The Critical Review of Social Sciences Studies

Online ISSN: 3006-7170
Print ISSN: 3006-7162
Volume 3, Number 3, 2025, Pages 1715 – 1733
Journal Home Page
https://thecrsss.com/index.php/Journal/about

The Impact of Technological Advancements and Globalization on Job Market Polarization: A Comparative Study of the UK, Oman, and Pakistan

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ARTICLE INFO

Article History:

Received:	*July*	*02, 2025*
Revised:	*August*	*03, 2025*
Accepted:	*August*	*12, 2025*
Available Online:	*August*	*21, 2025*

Keywords:

Technological Innovations, Globalization, Job Polarization, Labor Demand, ARDL

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ABSTRACT

Job polarization refers to the widening gap in the labor market, where high-skill and low-skill employment are expanding, while middle-skill jobs are declining. Technological advancement and globalization drive this phenomenon, which is transforming employment patterns and income distribution. This study aims to analyze the impact of technological innovations and globalization on job polarization between high-skilled UK and low-skilled Oman, relative to middle-skilled Pakistan. In doing so, we use time series data from 1991 to 2021. For estimation, we employ the Autoregressive Distributed Lag (ARDL) approach to cointegration and find that middle-skilled Pakistan, in terms of jobs, is hollowing out due to technological innovations and globalization. However, the displaced Pakistani workers concentrate either in the high-skilled UK or the low-skilled Oman. Based on these findings, we suggest that Pakistani policymakers focus on labor skills, reduce reliance on imported goods, and provide job opportunities to displaced workers within the country to address the issue of Pakistan's declining net migration relative to the UK and Oman.

Introduction

One of the key features of modern labor markets is job polarization, defined by Autor, Levy, and Murnane (2003) (hereafter ALM) as the coexisting growth of high-skill and low-skill employment opportunities coupled with the decrease in middle-skill professions (Autor, 2010), this phenomenon is termed as routine biased technological change (hereafter RBTC). Previous literature suggests two main forces of job polarization: technological advancement and globalization. These forces interact dynamically, impacting regional, industrial, and skill-level employment trends.

Before the RBTC hypothesis, researchers would analyze the impact of technological change on jobs in the light of skilled-biased technological change (hereafter SBTC). The SBTC hypothesis shows a race between skills and technology, because technological innovations complement the high-skilled workers, while the low-skilled workers are substituted (Tinbergen, 1974, 1975). Empirically, this hypothesis has been examined by several studies (Katz & Autor, 1999; Goldin & Katz, 2007, 2009; Acemoglu & Autor, 2011; Goos, 2018). Technological innovations are widely understood to be skill-biased, as they tend to complement high-skilled workers while substituting for low-skilled labor. Hence, this hypothesis paints a completely bleak future for the low-skilled workers.

However, the RBTC hypothesis, as we have discussed earlier, is initiated by ALM; unlike the SBTC hypothesis, the RBTC hypothesis suggests that technological innovations complement both the high (cognitive skills) and low-skilled (manual skills) workers, while the middle-skilled (routine skills) workers are substituted. Rather than predicting a bleak future for low-skilled workers, this theory highlights the declining relevance of middle-skilled jobs involving routine tasks. The advantage of this theory lies in considering the uneven distribution of income. Hence, this theory addresses the issue of income inequality.

The modern literature on the labor market in general and job polarization, in particular, has suggested two forces of job polarization. The first force is technological advancement, and the second is globalization, and more particularly, import competition. Technological innovations polarize the job market by complementing the high and low-skilled, cognitive, and manual task performers while substituting the middle-skilled routine task performers. The second force of globalization polarizes the labor market due to import competition and offshoring. It is empirically concluded that both forces polarize the labor market (Goos et al., 2014; Breemersch et al., 2019).

Additionally, globalization is another force of job polarization. The existing literature has investigated two sub-forces of economic globalization: import competition and job offshoring (Oldenski, 2014; Goos et al., 2014; Breemersch et al., 2019; Keller & Utar, 2023). The competition for imports from labor-abundant countries reduces the demand for domestically produced manufacturing goods. Labor-rich countries can create manufacturing products at a reduced cost due to their lower labor costs. Hence, the domestic industries are downsizing due to the import competition, creating unemployment domestically. It is noted that the downsizing takes place in the manufacturing sector, due to which the middle-skilled workers are losing their jobs.

The existing literature has used different methods for the measurement of job polarization. One approach is that the occupations are classified according to the level of skills, such as high, middle, and low skills, utilizing labor's Dictionary of Occupational Titles[1] (hereafter DOT) and the Occupational Information Network[2] (ONET). The other one is based on wage level, for example, workers with high wages are considered high-skilled workers, with middle wages as middle-skilled, and with low wages as low-skilled workers. In doing so, they have tried to capture the job polarization by identifying the decline in middle-skilled jobs and the growth in low and high-skilled jobs. Furthermore, the jobs are classified based on tasks required for the performance of those jobs, such as cognitive, routine, and manual tasks. For a comprehensive understanding of

[1] The Dictionary of Occupational Titles (DOT) is a publication by the U.S. Department of Labor that provides standardized job descriptions and occupational classifications. It was used to help employers, government agencies, and workforce development professionals understand and categorize different types of work. The DOT categorizes over 13,000 different jobs, and the latest edition was published in 1991.

[2] The Occupational Information Network (ONET) is a comprehensive online database maintained by the U.S. Department of Labor that provides detailed information about various occupations. It serves as the nation's primary source of occupational information, replacing the older Dictionary of Occupational Titles (DOT). ONET offers data on worker attributes, job characteristics, and the skills, knowledge, and abilities needed for different jobs.

these measures (Blinder, 2009; Goos et al., 2014; Breemersch et al., 2017, 2019; Keller & Utar, 2023).

