International Journal of Business and Society, Vol. 24 No. 1, 2023, 164-183

UNEMPLOYMENT BEHAVIOUR IN THE COVID-19 PANDEMIC: EVIDENCE FROM DEVELOPING COUNTRIES

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ABSTRACT

This paper explores the impacts of the COVID-19 pandemic, corruption and other determinants on unemployment in developing countries using panel dataset for 89 developing countries from January to December 2020. The proposed unemployment model is estimated utilising a newly formulated conceptual framework to examine whether COVID-19 pandemic, corruption, and human capital, play a moderating role on unemployment determination in our selected developing countries. The model is estimated using the dynamic panel system generalised method of moments (GMM) estimator. Apart from output, inflation and human capital, our results show that the COVID-19 pandemic and corruption are major variables in explaining the unemployment rate for our sampled countries. Furthermore, and more notably, we find evidence that the COVID-19 pandemic and corruption appear to significantly restrain and alter the role of outputs and human capital in impacting unemployment. Therefore, the detrimental effects of the COVID-19 pandemic and corruption on the economies and labour markets of countries examined should not be under-estimated. Additionally, findings show that, while policy initiatives to combat the COVID-19 pandemic are critical, strengthening anti-corruption regulations would further improve the efficiency of any attempt to reduce unemployment rates associated with the COVID-19 period.

Keywords: COVID-19, corruption, developing countries, GMM, unemployment rate.

Received: 8 October 2021
Accepted: 28 April 2022

1. INTRODUCTION

Unemployment is considered a major macroeconomic problem as it causes many social economics problems including poverty, crime, environmental degradation, mental health and depression problems (Tang, 2010; Saunders, 2002). Therefore, economists and policymakers proposed a variety of measures to effectively promote economic growth and prosperity to minimise the unemployment rate. However, as economic activities grounded to a halt in March 2020 due to the COVID-19 pandemic, the unemployment rate escalated in almost all countries, particularly in the developing countries. According to the statistics reported by the International Labour Organisation (ILO), the global average unemployment rate which was about 5 per cent, increased to

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approximately 6.5 per cent in 2020 (ILO, 2021). In this pandemic, millions of people lost their jobs or experienced a significant reduction of income or working hours in most developing countries where low skilled workers were more exposed to lay offs and wage cuts and with weak social protection programmes, such workers were particularly hard hit. During the early months of the COVID-19 crisis, many countries provided unprecedented levels of support to help households and firms to protect jobs and incomes as well as to prevent their economies from crumpling. As the pandemic subsides, many countries turned to re-opening their economies, policymakers would not be able to maintain this kind of supports as governments' efforts to minimise job losses face more constrained public funding.

Therefore, it is essential to look at the factors that determine today's unemployment rate and their interactions, so the economies can produce sustainable labour market outcomes and determine appropriate policy interventions within the constrained public funding. As every government in a developing country must attempt to create employment opportunities for the unemployed workers, the questions about the factors that influence the unemployment rate and the policies to be implemented to eradicate it are becoming more crucial. This study contributes to the literature mainly in two aspects. First, this paper examines the direct and indirect impacts of the COVID-19 on the unemployment rates in developing countries using the dynamic panel data generalised method of moments (GMM) estimator. The findings of this study will provide valuable information for the policymakers to understand not merely the impacts but also the plausible channels of how the COVID-19 pandemic jeopardised the labour market. This information is extremely important for policymakers to develop needed and responsive policy to lower the unemployment rates. Second, this study will examine the interesting issue as to whether the COVID-19 pandemic and corruption have restrained, expanded or has no impact on the role of outputs and human capital in reducing unemployment. This issue seems to have unjustifiably attracted less attention, if any, in the literature and it forms the originality and the main contribution of this paper.

The balance of this paper is organised as follows. The literature review will be discussed in the next section. The methodology and findings of this study will be presented in Section 3 and Section 4 respectively. The last section provides the conclusion and its implications on policy.

2. LITERATURE REVIEW

Economic literature provides many explanations for the causes of unemployment. Some of such causes relate to the level of GDP, the economic system of the country, external source, technology, quality of institutions, deficiency in aggregate spending and innovations among many other variables that are studied as a reason for the unemployment problem. Accordingly, increases in domestic investments, improved skills of workers, reduction in real interest rate and in uncertainty, improvement in productivity and technological progress and innovations are among the important variables that are considered to lower unemployment rate in a given economy. We focus on four variables that relate closely to the mentioned causes of unemployment including output, inflation, education, corruption and shocks (infectious diseases, epidemic, pandemic).

2.1. Outputs and Unemployment

In our review of past literature, we note that the relationship between unemployment and output has been carefully investigated, particularly the Okun's law. This law is a rule of thumb for calculating the potential loss of output caused by changes in unemployment rates. Okun (1962) examined quarterly data of the United States for the period 1948:Q2 to 1960:Q4 and reported a negative relationship between the real output and unemployment rates with their trade-off relation in the ratio 3:1. This implies that a 1 per cent increase in the unemployment rate above the natural rate of unemployment corresponds to a reduction in real GNP by 3 per cent. Since then, many studies have looked at the empirical validity of the Okun's law (e.g., Hamada & Kurosaka, 1984; Attfield & Silverstone, 1998; Christopoulos, 2004; Gabrisch & Buscher, 2006; Canarella & Miller, 2017; Neely, 2010; Moosa, 1997; Pizzo, 2020; Huang & Yeh, 2013; Ball et al., 2019).

