement for faster development to achieve the objectives by 2030.

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