Despite an extensive body of literature, many questions remain unanswered regarding the dynamics of employment polarization—particularly at the macroeconomic and cross-national scales. Hence, a noteworthy drawback of the existing literature is its dependence on occupational classifications for quantifying job polarization, which leaves out more comprehensive macroeconomic data and cross-national comparisons. While micro-level analyses that concentrate on industries or occupational categories have yielded valuable insights. A macroeconomic perspective that considers aggregate employment trends, skill distributions, and global integration patterns is necessary to offer a comprehensive understanding of job polarization.

A large body of literature has investigated the recent phenomenon of job polarization. The measurement of job polarization in the existing literature is based on the classification of skills into different categories; workers with cognitive skills are high-skilled and high-paid, workers with routine skills are considered middle-skilled and middle-paid, and workers with manual skills are considered low-skilled and low-paid. This type of analysis is possible on the availability of data on wages of all occupations. However, the existing literature has largely overlooked cross-country assessments of job polarization. It might be due to a lack of data on wages and salaries.

Therefore, to address this gap, this study applies the macro-level approach to identify the job polarization among different countries, such as Pakistan, the United Kingdom, and Oman. Hence, following the 'task-based approach', we rank the selected three countries based on World Indicators for Skills and Employment (hereafter WISE). Country-level skill scaling indicates that the United Kingdom ranks as high-skilled, Pakistan as middle-skilled, and Oman as low-skilled. This classification enables a deeper understanding of job polarization across varying skill economies—particularly between the high-skilled UK and low-skilled Oman, with Pakistan serving as a comparative benchmark.

This paper examines the interplay between technological change, globalization, and job polarization by analyzing the contraction of Pakistan's labor market relative to high- and low-skilled economies. It explores the disproportionate concentration of jobs in the high-skilled United Kingdom and low-skilled Oman. Net migration is employed as a proxy indicator for job polarization, providing insights into the structural employment shifts across the three selected countries.

Data and Methodology

This study utilizes the annual time series data of the United Kingdom (UK), Oman, and Pakistan from 1991 to 2021 to investigate the impact of technological change and globalization on job polarization. The sources of this data are the United Nations Population Division (UNPD), World Development Indicators (WDI), Penn World Table (PWT), and Organization for Economic Co-operation and Development (OECD) Database.

Following the 'task-based' approach, we ranked the selected three countries based on WISE, where the UK has the highest level of skills, followed by Pakistan, which has the second-highest level of skills. Lastly, Oman has fewer skills than the UK and Pakistan. We categorize the countries into high-, middle-, and low-skilled levels and define the dependent variable for job polarization by calculating the ratio of net migration into the high-skilled United Kingdom relative to middle-skilled Pakistan, as outlined below.

$$ln\text{JCUK}_{it} = \ln(\frac{NM_{UK}}{NM_{PK}})_{it} \quad (1)$$

Equation (1) helps us get the first polar of job concentration in the high-skilled UK (JCUK) relative to the middle-skilled Pakistan.

Similarly, to capture job concentration in low-skilled Oman (LJCOM), we divide the net migration in Oman by the net migration in Pakistan as follows.

$$ln\text{JCOM}_{it} = \ln(\frac{NM_{OM}}{NM_{PK}})_{it} \quad (2)$$

Further, to measure the two forces of job polarization, we first measure technological innovation by calculating the total factor productivity growth (TFPG) for the selected three countries. Secondly, globalization is measured using the KOF Globalization Index (KOF Globalization Index), a composite metric that incorporates three dimensions—economic, political, and social—across nearly all countries worldwide. The index ranges from 1 (least globalized) to 100 (most globalized), developed by Dreher (2006) and later updated by Dreher et al. (2008). The revised index differentiates trade from financial globalization. In general, the index is the sum of 43 different variables, and these 43 variables are aggregated based on various dimensions. The variables are distributed in 27 different indices; hence, following Potrafke (2013), globalization indices averaged from 1991 to 2020 are used in this study. The other control variables are Employment (EMP), Exchange Rate (ER), Net Personal Remittances Paid (NPR), and Real Minimum Wage (RMW). A list of variables and their construction for both models is given in Table A1, Appendix.

The econometric models are given as follows:

$$lnJCUK_t = \alpha_0 + \alpha_1 lnTFPG_t + \alpha_2 ln\text{KOFGI}_t + \alpha_3 lnEMP_t + \alpha_4 lnER_t + \alpha_5 lnNPR_t + \alpha_6 lnRMW_t + \varepsilon_t \quad (5)$$

$$lnJCOM_t = \beta_0 + \beta_1 lnTFPG_t + \beta_2 lnKOFGI_t + \beta_3 lnEMP_t + \beta_4 lnWOP_t + \beta_5 lnNPR_t + \beta_6 lnPOP_t + \varepsilon_t \quad (6)$$

All the independent variables are constructed with the same formulas. The dependent variable in equation (5) is JCUK, which represents the job concentration in the UK relative to Pakistan. In contrast, the dependent variable in equation (6) is JCOM, which represents the job concentration in Oman relative to Pakistan. The term ε_t represents the error term, and *t* is for time.