Gil-Alana et al. (2020) provides a very extensive review of the literature covering the Okun's law from 1974 to 2019. In general, majority of the results obtained, which covered various sample periods and a variety of countries such as Latin America, the G7, the OECD, non-OECD, developed and developing countries, have confirmed the validity of Okun's law, with higher estimated Okun's coefficients found in countries with more rigid labour market provisions associated with the presence of stronger trade unions in such countries. Okun's estimated coefficient has changed since 1962 and many researchers have shown that the coefficient increased with time (International Monetary Funds (IMF), 2010; Ballet al., 2017). Moreover, some studies highlighted the non-linear and asymmetric relationships between unemployment and output (Cuaresma, 2003; Perman et al., 2015; Silvapulle et al., 2004; Huang & Chang, 2005; Marinkov & Geldenhuys, 2007; Owyang & Vermann, 2013). Recently, Gil-Alana et al. (2020) tested the validity of the Okun's law taking into consideration modern economic circumstances and new operational specifications. They used fractionally integrated methodologies to look at the issue for 24 countries. While unemployment and output growth rates series are shown to have some degree of long memory behaviour in most countries, the stability of Okun's coefficient was found to fluctuate drastically. Furthermore, estimated gaps are shown to be high, not only for −0.30 standard coefficient values, but also when compared with other studies' results.

2.2. Inflation and Unemployment

The relationship between inflation and unemployment has also been a major object of macroeconomic analysis, resulting in intense academic activity during the last decades. Phillip (1958) documented an empirical link between the growth rate of wages and the unemployment level in the British economy over the period 1861 to 1957. Samuelson and Solow (1960) deduced a trade-off between inflation and unemployment that was refuted later by Phelps (1967) and Friedman (1968). According to Friedman (1968), there is an inflation-unemployment trade-off in the short-run. If the initial unemployment rate falls below the natural rate of unemployment, there is an associated increase in the inflation rate due to an increase in labour costs. Lucas (1973) is the next protagonist in the story of the natural rate of unemployment, whose research was responsible for full recognition of the concept in the economic literature, yet the debate is still going on. Recently, this concept still forms an important challenge the policymakers face because it is important to identify the rate of capacity utilisation that is sustainable in the sense that it is associated with reasonably stable inflation, over the medium- to longer-term. Furthermore, since

2010s the slope of the Phillips curve seems to have declined and there has been disagreement over the utility of the Phillips curve in forecasting inflation.

Various empirical studies were undertaken on unemployment and inflation relation as indicated by the Phillip's curve. For example, Fedderke and Schaling (2005), Burger and Marinkov (2006), Furuoka (2007), Touny (2013), and Phiri (2015). Some of the above-mentioned studies confirmed the existence of a long-run trade-off relationship between the two variables, and others found no evidence of inflation unemployment trade-off. A review of the empirical literature though seems to indicate that the Phillips curve relationship is not well-defined in developed countries, but it points to the existence of the Phillips curve relationship in most developing countries. The question as to whether the Phillips curve relationship holds true seems to remain controversial despite advances in both theoretical and empirical evidence of the subject. Today, the modern Phillips curve models still take into consideration inflationary expectations and distinguish between short-run and long-run effects of inflation on unemployment. They include both short- and long-run Phillips curve. Most studies concurred that there appears to be an inverse relationship between inflation and unemployment rate in the short-run, but in the long-run, that relationship appears to stall as the economy returns to the natural rate of unemployment, irrespective of inflation rate.

2.3. Education and Unemployment

In general, people with advanced levels of education have shown to have better job projections as each level of education they complete increase their skills, give them access to higher paying occupations. Therefore, education level attainments are seen to enhance the probability of securing employment and are considered important in improving the individual's adaptability to changes in the labour markets. Accordingly, enhancing access and achieving higher participation in education are usually associated with a higher level of employment. The apparatuses by which education affects labour market outcomes are varied including years of schooling; educational level attained; investments in education; schooling quality; curriculum type among other variables. Previous research has shown that education has substantial impacts on labour market outcomes (earnings and employment), and therefore investment in education is seen to stimulate the level of employment in general. Card (2001), Farber (2004), Grossman (2006), Oreopoulos and Salvanes (2011), Schuring et al. (2013), Thielen et al. (2013), Alavinia and Burdorf (2008), Siegrist et al. (2007), Barham et al. (2009), Riddell and Song (2011), van Zon et al. (2017), and Dachito, Alemu and Alemu (2020) are among the studies that supported this assertion.

Such research showed that low education level is one of the most important determinants of employment status. Furthermore, it shows that it is more difficult to enter the labour market for both younger and older adults with low education relative to their peers. Additionally, low education is one of the most important determinants of employment status, it also showed that low educated individuals are at higher risk for transition into unemployment than individuals with higher level of education. It also showed that additional education obtained by individuals while working improves their ability to adjust to economic and business shocks.

2.4. Corruption and Unemployment

According to the World Bank's definition, corruption is a "form of dishonesty or criminal offense undertaken by a person or organisation entrusted with a position of authority, to acquire illicit benefit or abuse power for one's private gain". The relationship between corruption and economic growth is described by two hypotheses. The first is the "grease the wheels" hypothesis, which claims that corruption boosts economic progress by avoiding ineffective restrictions. The alternative is the "sand the wheels" hypothesis, which states that corruption slows economic progress by preventing capable output and innovation. However, the majority of empirical studies (e.g., Mo 2001; Méon & Sekkat 2005; Aidt et al., 2008; Hodge et al., 2011; d'Agostino et al., 2016; Huang, 2016; Tsanana et al., 2016; Potrafke, 2019) show evidence that corruption reduces economic growth.

While the nexus between corruption and economic growth has received a large amount of attention, the nexus between corruption and unemployment has received little attention from the academic community. This is very surprising as the World Bank, the International Monetary Funds (IMF) and academics have frequently identified corruption and unemployment as two of the most frustrating policy concerns confronting many economies. Since high levels of corruption have long been a problem in many developing countries, they have reduced governmental investment and demoralised private physical and human capital, resulting in lower growth and, as a result, prolonged unemployment. This unemployment then can cause a further increase in illegal activities which then feeds the growth of more corrupt practices. To our knowledge, there are merely three studies that have looked at the link between corruption and unemployment (e.g., Lim, 2018; Bouzid, 2016; Lackó, 2004). More specifically, Lim (2018) presented an endogenous growth model with heterogeneous labour, endogenous unemployment, and public sector corruption. The study examined the associations using numerical policy experiments based on a stylised illustration of a middle-income African country which suffers high corruption and unemployment. The study reports that large-scale public infrastructure projects are likely to have little effect on rising growth in a high-corruption economy unless it is preceded by anti-corruption policies.