Autoregressive Distributed Lag Model (ARDL)

This paper uses the auto-regressive distributed lag (hereafter ARDL) bounds testing approach proposed by Pesaran et al. (1999) and Pesaran et al. (2001). The ARDL approach offers several distinct advantages over other estimation methods (Engle & Granger, 1987; Johansen & Juselius, 1990). First, it accommodates variables integrated at levels I(0), I(1), or a combination thereof. Second, it facilitates simultaneous estimation of both short- and long-run dynamics. Third, ARDL remains effective even with small sample sizes. Lastly, selecting appropriate lag lengths it helps mitigate issues of endogeneity and serial correlation. Given these strengths, this study employs the ARDL co-integration technique to analyze long-run relationships among the variables. The specification of the model is presented below.

$$\begin{aligned} \Delta lnJCUK_t = {} & \phi_0 + \phi_1 lnJCUK_{t-1} + \phi_2 lnTFPG_{t-1} + \phi_3 lnGLOB_{t-1} + \phi_4 lnOERH_{t-1} \\ & + \phi_5 lnEMP_{t-1} + \phi_6 lnNPR_{t-1} + \phi_7 lnRMW_{t-1} + \sum_{i=1}^{p} \alpha_1 \Delta lnJCUK_{t-1} \\ & + \sum_{i=1}^{q} \alpha_2 \Delta lnTFPG_{t-1} + \sum_{i=1}^{q} \alpha_3 \Delta lnGLOB_{t-1} + \sum_{i=1}^{q} \alpha_4 \Delta lnOERH_{t-1} \\ & + \sum_{i=1}^{q} \alpha_5 \Delta lnEMP_{t-1} + \sum_{i=1}^{q} \alpha_6 \Delta lnNPR_{t-1} + \sum_{i=1}^{q} \alpha_7 \Delta lnRMW_{t-1} + \varepsilon_t \end{aligned} \tag{7}$$

In equation (7), Δ represents the differencing operator, $t-1$ represents the lagged value of each variable in the research. The optimal lags are determined by the Akaike Information Criterion (AIC).

The ARDL model verifies the presence of a long-term association among variables by testing several hypotheses. To be more specific, bounds testing is used to evaluate the significance of these correlations. A long-term association is suggested if the estimated F-statistic from this test is greater than the critical value of the upper bound. This methodological process ensures the robust investigation of long-term links, enabling the ARDL model to capture dynamic relations between time series variables efficiently. Hypotheses based on job concentration in the high-skilled UK are given in equations (8) and (9) as follows.

$$\text{H0} = \phi_0 = \phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi_5 = \phi_6 = \phi_7 = 0 \tag{8}$$

$$\text{H1} \neq \phi_0 \neq \phi_1 \neq \phi_2 \neq \phi_3 \neq \phi_4 \neq \phi_5 \neq \phi_6 \neq \phi_7 \neq 0 \tag{9}$$

Similarly, to investigate the job concentration in the low-skilled Oman (JCOM) due to technological innovations and globalization, the equation is given as follows.

$$\begin{aligned} \Delta \text{lnJCOM}_t = {} & \varphi_0 + \phi_1 \text{lnJCOM}_{t-1} + \varphi_2 \text{lnTFPG}_{t-1} + \varphi_3 \text{lnGLOB}_{t-1} + \varphi_4 \text{lnEMP}_{t-1} \\ & + \varphi_5 \text{lnWOP}_{t-1} + \varphi_6 \text{lnNPR}_{t-1} + \varphi_7 \text{lnPOP}_{t-1} + \sum_{i=1}^{p} \beta_1 \Delta \text{lnJCOM}_{t-1} \\ & + \sum_{i=1}^{q} \beta_2 \Delta \text{lnTFPG}_{t-1} + \sum_{i=1}^{q} \beta_3 \Delta \text{lnGLOB}_{t-1} + \sum_{i=1}^{q} \beta_4 \Delta \text{lnEMP}_{t-1} \\ & + \sum_{i=1}^{q} \beta_5 \Delta \text{lnWOP}_{t-1} + \sum_{i=1}^{q} \beta_6 \Delta \text{lnNPR}_{t-1} + \sum_{i=1}^{q} \beta_7 \Delta \text{lnPOP}_{t-1} + \varepsilon_t \end{aligned} \tag{10}$$

In the case of job concentration in Oman, all the variables are named and formulated in the same way, but the dependent variable is job concentration in low-skilled Oman (JCOM). The ARDL-mandated hypotheses listed below are investigated to determine the long-term connections.

$$\text{H0} = \varphi_0 = \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = \varphi_6 = \varphi_7 = 0 \tag{11}$$

$$\text{H1} \neq \varphi_0 \neq \varphi_1 \neq \varphi_2 \neq \varphi_3 \neq \varphi_4 \neq \varphi_5 \neq \varphi_6 \neq \varphi_7 \neq 0 \tag{12}$$

The bounds test is recommended by Pesaran et al. (2001) to identify the presence of long-run co-integration. The null hypothesis of no level relation is tested against the alternative hypothesis. If the calculated F-statistic exceeds the upper critical bounds value, we reject the null hypothesis (H0). Conversely, if the F-statistic lies between the critical bounds, the test result is inconclusive.

Finally, if the F-statistic is below the lower critical bounds value, it indicates the absence of co-integration. The short-run ARDL models employ the following error-correcting mechanism.

$$\begin{aligned} \Delta lnJCUK_t = \alpha_0 &+ \sum_{i=1}^{p} \sigma_1 \Delta lnJCUK_{t-1} + \sum_{i=1}^{q} \sigma_2 \Delta lnTFPG_{t-1} + \sum_{i=1}^{q} \sigma_3 \Delta lnGLOB_{t-1} \\ &+ \sum_{i=1}^{q} \sigma_4 \Delta lnEMP_{t-1} + \sum_{i=1}^{q} \sigma_5 \Delta lnOERH_{t-1} + \sum_{i=1}^{q} \sigma_6 \Delta lnNPR_{t-1} \\ &+ \sum_{i=1}^{q} \sigma_7 \Delta lnRMW_{t-1} + \phi ECT_{t-1} + \varepsilon_t \end{aligned} \qquad (13)$$

Equation (13) denotes the short-run variation in the parameters. The coefficient of the error correction term (ϕ) shows how quickly the system adjusts after facing a disturbance, with distinctive values dwindling between -1 and 0. Furthermore, to elaborate that each disruption is corrected and the system is adjusted back towards the equilibrium in the following period, the coefficient of the ECT should be negative and significant. This recommends that the system can efficiently return to its long-term equilibrium state and is sensitive to deviations.

Allowing the same strategy and steps of the equation as for the above theme. The following model is UECM, which is used to determine the long-run association among these variables in the case of job concentration in low-skilled OM relative to the middle-skilled PK (JCOM).

$$\begin{aligned} \Delta lnJCOM_t = \beta_0 &+ \sum_{i=1}^{p} \rho_1 \Delta lnJCOM_{t-1} + \sum_{i=1}^{q} \rho_2 \Delta lnTFPG_{t-1} + \sum_{i=1}^{q} \rho_3 \Delta lnGLOB_{t-1} \\ &+ \sum_{i=1}^{q} \rho_4 \Delta lnEMP_{t-1} + \sum_{i=1}^{q} \rho_5 \Delta lnWOP_{t-1} + \sum_{i=1}^{q} \rho_6 \Delta lnNPR_{t-1} \\ &+ \sum_{i=1}^{q} \rho_7 \Delta lnPOP_{t-1} + \varphi ECT_{t-1} + \varepsilon_t \end{aligned} \qquad (14)$$

We perform diagnostic tests to authenticate the model's stability, such as CUSUM and CUSUMSQ tests. Further, the Breusch-Godfrey LM serial correlation test is used to test the presence of serial correlation. This paper also uses normality and heteroscedasticity tests.

Job Market Concentration in the UK and Oman: Empirical Insights Relative to Pakistan

To estimate the models for job concentration in the high-skilled UK and Oman relative to the Middle-skilled Pakistan, we performed the unit root test to confirm the stationarity of the variables included in this model.

Before implementing the ARDL model, it is necessary to test the stationarity of the different series mentioned in the descriptive statistics; we apply the most famous unit root tests to check the stationarity: ADF, PP, and KPPS, respectively. Hence, to check the order of integration, we aim to ensure that none of the selected variables is integrated in order I (2). In addition, it confirms that the dependent variable is integrated of order I (1), and the integration of independent variables is the mixture of I (0) and I (1). Some variables are stationary at a level, while others are stationary at first differences. The results of the stationarity through the ADF, PP, and KPSS tests for variables based on job concentration in the UK and Oman relative to Pakistan are given in Tables A4 and A5 simultaneously. As a result of the stationarity test, we can now proceed with the ARDL bounds co-integration method.

ARDL Co-integration for Job Concentration in high-skilled UK Relative to Pakistan

Next, we check whether the long-run co-integration exists; for this purpose, we use the F-bonds test. Pesaran et al. (2001) recommend this test to identify the presence of long-run co-integration. Thus, Table 1 indicates that the calculated value of the F-statistic exceeds the upper bounds critical, confirming the long-term co-integration among the variables of interest.

Table 1: Bounds Test for Job Concentration in the UK Relative to Pakistan

F-Bounds Test		**H_0: No levels of relationship**		
Test Statistic	Value	Sig.	I(0)	I(1)
F-statistic	7.4686***	10%	1.99	2.94
K	6	5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99
Note: *** indicates significance at a 1% level.				

Thus, Table 1 shows that the calculated F-test value 7.468 exceeds the critical value of the upper bound, suggesting that long-run co-integration among research variables such as LJCUK, TFPG, GLOB, LEMP, LOERH, LNPR, and LRMW exists.

Hence, the confirmation of the existence of co-integration, we will now discuss the long and short-term association between the explained and explanatory variables. Tables 2 and 3 report the coefficients of the long-run and short-run, respectively.

The first job polarizing force is technological innovations; our finding shows that technological change is highly significant at a level of 1 percent and is positively associated with job concentration in the UK, both in the short run and long run. The long-run and short-run results show that a 1% increase in TFPG increases LJCUK significantly by 0.3123 and 0.138, respectively. Hence, it is confirmed that technological advancement in the UK complements the high-skilled Pakistani migrants and takes the form of job concentration. This result is in line with the RBTC hypothesis, empirically tested by several researchers (Autor et al., 2006; Deming, 2017; Echeverri-Carroll et al., 2018; Goos & Manning, 2007; Goos et al., 2014; Holm et al., 2020; Keller & Utar, 2023; Michaels et al., 2014). This result also confirmed that Pakistan, being a middle-skilled country, is hollowed out in terms of jobs and concentrates on the high-skilled UK.

The second job-polarizing force is globalization. This force is highly significant and positively related to job concentration in the UK in the short and long run. Hence, the long-run and short-run results show that a 1% increase in GLOB increases LJCUK by 0.0341 in the long run and by 0.0496 in the short run. Our result is supported by the existing literature (Breemersch et al., 2019; Goos et al., 2014; Keller & Utar, 2023). Globalization increases the concentration of jobs in the form of migrants due to different job opportunities. Developed countries like the UK attract high-skilled workers for high-skilled tasks, while job polarization creates demand for both high- and low-skilled workers. Until now, we have dealt with the concentration of high-skilled migrants in the high-skilled UK relative to middle-skilled Pakistan. However, the other side of the picture for complete job polarization will be discussed in the subsequent estimation of low-skilled job concentration in Oman.

Furthermore, the additional explanatory variables, such as employment LEMP, are highly significant at a level of one percent and positively affect the job concentration in the UK relative to Pakistan, both in the short and long run. The result shows that a 1% increase in LEMP increases the LJCUK by 0.4310 percent in the long run and by 0.331 percent in the short run. Employment opportunities in developed economies like the UK attract migrants worldwide, especially from countries that were colonised by Britain, like Pakistan. The UK attracts skilled labor by offering improved wages. security of jobs, providing professional opportunities, and raising their standard of living and financial security. Hence, Bongers et al. (2018) have concluded that high-skilled migrants from lower-income countries emigrate to high-income countries for better employment opportunities and higher wages.