Furthermore, Bouzid (2016) used a GMM technique to investigate the causal relationship between corruption and youth unemployment, accounting for the dynamic influence between perceived bribery among officials and youth unemployment rates. The study examined endogeneity and reverse causality between government corruption and youth unemployment. It showed that corruption activities raise the unemployment rate among youth and job seekers (educated), which is then contributing to the prolongation of illegal practices. Lackó (2004) looked at how tax rates, corruption, and a variety of labour market institutional factors affecting unemployment, employment, self-employment, hidden economy activities, and the tax revenues in developed and transition economies. This was tested using alternative econometric investigations on data for 28 OECD countries and partly on 18 transition countries for the period 1995-2000. Empirical results of Lackó (2004) reported that, in addition to labour market institutional disparities, subjective tax rates are important determinants in explaining cross-country differences in unemployment, employment, and self-employment rates, as well as the extent of the hidden economy.

2.5. Shocks (Infectious Diseases, Epidemic, Pandemic) and Unemployment

The COVID-19 pandemic began in the early half of 2020 in Wuhan, China's Hubei province, and has since spread rapidly across the world, causing a human calamity and significant economic devastation. Many public health measures including social distancing, required businesses, schools, and many governmental and non-governmental organisations to close in an effort to "flatten the curve". According to Carlsson-Szlezak et al. (2020a, 2020b), the potential negative economic impact of COVID-19 is spread via three main transmission channels, namely (1) direct impact of the reduced product consumption, (2) indirect impact of financial market shocks on the real economy (reduction in wealth causing further reduction in consumption), and (3) supply-side disruptions. Consequently, COVID-19 pandemic kept production halted, thus impacting labour demand, and rising unemployment.

Ludvigson et al. (2020) examined the economic impact from a historical perspective, however, Baker et al. (2020) argued that using historical data might not be sufficient as COVID-19 has led to gigantic increase in uncertainty not similar to any recent historical matches. Therefore, there is a need to use forward-looking procedures to discover its economic impact. For example, Lewis et al. (2020) established a weekly economic index (WEI) using ten economic variables to trail the economic impacts of COVID-19 in the United States.

The macroeconomic impacts of COVID-19 are usually calculated using aggregate time series data such as GDP, industrial production, unemployment rate, consumption, and others. Indeed, the impact of COVID-19 on the labour market has been studied by several studies. For example, Adams-Prassl et al. (2020) looked at job loss inequality in the United States and the United Kingdom. They found that workers who cannot accomplish any of their obligations from home are more likely to lose their jobs. Yasenov (2020) documented that younger worker, those with lower education level, and immigrants are mostly in jobs that are less likely can be completed at home. As such, they are likely to lose their job in this COVID-19 pandemic. Béland et al. (2020) also showed that occupations that have a higher likelihood of remote workers are less affected by the pandemic than occupations with a higher number of people working in close proximity. According to Forsythe et al. (2020), firms in the United States began drastically reducing employment vacancies in the second week of March 2020. The study also found that labour market reductions were consistent across states where the epidemic spread earlier than others or those that implemented stay-at-home policy first.

Furthermore, Dingel and Neiman (2020) looked at the possibility of jobs that can be done from home in relation to how much face-to-face interaction the work requires in the United States. They found that about 37 per cent of jobs can be performed from home. In the United States, the COVID-19 pandemic has had a significant impact on labour market metrics for every state, economic sector, and major demographic group. The unemployment rate in the United States hit 14.8 per cent in April 2020, the highest level since data collection began in 1948. According to more current data, however, the unemployment rate in many developed countries fell in March 2021. For example, in the United States, the unemployment rate declined by 0.2 percentage point to 6 per cent from 6.2 per cent in February. As of February 2021, the rate in Canada had decreased by 0.7 percentage point to 7.5 per cent, while the rate in Australia had decreased by 0.5 percentage point to 5.8 per cent. In February 2021, the unemployment rate in the OECD area fell to 6.7 per cent, while Japan and Mexico remained stable at 2.9 per cent and 4.5 per cent respectively. Finally, their results show that while unemployment hit all demographic categories, those who identify as black or younger workers, as well as those with lesser educational attainment, appear to have had very high peaks in unemployment in most nations throughout the epidemic.

3. METHODOLOGY

3.1. Theoretical Model and Data

The primary goal of this study is to investigate the impacts of the COVID-19 pandemic, corruption and other key determinants on the unemployment rates in developing countries. According to Holden and Peel (1975, 1979), the unemployment model is dynamic in nature where unemployment is associated with output level and the lagged unemployment as explained by the Koyck adjustment mechanism. To effectively achieve the goal of this study, we therefore use the dynamic unemployment model as presented in Equation (1):

$$\mathrm{UN}_{it} = \beta_0 + \beta_1 \mathrm{UN}_{it-1} + \beta_2 \mathrm{lnGDP}_{it} + \beta_3 \mathrm{lnCOVID}_{it} + \beta_4 \mathrm{COR}_{it} + \theta_i \mathrm{X}_{it} + \lambda_i + \varepsilon_{it} \tag{1}$$

where λ_i is the country-specific effect and ε_{it} is the disturbance term. UN_{it} represents the unemployment rate, UN_{it-1} is the one-period lagged unemployment rate, lnGDP_{it} is the log of per capita real gross domestic product (GDP) and $\mathrm{lnCOVID}_{it}$ is the log of number of coronavirus infected cases per 100000 population, and COR_{it} refers to the degree of corruption. X_{it} is a vector of other explanatory variables that affect the rate of unemployment such as the inflation rate (INF_{it}), and education or human capital index (HC_{it}). Alternatively, we can also re-write our dynamic unemployment model in the following form:

$$\begin{aligned}\mathrm{UN}_{it} = \beta_0 + \beta_1 \mathrm{UN}_{it-1} + \beta_2 \mathrm{lnGDP}_{it} + \beta_3 \mathrm{lnCOVID}_{it} + \beta_4 \mathrm{COR}_{it} + \theta_1 \mathrm{INF}_{it} \\ + \theta_2 \mathrm{HC}_{it} + \lambda_i + \varepsilon_{it}\end{aligned} \tag{2}$$

Here, we hypothesise that β_1, β_3 and $\beta_4 > 0$ whereas β_2, θ_1 and $\theta_2 < 0$ with respect to the Philips curve and past empirical studies (e.g. Ali et al., 2022; Bouzid, 2016; Maqbool et al., 2013; Lackó, 2004). This study covers the unbalanced monthly panel data from January 2020 to December 2020 across 89 developing countries, which are listed in the Appendix.