The exchange rate LOER is significant at a level of 5 percent in the long run, while in the short run, it is highly significant at a 1 percent level of significance. LOER is positively related to LJCUK both in the short and long run. Thus, the long-run and short-run results show that a 1% change in the exchange rate will increase the LJCUK by 0.8319 and 0.0935. Hence, the exchange rate affects migration by disturbing the value of remittances sent home. A favorable exchange rate increases the local remittance amount, therefore incentivizing migration. however, it is concluded by the existing literature that the jolts of exchange rate negatively affect the real income of the migrants earned in the destination country (e.g., see Hanson & Spilimbergo , 1999; Mishra & Spilimbergo, 2011).

Table 2: Long Run Results for Job Concentration in the UK Relative to Pakistan

Selected Model: ARDL (2, 3, 3, 0, 3, 3, 3)				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**p-Values**
TFPG	0.3123***	0.0491	6.3541	0.0031
GLOB	0.0341***	0.0071	4.7982	0.0087
LEMP	0.4310***	0.0561	7.6752	0.0015
LOERH	0.8319**	0.5055	3.6236	0.0223
LNPR	0.6743**	0.1601	4.2096	0.0136
LRMW	-0.0001***	1.59E-	-6.6008	0.0027
C	18.3301***	0.8278	22.1406	0.0000
Note: ** and *** denote significance at 5% and 1%, respectively				

Net personal remittances LNPR are significant at 5 and 1 percent in the long and short run, respectively. The result shows that LNPR plays a positive role in job concentration in the UK compared to Pakistan. Hence, a 1% increase in LNPR in the long run increases the LJCUK by 0.6743 percent. Similarly, in the short run, a 1% increase in remittances increases the LJCUK by 0.569. Remittances are an important source of income for many families in South Asian labor-abundant countries like Pakistan. Remittances can be used directly to fund the economy or to reduce credit restraint in the home country (Adams & Cuecuecha, 2010; Giuliano & Ruiz-Arranz, 2009; Poirine, 1997). Hence, remittances are a pull factor that attracts skilled labor from lower-income countries into higher and technologically developed economies like the UK. Furthermore, remittance inflows also stimulate economic development, job creation, and investment opportunities, which draw in more migrants searching for excellent economic opportunities.

Lastly, the absolute minimum wage LRMW is highly significant at a level of one percent both in the short-run and long-run, and it is negatively related to the job concentration in the UK, but with a mild effect; the result shows that a 1% increase in the LRMW reduces the job concentration by 0.0001. Economically, we justify that a reduction in the minimum wage makes the destination country less attractive to migrants. Hence, lower wages reduce the prospective income migrants can receive, discouraging them from migrating. Minimum wage work is both a pull and push factor for migrants; a higher minimum wage pulls migrants into the destination country, while a lower minimum wage pushes migrants from the host country. Temporarily, it is noted by Boffy-Ramirez (2013) that the selection of the destination is sensitive to the changes in the minimum wage. Giulietti (2014) shows that the minimum wage appeals to legal migrants, while the illegal migrants are unaffected.

Table 3: Short Run Results for Job Concentration in the UK Relative to Pakistan

Selected Model: ARDL (2, 3, 3, 0, 3, 3, 3)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p-Values**
TFPG	0.13812***	0.008802	15.6919	0.0001
GLOB	0.0496***	0.0016	30.0729	0.0000
LEMP	0.3310***	0.0061	7.67529	0.0005
LOERH	0.0935***	0.4446	6.95654	0.0022
LNPR	0.5691***	0.0252	22.5804	0.0000
LRMW	-0.0001***	7.7502	-13.5756	0.0002
CointEq(-1)*	-0.5114***	0.0100	-50.8361	0.0000

Likewise, the last row of Table 3 reports that the lagged error correction term (ECT) is both significant and negative at the 1% level, specifying a necessary adjustment toward long-run equilibrium. The ECT displays that the speed of adjustment is 51.14%, meaning that around 51.14% of any deviation from the long-run equilibrium is corrected each period.

ARDL Co-integration for Job Concentration in Low-Skilled Oman Relative to Pakistan

Similarly, in the estimation of the second model, first after the stationarity test, we identify the long-run co-integration among the variables, and the null hypothesis of no level relation is tested against the level relation. The result in Table 4 shows that the F-statistic calculated value exceeds the upper bound's critical value, so we reject the null hypothesis with no level of relationship. Hence, the long-run association exists among the variables of interest, such as LJCOM, TFPG, LGLOB, LEMP, LWOP, LNPR, and LPOP.

After confirming the long-run association among the variables of interest, we obtained the long-run and short-run coefficients for job concentration in low-skilled Oman relative to middle-skilled Pakistan. The following tables, 5 and 6, report the long-run and short-run ARDL coefficients.

Table 4: Bounds Test for Job Concentration in Oman Relative to Pakistan

F-Bounds Test		**Null Hypothesis: No levels of relationship**		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	7.0700***	10%	1.99	2.94
K	6	5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99
Note: *** indicates significance at a 1% level.				

The result indicates a statistically significant effect of TFPG on job concentration in Oman LJCOM at a 1% significance level. Moreover, TFPG is positively related to job concentration in Oman in the long and short run. Precisely, a 1% increase in the TFPG, in the long run, increases the LJCOM by 3.868 percent, and a 1% increase in TFPG in the short run increases the LJCOM by 1.291 percent. Results are reported in Tables 5 and 6 for long-run and short-run results, respectively. Hence, technological innovations in Oman attract low- and middle-skilled Pakistani workers such as Carpenters, electricians, drivers, plumbers, and technicians. This result is in line with modern literature on job polarization. The RBTC hypothesis is based on the concept that technological innovations complement high and low-skilled workers while middle-skilled workers are substituted. In the case of this study in the first theme, we find that middle-skilled Pakistanis concentrate either in technologically developed or high-skilled UK. Now, getting the same result in the case of the concentration of middle-skilled Pakistanis in low-skilled Oman, the picture of job polarization is complete.

The second polarizing force is globalization; the result designates a statistically significant impact of GLOB on LJCOM at the 5% significance level. Specifically, a 1% increase in GLOB increases the job concentration in Oman relative to Pakistan by 1.243 percent in the long run. Similarly, the short-run result indicates that GLOB is highly significant at the level of 1%, and it is positively associated with job concentration in Oman. Hence, a 1% increase in GLOB increases the relative job concentration in Oman by 1.555 percent. Globalization is an essential factor and positively affects job concentration in Oman. This result completes the picture of job polarization by confirming the concentration of jobs in low-skilled Oman relative to middle-skilled Pakistan. Moreover, this result is to the existing literature on job polarization, which has shown that globalization polarizes the job market, see, for example, (Breemersch et al., 2019; Goos et al., 2014; Keller & Utar, 2023).

Table 5: Long Run Results for Job Concentration in Oman Relative to Pakistan

Selected Model: ARDL (1, 3, 3, 3, 0, 3, 3)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**p-Value**
TFPG	3.8685***	0.7495	5.1610	0.0036
LGLOB	1.2431**	0.3766	3.3008	0.0215
LEMP	3.1157***	0.6188	5.0345	0.004
LWOP	0.2933**	0.0909	3.2242	0.0234
LNPR	0.6656**	0.2148	3.0982	0.0269
LPOP	0.7076*	0.2988	2.3675	0.0641
C	40.7214***	5.6429	7.2163	0.0008
Note: ** and *** denote significance at 5% and 1%, respectively				

Furthermore, the result shows a statistically significant impact of Employment LEMP on LJCOM at the level of 1%, and it is positively related to the job concentration in Oman. Hence, a 1% increase in employment in the long run escalates the job LJCOM by 3.115 percent, as reported in Table 5. On the other hand, in the short run, the LEMP is highly significant at the 1% significance level, but it is negatively associated with LJCOM; a 1% increase in the LEMP in the short run decreases the LJCOM by 0.831. More excellent employment opportunities in the long run appeal to the migrants; as a result, job concentration takes place in that region with sufficient job opportunities. While in the short run, the abrupt influx of migrants floods the job market and, as a result, increases the competition for available job opportunities. The nexus between migrants and the Omani labor market is discussed by De Bel-Air (2015). Hence, in the case of this study, the empirical result shows that the long-run positive impact of LEMP on LJCOM is more significant than the short-run negative. Overall, increasing employment opportunities in the Omani labor market will be a pull factor for Pakistani low-skilled workers in the long run. As a result, we find that the Pakistani low-skilled workers are concentrated in the Omani labor market regarding migration. Meanwhile, De Bel-Air (2015) noted that in 2013, 87 percent of the foreign workforce was from Asian subcontinents such as Pakistan, India, and Bangladesh. In addition, the result on other factors indicates that the impact of WOP is statistically significant on LJCOM at the 1% significance level. Hence, the crude oil prices, in the long run, are positively associated with the job concentration in Oman LJCOM. It shows that a 1% increase in the price of crude oil in the international market increases the job concentration in Oman by 0.293 percent, see Table 5. Similarly, the impact of WOP on LJCOM is statistically significant. The result shows that a 1% increase in the WOP raises LJCOM by 0.193 percent, as shown in Table 6. Many studies have reported that after 1973, when Oman became an oil-producing nation, the demand for labor increased.

Moreover, it is concluded that the oil price is unevenly related to the outflow of remittances in the short and long run (Akçay, 2019). Hence, the increase in oil prices works as a pull factor for migrants from Oman's perspective. Since the 1970s oil boom, Pakistan has been sending a large number of workers to Middle Eastern countries, as noted (Arif & Amjad, 2014).

Table 6: Short Run Results for Job Concentration in Oman Relative to Pakistan

Variable	Coefficient	Std. Error	t-Statistic	p-Value
TFPG	1.2910***	0.0928	13.9081	0.0000
LGLOB	1.5551***	0.1556	9.9915	0.0002
LEMP	-0.8311***	0.1214	-6.84507	0.001
LWOP	0.1933***	0.0189	3.2242	0.0034
LNPR	0.3656***	0.0822	8.0921	0.0005
LPOP	0.7076***	0.0954	7.4164	0.0007
CointEq(-1)*	-1.4252***	0.0708	-20.1133	0.0000

Remittances are an essential determinant of the Pakistani economy. It is noted that remittances sent home have helped reduce the balance of payments and poverty (Aqeel & Aqeel, 2015). Furthermore, capital remittances are Pakistan's third leading source (Hasan & Raza, 2009). Our finding shows a statistically significant impact of LNPR on LJCOM at a 1% significance level. The long-run result reported in Table 5 shows that a 1% increase in LNPR increases the LJCOM by 0.665 percent.

Similarly, Table 6 reports the short-run results, which show that a 1% increase in the LNPR increases the LJCOM by 0.365 percent. The positive impact of LNPR on LJCOM in both long and short-run ARDL confirms that remittances play a crucial role in job concentration in low-skilled Oman. In 2016, the amount of remittances sent back home by migrants from developing countries was $413 billion. Remittances are a pull factor for the concentration of migrants because they are essential for improving their living standards, primarily when investing in health, sanitation, education, and infrastructure (UN, 2017).

Lastly, overpopulation is another critical economic push factor for migrants. Our result shows that the population in the impact of LPOP is statistically significant on LJCOM at the 1% significance level. The long-run ARDL result shows that a 1% surge in the POP increases the LJCOM by 0.707 percent both in the short-run and long-run; the results are reported in Tables 5 and 6, respectively. Let us consider that the subcontinent countries like India, Pakistan, and Bangladesh are overpopulated. The abundance of labor in these countries is the source of enlisting these countries into the list of labor-exporting countries. It is reported by De Bel-Air (2015) that as of May 27, 2015, Oman's population was about 4.19 million, with roughly 1.85 million (44.2%) being foreignborn nationals. Most foreign laborers come from the Asian subcontinent. Indians, Bangladeshis, and Pakistanis comprised 87% of the labor force in 2013.