We use the cubic spline interpolation method to interpolate monthly data from annual series due to the absence of high frequency data. Indeed, there are two stages of interpolation process required to generate the monthly series from annual observation. Specifically, the series will first be interpolated from annual to quarterly, then this is followed by interpolating the quarterly observation to monthly. Unlike the Chow-Lin method of interpolation, the cubic spline interpolation is a non-parametric approach (or also known as a univariate smoothing technique) that used to compute a higher-frequency data (sub-annual) within the boundaries of two known points of lower-frequency (annual) data with respect to the context of this study. Moreover, this approach can be executed without supplying the sub-annual indicator to materialise the interpolation process. Hence, it is a widely used approach in applied research because the suitable sub-annual indicator is commonly unavailable. Technically, the temporal disaggregation objective of the cubic spline interpolation method is to fit a number of cubic polynomial functions between annual observations, then connecting them together in order to form a smooth line of sub-annual observations. To ensure the lines are smoothly connected, the first and second derivatives are required.

The annual data used for interpolation are gathered from a variety of important and reliable sources. Specifically, the macroeconomic series such as the unemployment rate, per capita real GDP, inflation rate, human capital index and population size are collected from the International Financial Statistics (IFS), World Development Indicators (WDI) and the CEIC database. The number of COVID-19 infected cases, on the other hand, is obtained from Our World in Data and the corruption data is obtained from the Transparency International (TI). This data assesses perceived levels of corruption in the public sector around the world.

Table 1: Summary of Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Unemployment rate, UN_{it}	850	8.092	5.510	0.540	28.74
Inflation rate, INF_{it}	850	11.347	52.571	–2.780	622.8
Human capital, HC_{it}	850	51.137	10.567	30.447	78.872
Corruption, COR_{it}	850	68.474	35.553	4	163
Output per labour, GDP_{it}	850	6579.797	6140.385	2.274	36493.71
Coronavirus, COVID_{it}	850	397.429	814.121	0.003	7681.883

3.2. Dynamic Panel Generalised Method of Moments

Given that specified unemployment model is dynamic in nature, the application of static panel data approaches such as the fixed and random effects models may provide biased results due to the presence of endogeneity. Therefore, the dynamic panel generalised method of moments (GMM) introduced by Arellano and Bond (1991) and Blundell and Bond (1998) is applied in the present study as it helps to remove the country-specific effect and also the endogeneity problem. Indeed, the structure of panel data of the present study is well-suited this approach as we have small time series (*T*=12) and large cross-section (*N*=89).

To control the country-specific effect (λ_i) in Equation (2), we can take the first difference since the effect is time-invariant. The first difference form of unemployment rate model is written below:

$$\begin{aligned}\mathrm{UN}_{it} - \mathrm{UN}_{it-1} = {} & \beta_1(\mathrm{UN}_{it-1} - \mathrm{UN}_{it-2}) + \beta_2(\mathrm{lnGDP}_{it} - \mathrm{lnGDP}_{it-1}) \\ & + \beta_3(\mathrm{lnCOVID}_{it} - \mathrm{lnCOVID}_{it-1}) + \beta_4(\mathrm{COR}_{it} - \mathrm{COR}_{it-1}) \\ & + \theta_1(\mathrm{INF}_{it} - \mathrm{INF}_{it-1}) + \theta_2(\mathrm{HC}_{it} - \mathrm{HC}_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \end{aligned} \tag{3}$$

Despite the country-specific effect has been controlled, there is a correlation between lagged dependent variable $(\mathrm{UN}_{it-1} - \mathrm{UN}_{it-2})$ and the disturbance term $(\varepsilon_{it} - \varepsilon_{it-1})$ resulting in the endogeneity problem. To deal with the endogeneity problem, we borrow the strategy of Arellano and Bond (1991) by estimating the model with lagged level variables as the instrumental variables with respect to the following moment conditions. This is strategy is also known the difference GMM estimation.

$$E[(\mathrm{UN}_{it-s})(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \text{ for } s \geq 2; t = 3, \dots T$$
$$E[(\mathrm{lnGDP}_{it-s})(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \text{ for } s \geq 2; t = 3, \dots T$$
$$E[(\mathrm{lnCOVID}_{it-s})(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \text{ for } s \geq 2; t = 3, \dots T$$
$$E[(\mathrm{COR}_{it-s})(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \text{ for } s \geq 2; t = 3, \dots T$$
$$E[(\mathrm{INF}_{it-s})(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \text{ for } s \geq 2; t = 3, \dots T$$
$$E[(\mathrm{HC}_{it-s})(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \text{ for } s \geq 2; t = 3, \dots T$$

However, if the variables under review are persistent, then the lagged level variables cannot be a good instrumental variable. This is because the first difference variables and the lagged level variables can be weakly correlated if the series behave persistently (Blundell & Bond, 2000). To deal with this, Blundell and Bond (1998) suggested an alternative GMM estimator, namely the dynamic panel system GMM estimator by accommodating additional moment conditions as below:

$$E[(\mathrm{UN}_{it-s} - \mathrm{UN}_{it-s-1})(\lambda_i + \varepsilon_{it})] = 0 \text{ for } s = 1$$
$$E[(\mathrm{lnGDP}_{it-s} - \mathrm{lnGDP}_{it-s-1})(\lambda_i + \varepsilon_{it})] = 0 \text{ for } s = 1$$
$$E[(\mathrm{lnCOVID}_{it-s} - \mathrm{lnCOVID}_{it-s-1})(\lambda_i + \varepsilon_{it})] = 0 \text{ for } s = 1$$
$$E[(\mathrm{COR}_{it-s} - \mathrm{COR}_{it-s-1})(\lambda_i + \varepsilon_{it})] = 0 \text{ for } s = 1$$
$$E[(\mathrm{INF}_{it-s} - \mathrm{INF}_{it-s-1})(\lambda_i + \varepsilon_{it})] = 0 \text{ for } s = 1$$
$$E[(\mathrm{HC}_{it-s} - \mathrm{HC}_{it-s-1})(\lambda_i + \varepsilon_{it})] = 0 \text{ for } s = 1$$

Based on these additional moment conditions, the dynamic panel system GMM estimator will use the first difference variables as the instrument instead of the lagged level variables. Indeed, the Monte Carlo simulation evidence provided by Blundell and Bond (1998) affirmed that the system GMM estimator is consistently superior to the difference GMM estimator, particularly when the series are persistent. However, the difference Sargan test will be used to determine the best choice of estimator as suggested by Bond (2002). Furthermore, two additional tests such as Hansen (1982) *J*-test for the validity of the instrumental variables and Arellano and Bond (1991) test for autocorrelation will be properly implemented to enhance the reliability of the estimate results.

4. RESULTS AND DISCUSSION

In the previous section, we discussed the estimator, data and model used to understand the behaviour of unemployment rates in developing countries. Here, we would like to present and discuss the results of the estimates in greater details, including the plausible channels by which the COVID-19 pandemic and corruption might jeopardise the demand for labour which eventually increase the unemployment rates in developing countries. This analysis is focused mainly on 89 developing countries from January to December 2020. In general, the findings of this study are segregated into direct and indirect (moderating) impacts of the COVID-19 pandemic, corruption and other determinants on unemployment rate. Moreover, the attention will also be given to the long-run impacts on unemployment rate in developing countries.

4.1. Direct Impacts on Unemployment Rate

The dynamic panel system GMM estimation results are reported in Table 2. Before looking at the estimate impacts on unemployment rate, it is essential to verify the validity of the estimate models. At the 5 per cent significant level, we find that the statistics of difference Sargan test reported in Table 2 fail to reject the null hypothesis, implying that the system GMM estimator is suitable for the present study. Similarly, our results also suggest that the statistics of Wald test are highly significant, meaning that the unemployment models used in this study are well-fitted to the dataset of developing countries. More importantly, the Arellano-Bond tests show that our models only subjected to first-order autocorrelation, AR(1) but they are free from the second-order autocorrelation, AR(2). These results complied with many other past studies (e.g., Tang, 2018; Tang & Tan, 2018) indicating the appropriateness of applying dynamic panel GMM estimator. In addition, we find that the statistics of the Hansen J-test do not reject the null hypothesis of no over-identifying restriction, implying that the endogeneity problem has been effectively addressed without excessive size of instrumental variables. Given that the size of instrumental variables may affect the efficiency in estimation, we borrow the rule-of-thumb suggested by Roodman (2009) to further verify the size of instrumental variables. According to Roodman (2009), the ideal number of instrumental variables used in estimation should not be greater than the number of cross-sectional (N) dimension in order to yield an efficient GMM estimation. Advantageously, we find that the total number of instrumental variables used for estimation are consistently less than it's cross-sectional, signifying the absence of over-instrumental problem. After passing all the diagnostic and specification tests, we can extend our discussion to the estimate impacts on unemployment rate as reported in Table 2.

Overall, we find that both output ((lnGDP_{it})and inflation rate (INF_{it}) are negatively associated with the unemployment rate in developing countries. These findings are within expectation and comply with the Philips curve. Indeed, the past unemployment studies, for example, Ali et al. (2022), Bruno et al. (2017), Matuzeviciute et al. (2017), and Maqbool et al. (2013) also discovered the similar inverse relationships. Based on the significant coefficients, we find that a 1 per cent increase in output, would result in the unemployment rate in developing countries on average to be reduced 0.05 to 0.07 percentage points. On the other hand, a one percentage point increase in the inflation rate, holding other factors are constant, result in unemployment rate reduction from approximately 0.0005 to 0.0009 percentage point. Likewise, we also find a significant negative impact of human capital (education) on the unemployment rate in developing countries. This negative impact may be associated with the notion that education aids to enhance the likelihood to be employed, thus reduce unemployment. Moreover, skilled workers are likely to improve economic efficiency and productivity which eventually increase the overall economic growth. Consequently, this will increase the demand for labour and mitigate the unemployment rate. Looking at the significant direct impact of human capital on unemployment rate (i.e., Model 1, 2, 5 and 6), we find that unemployment rate drops about 0.08 to 0.26 percentage points for every 10 points increase in human capital. Besides, we find that unemployment rate reacts positively to both corruption and COVID-19 pandemics, meaning that a country with serious corruption and COVID-19 are more likely to have higher rate of unemployment. Results in Table 2, particularly Model (1) and Model (5) illustrate that a 10 percent increase in COVID-19 cases, will directly uplift the unemployment rate by approximately 0.98 to 1.03 percentage point. However, for every 10 points increase in corruption, the unemployment rate increases about 0.049 to 0.053 percentage point. As such, we may surmise that among many determinants under investigation, our results suggest that COVID-19 pandemic seems to provide the most significant impact on the unemployment rate in developing countries. This is because the COVID-19 pandemic has retarded almost 90 per cent of the world productivity growth via a variety of conduits including human capital erosion, reduction in investment and business trading (Bloom et al., 2020).