The last row of Table 6 reports that the lagged error correction term (ECT) is both significant and negative at the 1% level, specifying an important adjustment toward long-run equilibrium. The ECT displays that the speed of adjustment is 1.425% and recommends that the adjustment be more than complete within one period. More specifically, the system adjusts 1.42 units in the following period for each divergence unit from the long-run equilibrium.

The CUSUM test, when functional to the error correction model (ECM) residuals, aids in assuring that the parameter estimates of the model hold over time. Hence, Figures 1 and 2 show that the models' parameters are stable across the sample period because the CUSUM statistic plot remains within the crucial limits, typically shown as a confidence band, like the 5% significance level. Besides the CUSUM test, we utilized the cumulative sum of squares (CUSUMSQ) test to judge the stability of our models. The same Figures show that our model is stable because CUSUMSQ tests separate statistics to remain within the critical bounds and specify the overall stability of the model. This means the probable parameters and their variances are steady over the period studied, adding confidence to the model's trustworthiness.

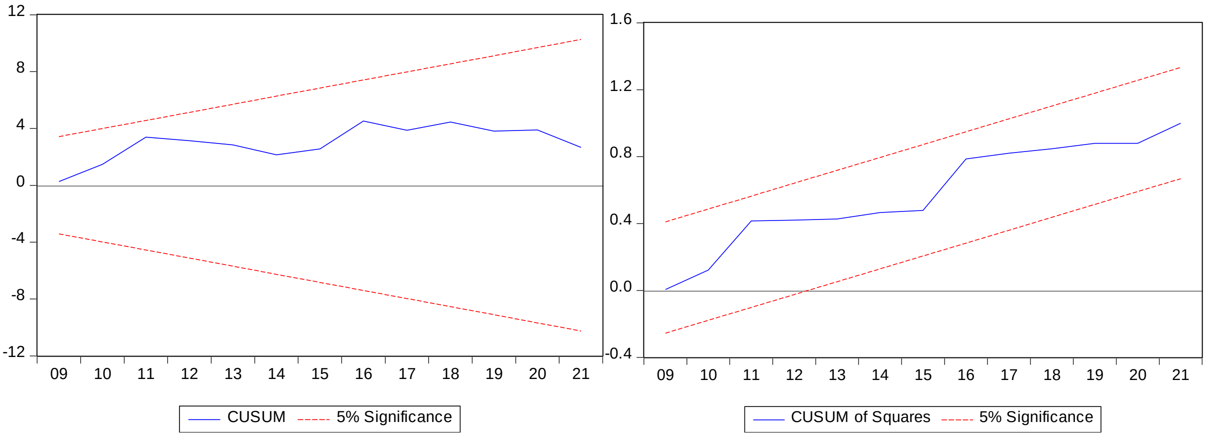

Figure 1: CUSUM Stability Test

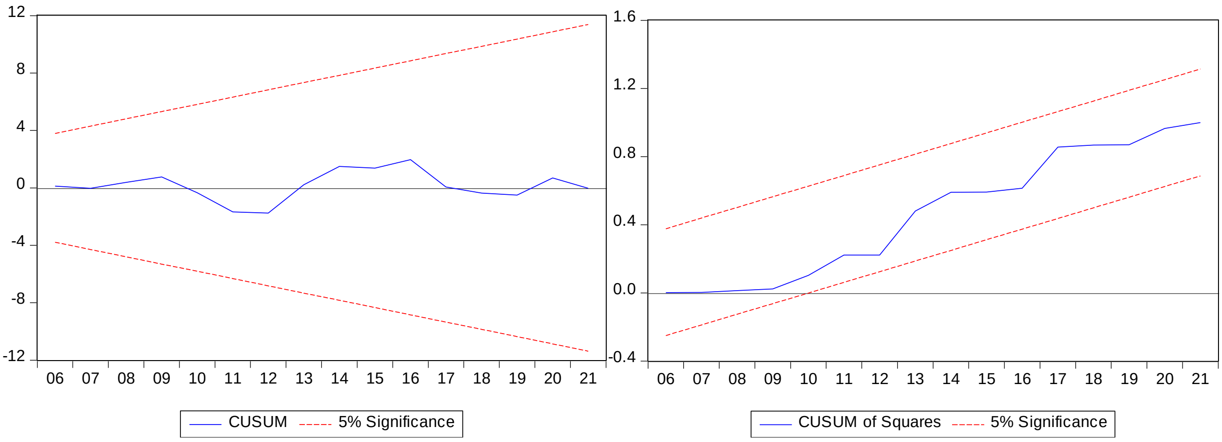

Figure 2: CUSUM-SQ Stability Test

In addition, to check whether the serial correlation exists, we perform the Breusch-Godfrey LM test and the normality and heteroscedasticity ARCH tests. The results of these tests are considered to determine the model's soundness and fitness. Hence, Table 7 reports the results of the diagnostic tests mentioned in this paragraph.

To ensure the validity and reliability of the model for job concentration in the UK relative to Pakistan, we perform several diagnostic tests reported in Table 7. The table's first row reports the serial correlation langrage multiplier (LM) test. The null hypothesis of this test is "there is no serial correlation in the residuals up to lag order p." " The acceptance and rejection of the null hypothesis is based on the p-value in this test. Therefore, the decision to specify model specification relies on the p-value obtained from the LM test, which confirms whether the time series residuals are serially correlated. Hence, in the case of this model, the p-value 0.1178 is more significant than 0.05, so we fail to reject the null hypothesis. This recommends that there is no indication of serial correlation in residuals.