Table 2: Results of Dynamic Panel System GMM Estimation

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Constant	0.810**	0.8399**	5.2812***	2.371***	4.3678**	2.2265***
	(0.017)	(0.014)	(0.003)	(0.002)	(0.027)	(0.001)
Unemployment, UN_{it-1}	0.9179***	0.9093***	0.8913***	0.9085***	0.9165***	0.9027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Output, $\ln\text{GDP}_{it}$	–0.0543**	–0.0451*	–0.0692*	–0.2411***	–0.3551**	–0.0984**
	(0.043)	(0.051)	(0.061)	(0.007)	(0.029)	(0.015)
Coronavirus, $\ln\text{COVID}_{it}$	0.0983***	0.1004***	–0.9687**	–0.2986**	0.1027***	–0.1099*
	(0.000)	(0.000)	(0.012)	(0.038)	(0.000)	(0.096)
Corruption, COR_{it}	0.0049**	0.0049**	0.0056	0.0053**	–0.0836*	–0.0081*
	(0.028)	(0.033)	(0.140)	(0.031)	(0.077)	(0.081)
Inflation, INF_{it}	–0.0002	–0.0002	–0.0001	–0.0003	–0.0009**	–0.0005**
	(0.336)	(0.309)	(0.407)	(0.271)	(0.042)	(0.035)
Human capital, HC_{it}	–0.0079*	–0.0088*	–0.0928***	–0.0080	–0.0257***	–0.0091*
	(0.083)	(0.081)	(0.002)	(0.108)	(0.008)	(0.096)
$\ln\text{COVID}_{it} \times \text{COR}_{it}$	–	0.0007	–	–	–	–
		(0.190)				
$\text{HC}_{it} \times \ln\text{COVID}_{it}$	–	–	0.0207***	–	–	–
			(0.006)			
$\ln\text{GDP}_{it} \times \ln\text{COVID}_{it}$	–	–	–	0.0477***	–	–
				(0.009)		
$\ln\text{GDP}_{it} \times \text{COR}_{it}$	–	–	–	–	0.0100*	–
					(0.068)	
$\ln\text{GDP}_{it} \times \text{COR}_{it} \times \ln\text{COVID}_{it}$	–	–	–	–		0.0003***
						(0.003)
Wald test	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Arellano-Bond AR(1)	(0.003)***	(0.005)***	(0.010)**	(0.004)***	(0.002)***	(0.007)***
Arellano-Bond AR(2)	(0.342)	(0.312)	(0.135)	(0.646)	(0.559)	(0.560)
Hansen *J*-test	(0.199)	(0.265)	(0.343)	(0.245)	(0.264)	(0.267)
Difference Sargan test	(0.301)	(0.144)	(0.570)	(0.490)	(0.582)	(0.239)
Number of Instruments	82	83	83	82	83	83

Note: ***, ** and * denotes statistically significant at the 1, 5 and 10 per cent, respectively. Figures in parenthesis (.) indicates the *p*-values generated from Windmeijer (2005) robust standard errors.

4.2. Moderating or Indirect Impacts on Unemployment Rate

Apart from the direct impact discussed above, it is also critical to comprehend the indirect effect such as the role of COVID-19 pandemic and corruption in moderating the impact of output, human capital and other variables in explaining unemployment rates. To assess the moderating effect, we extend our analysis by accommodating the interaction terms, namely $(\ln\text{COVID}_{it} \times \text{COR}_{it})$, $(\text{HC}_{it} \times \ln\text{COVID}_{it})$, $(\ln\text{GDP}_{it} \times \ln\text{COVID}_{it})$, $(\ln\text{GDP}_{it} \times \text{COR}_{it})$, and $(\ln\text{GDP}_{it} \times \text{COR}_{it} \times \ln\text{COVID}_{it})$ into the unemployment models. Findings from these augmented unemployment models may provide useful information for policymaking. The augmented models are be written below:

$$\text{UN}_{it} = \beta_0 + \beta_1\text{UN}_{it-1} + \beta_2\ln\text{GDP}_{it} + \beta_3\ln\text{COVID}_{it} + \beta_4\text{COR}_{it} + \beta_5\text{INF}_{it} + \beta_6\text{HC}_{it} + \pi_1(\ln\text{COVID}_{it} \times \text{COR}_{it}) + \lambda_i + \varepsilon_{it} \tag{4}$$

$$\text{UN}_{it} = \beta_0 + \beta_1\text{UN}_{it-1} + \beta_2\ln\text{GDP}_{it} + \beta_3\ln\text{COVID}_{it} + \beta_4\text{COR}_{it} + \beta_5\text{INF}_{it} + \beta_6\text{HC}_{it} + \pi_2(\text{HC}_{it} \times \ln\text{COVID}_{it}) + \lambda_i + \varepsilon_{it} \tag{5}$$

$$\mathrm{UN}_{it} = \beta_0 + \beta_1\mathrm{UN}_{it-1} + \beta_2\mathrm{lnGDP}_{it} + \beta_3\mathrm{lnCOVID}_{it} + \beta_4\mathrm{COR}_{it} + \beta_5\mathrm{INF}_{it} + \beta_6\mathrm{HC}_{it} + \pi_3(\mathrm{lnGDP}_{it} \times \mathrm{lnCOVID}_{it}) + \lambda_i + \varepsilon_{it} \quad (6)$$

$$\mathrm{UN}_{it} = \beta_0 + \beta_1\mathrm{UN}_{it-1} + \beta_2\mathrm{lnGDP}_{it} + \beta_3\mathrm{lnCOVID}_{it} + \beta_4\mathrm{COR}_{it} + \beta_5\mathrm{INF}_{it} + \beta_6\mathrm{HC}_{it} + \pi_4(\mathrm{lnGDP}_{it} \times \mathrm{COR}_{it}) + \lambda_i + \varepsilon_{it} \quad (7)$$

$$\mathrm{UN}_{it} = \beta_0 + \beta_1\mathrm{UN}_{it-1} + \beta_2\mathrm{lnGDP}_{it} + \beta_3\mathrm{lnCOVID}_{it} + \beta_4\mathrm{COR}_{it} + \beta_5\mathrm{INF}_{it} + \beta_6\mathrm{HC}_{it} + \pi_5(\mathrm{lnGDP}_{it} \times \mathrm{COR}_{it} \times \mathrm{lnCOVID}_{it}) + \lambda_i + \varepsilon_{it} \quad (8)$$

Table 2 shows the estimate impacts of the above unemployment models with interaction terms. We find that majority of the interaction terms are statistically significant at the 10 per cent level or better, except for $(\mathrm{lnCOVID}_{it} \times \mathrm{COR}_{it})$. Nonetheless, it is important to note that since the variables in the models are interacted, there are no direct interpretation for the estimate coefficients (see Wooldridge, 2002). Therefore, the marginal effects should be calculated by the following partial derivation:

$$\frac{\partial \mathrm{UN}_{it}}{\partial \mathrm{lnCOVID}_{it}} = \beta_3 + \pi_1\mathrm{COR}_{it} \quad (9)$$

$$\frac{\partial \mathrm{UN}_{it}}{\partial \mathrm{HC}_{it}} = \beta_6 + \pi_2\mathrm{lnCOVID}_{it} \quad (10)$$

$$\frac{\partial \mathrm{UN}_{it}}{\partial \mathrm{HC}_{it}} = \beta_6 + \pi_2\mathrm{lnCOVID}_{it} \quad (11)$$

$$\frac{\partial \mathrm{UN}_{it}}{\partial \mathrm{HC}_{it}} = \beta_6 + \pi_2\mathrm{lnCOVID}_{it} \quad (12)$$

$$\frac{\partial \mathrm{UN}_{it}}{\partial \mathrm{HC}_{it}} = \beta_6 + \pi_2\mathrm{lnCOVID}_{it} \quad (13)$$

The calculated marginal impacts and their inferential statistics are reports in Table 3. We can find from the reported statistics, that they are statistically significant at the 10 per cent level or better. The results show that the COVID-19's impacts on unemployment rates are dependent on the perceived level of corruption. Moreover, the impacts of output are found to be dependent on both the perceived levels of corruption and the COVID-19 pandemic. Indeed, the COVID-19 pandemic also has impacted the role of human capital on unemployment rates. More specifically, the results in Table 3 illustrate that COVID-19 has a significant positive effect on the unemployment rates (e.g. approximately 0.103, 0.152 and 0.222 percentage points) and that this impact increases as corruption increases. More importantly, as corruption rises, the role of outputs in unemployment change from controlling (–0.315 percentage point) to encouraging unemployment (approximately 1.297 percentage points) when corruption increase.

Nine plausible outcomes are estimated by looking at the interacting relationships of the three variables $(\mathrm{lnGDP}_{it} \times \mathrm{COR}_{it} \times \mathrm{lnCOVID}_{it})$. We find that at all levels of COVID-19, when corruption is minimum, the impacts of outputs on unemployment remain negative (ranging from approximately –0.106 to –0.086 percentage points). Regardless of the attaining level of COVID-19, our findings suggest that at the mean and maximum levels of corruption, the impacts of outputs on unemployment change from negative (–0.235 and –0.429 percentage points) to positive (0.110 and 0.403 percentage points). These results show that institutional weakness, such as corruption, has enlarged the effects of the COVID-19 pandemic and slowed production growth, putting the unemployment rate in developing countries in jeopardy. Hence, we can conclude that the unemployment rates tend to be higher if the developing countries has poor governance and no corruption control as well as confronted with the COVID-19 pandemic.

Table 3: Results of Marginal Impacts on Unemployment Rate

	Minimum	**Mean**	**Maximum**
$\partial \mathrm{UN}_{it}/\partial \mathrm{lnCOVID}_{it} = \beta_3 + \pi_1 \mathrm{COR}_{it}$			
Marginal impacts of COVID-19	0.1034***	0.1517***	0.2224**
	(0.000)	(0.002)	(0.030)
$\partial \mathrm{UN}_{it}/\partial \mathrm{HC}_{it} = \beta_6 + \pi_2 \mathrm{lnCOVID}_{it}$			
Marginal impacts of human capital	–0.2149***	–0.0098	0.0923**
	(0.004)	(0.387)	(0.018)
$\partial \mathrm{UN}_{it}/\partial \mathrm{lnGDP}_{it} = \beta_2 + \pi_3 \mathrm{lnCOVID}_{it}$			
Marginal impacts of outputs	–0.5229***	–0.0496	0.1860**
	(0.007)	(0.161)	(0.036)
$\partial \mathrm{UN}_{it}/\partial \mathrm{lnGDP}_{it} = \beta_2 + \pi_4 \mathrm{COR}_{it}$			
Marginal impacts of outputs	–0.3150*	0.3303	1.2966*
	(0.059)	(0.101)	(0.074)
$\partial \mathrm{UN}_{it}/\partial \mathrm{lnGDP}_{it} = \beta_2 + \pi_5 (\mathrm{COR}_{it} \times \mathrm{lnCOVID}_{it})$			
Marginal impacts of outputs	$\mathrm{lnCOVID}_{\mathrm{MIN}}$	$\mathrm{lnCOVID}_{\mathrm{MEAN}}$	$\mathrm{lnCOVID}_{\mathrm{MAX}}$
$\mathrm{COR}_{\mathrm{MIN}}$	–0.1064**	–0.0929**	–0.0862**
	(0.023)	(0.036)	(0.045)
$\mathrm{COR}_{\mathrm{MEAN}}$	–0.2355***	–0.0052	0.1095*
	(0.004)	(0.892)	(0.062)
$\mathrm{COR}_{\mathrm{MAX}}$	–0.4289***	0.1262**	0.4025***
	(0.003)	(0.046)	(0.007)

Note: ***, ** and * denotes statistically significant at the 1, 5 and 10 per cent, respectively. Figures in parenthesis (.) indicates the *p*-values.

4.3. Long-Run Impacts on Unemployment Rate

We borrow the formula proposed by Bardsen (1989) to derive the long-run impacts on unemployment rate and the estimated results are presented in Table 4. Overall, we find that the pandemic of COVID-19 has the largest long-run impacts on unemployment rate, following by outputs (–0.6619), human capital (–0.0968) and corruption (0.0603). Additionally, the estimate coefficients are significant at the 10 per cent level or better. However, results demonstrate that inflation rate is statistically insignificant even at the 10 per cent level. This affirms that inflation rate does not influence the unemployment rate in the long-run which is consistent with the economic theory.

Table 4: Results of Long-Run Impacts on Unemployment Rate

Variables	**Coefficients**
Output, $\ln\text{GDP}_{it}$	–0.6619***
	(0.002)
Coronavirus, $\ln\text{COVID}_{it}$	1.1980***
	(0.000)
Corruption, COR_{it}	0.0603***
	(0.002)
Inflation, INF_{it}	–0.0023
	(0.143)
Human capital, HC_{it}	–0.0968*
	(0.082)

Notes: ***, ** and * denotes statistically significant at the 1, 5 and 10 per cent, respectively. Figures in parenthesis (.) indicates the p-values.

Moreover, the evidence of long-run negative relationship between outputs and unemployment found in this study is in accordance with some past empirical studies (e.g., Ali et al., 2022; Bruno et al., 2017; Maqbool et al., 2013). Specifically, a one per cent of outputs growth, on average, will reduce the long-run unemployment rate by approximately 0.662 percentage point. Similarly, we find that human capital is also negatively related to unemployment rate in the long-run, but its impact is only about 0.10 percentage point. More importantly, our results illustrate that unemployment rate in the long-run will increase by approximately 1.2 percentage point for a one per cent upward growing in the COVID-19 cases. Hence, this shows that the pandemic has had a very significant impact on unemployment rate in developing countries. The long-run impact of corruption on unemployment rate, however, is merely about 0.06 percentage point. Although this direct impact of corruption is relatively small, it is not a wise strategy to assume that corruption causes merely a minor damage to the labour market. This is because its impact on unemployment may also be through the channels of outputs, human capital and also the COVID-19 pandemic as mentioned earlier (see Table 3). Therefore, decision-makers must pay careful attention to policies on governance and corruption prevention in order to effectively control unemployment during this pandemic.

5. CONCLUSION AND POLICY IMPLICATIONS

We study the behaviour of unemployment rates during the period of the COVID-19 pandemic. As such, the panel data from January to December 2020 across 89 emerging economies are used. The unemployment model is estimated using the dynamic panel system GMM estimator. Our findings reveal that output, corruption, inflation, education, and the COVID-19 pandemic all have a major impact on unemployment rate. In addition, we also discovered evidence of moderating (interacting) effects among the explanatory variables in explaining the unemployment rate in developing countries.

As expected, the findings indicate that policymakers in developing countries should aim at increasing their GDP growth rates, improving their human capital (education), and striving to eliminate inflation and corruption to reduce unemployment. Such outcomes are to be expected, and they are theoretically reasonable. What we find to be intriguing is that anti-corruption efforts and the COVID-19 pandemic appear to dramatically limit and alter the function of outputs and human capital in lowering unemployment rates. To control the unemployment rate, both during and after the COVID-19 pandemic, the policy makers should aim at reducing corruption and continuing to enhance ongoing efforts to rid their economies of the pandemic. This is because any advantage from economic recovery packages and vaccination programmes will not reach the people and industry efficiently until the fight against corruption is taken seriously which is highlighted in our empirical findings. Therefore, we stress that delaying action to remove corruption will not only result in inefficiencies, but it will also allow unemployment to remain a key impediment to a reasonable recovery in such countries. Consequently, efforts should be implemented or continued to reduce the mismatch between education/training and labour market needs in post-COVID-19. Along with these measures, massive government efforts to reduce corruption will result in better and longer-term resource mobilisation.

ACKNOWLEDGEMENT

We would like to thank the anonymous reviewers for providing us with constructive comments and suggestions that significantly uplift the earlier version of this research paper. The usual disclaimer applies.

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APPENDIX

Appendix 1: List of Developing Countries Under Review

No.	Country	No.	Country	No.	Country
1.	Afghanistan	31.	Gambia	61.	Mozambique
2.	Albania	32.	Georgia	62.	Namibia
3.	Algeria	33.	Ghana	63.	Nepal
4.	Angola	34.	Guatemala	64.	Nicaragua
5.	Argentina	35.	Guinea	65.	Niger
6.	Armenia	36.	Guyana	66.	Nigeria
7.	Azerbaijan	37.	Haiti	67.	North Macedonia
8.	Bangladesh	38.	Honduras	68.	Pakistan
9.	Belarus	39.	India	69.	Papua New Guinea
10.	Benin	40.	Indonesia	70.	Paraguay
11.	Bosnia and Herzegovina	41.	Iran	71.	Peru
12.	Botswana	42.	Iraq	72.	Philippines
13.	Brazil	43.	Jamaica	73.	Russia
14.	Bulgaria	44.	Jordan	74.	Serbia
15.	Burkina Faso	45.	Kazakhstan	75.	South Africa
16.	Cameroon	46.	Kenya	76.	Sri Lanka
17.	Central African	47.	Kyrgyz	77.	Tajikistan
18.	Chad	48.	Lao PDR	78.	Tanzania
19.	China	49.	Lebanon	79.	Thailand
20.	Colombia	50.	Lesotho	80.	Togo
21.	Comoros	51.	Liberia	81.	Tunisia
22.	Congo, DR.	52.	Madagascar	82.	Turkey
23.	Congo	53.	Malawi	83.	Uganda
24.	Costa Rica	54.	Malaysia	84.	Ukraine
25.	Côte d'Ivoire	55.	Mali	85.	Uzbekistan
26.	Ecuador	56.	Mauritania	86.	Vietnam
27.	Egypt	57.	Mexico	87.	Yemen
28.	El Salvador	58.	Moldova	88.	Zambia
29.	Estonia	59.	Montenegro	89.	Zimbabwe
30.	Gabon	60.	Morocco		