Table 7: Diagnostic Tests for Job Concentration in The UK Relative to Pakistan

Diagnostic Tests for The Model of Job Concentration in The UK Relative to Pakistan		
Tests	**F-statistic**	**p-Value**
Serial Correlation LM	7.489667	0.1178
Hetero. Autoregressive Conditional Heteroscedasticity	2.566022	0.1217
Jarque-Bera Normality	5.9280	0.0516
CUSUM	Stability Confirmed	
CUSUM-sq	Stability Confirmed	
Diagnostic Tests for The Model of Job Concentration in Oman Relative to Pakistan		
Serial Correlation LM	2.4896	0.5178
Hetero. Autoregressive Conditional Heteroscedasticity	0.0474	0.8294
Jarque-Bera Normality	3.6106	0.7368
CUSUM	Stability Confirmed	
CUSUM-sq	Stability Confirmed	

Likewise, to detect the heteroscedasticity in the model, in the second row of Table 7, the Autoregressive Conditional Heteroscedasticity (ARCH) test is reported. The null hypothesis of this test is "there is no ARCH effect in the residuals up to lag order p." " In this case, the p-value reported in the second row of Table 7 is 0.1217, which is more significant than the 0.05 significance level; we fail to reject the null hypothesis. This result recommends no signs of ARCH effects in the residuals up to lag p; it confirms that the variance is constant over time, which means there is no heteroscedasticity in the model. In addition, the last test checks the normality of the model; we fail to reject the null hypothesis. As a result, the p-value from the Jarque-Bera test suggests that the residuals are distributed normally.

On the other hand, the lower part of the same table under the theme of diagnostic tests for the model of job concentration in Oman relative to Pakistan, reports the serial correlation langrage multiplier (LM) test. Hence, in the case of this model, the p-value 0.5178 is more significant than 0.05, so we fail to reject the null hypothesis. This recommends that there is no indication of serial correlation in residuals. Similarly, to identify the heteroscedasticity in the model, in the second row of Table 7, the Autoregressive Conditional Heteroscedasticity (ARCH) test is reported. In this case, the p-value reported in the second row of Table 7 is 0.8294, more significant than the 0.05 significance level; we fail to reject the null hypothesis. This result recommends no signs of ARCH effects in the residuals up to lag p; it confirms that the variance is constant over time, which means there is no heteroscedasticity in the model. The last test is to check the normality of the model; we fail to reject the null hypothesis. As a result, the p-value from the Jarque-Bera test suggests that the residuals are distributed normally.

Conclusion

In conclusion, the present study investigated the impact of technological innovations and globalization on job polarization in the selected three countries: the UK, Pakistan, and Oman. for relative analysis, we ranked the selected three countries based on WISE which ranked the UK as a high-skilled country, Pakistan as a middle-skilled, and Oman as a low-skilled country. Exhausting time series data from 1991 to 2021, we conducted estimations employing the ARDL co-integration methodology. After performing prerequisite tests, we employed this methodology separately on job concentration in the high-skilled UK relative to middle-skilled Pakistan and job concentration in low-skilled Oman relative to middle-skilled Pakistan.

The study finds a significant positive impact of technological innovations and globalization in job polarization in high-skilled UK and low-skilled Oman relative to middle-skilled Pakistan. It shows that Pakistan, being a middle-skilled country as compared to the UK and Oman, is becoming obsolete in terms of jobs, while the jobs are either concentrated in high-skilled UK or low-skilled Oman. The results of both models are aligned with the theory of job polarization a well-known RBTC hypothesis proposed by ALM.

Based on our findings, we suggest that Pakistani policymakers enhance and develop the skills of workers in the face of modern technology and a globalized world. To enhance the skills of the workers, we suggest that policymakers invest in education and skills training. From a globalisation point of view, it is recommended to ensure job growth in susceptible sectors and minimise reliance on imported goods. Furthermore, we propose to promote technological implementation programs to enable workers to be complemented by modern technology. Future researchers can deepen their understanding of this issue by investigating the socio-economic impact of job polarization on Pakistan.

This study divides skills into three categories: high, middle, and low, which may not fully portray the complexities of skill dynamics across industries. Furthermore, it concentrates on technological advancement and globalization, potentially ignoring other factors such as labor policies or demographic trends. The conclusions are further constrained by the quality and availability of data for the chosen nations and period. Future research could look into more detailed skill classifications, consider other potential factors, and use larger datasets to do a thorough analysis.

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Appendix

Table A1: List of Variables and Their Construction

Variable (Acronym)		**Sign of variable**	**Measurement**	**Expected impact on the dependent variable**	**Data source**
Dependent Variables	Job concentration in UK and Oman	$ln\mathrm{JCUK}_{it}$	$=(\frac{NM_{UK}}{NM_{PK}})_{it}$		Author formulation of variable
		$ln\mathrm{JCOM}_{it}$	$=(\frac{NM_{OM}}{NM_{PK}})_{it}$		
Core independent variable for technological change	Total factor productivity growth.	$TFPG_{\ it}$	$=\alpha lnAL_i^{\alpha} + \beta lnK_i^{\beta} + lne_i$	+ve	Author formulation of variable plus OWID
Core independent variable(s) for globalization	Globalization	$GLOB_{\ it}$	KOF Inex	-ve/+ve	KOF Swiss Economic Institute
Push-pull factors	employment	$LEMP_{it}$	number of person engaged in millions	+ve/-ve	WDI
	World Oil Prices	$LWOP_{it}$	measured in US dollars per cubic meter	+ve/-ve	WDI
	Net personal remittances	$LNPR_{it}$	Personal remittances received minus personal remittances paid.	+ve/-ve	WDI
	Real minimum wage	$LRMW_{it}$	Minimum wage adjusted for inflation.	+ve/-ve	WDI
	Official exchange rate	$LOER_{it}$	Official exchange rate (LCU per US$, period average)	+ve/-ve	WDI
	Population	$LPOP_{it}$	measured in millions.	+ve	PWT version 9.1

Table A2: Descriptive Statistics for Variables Based on Job Concentration in the UK Relative to Pakistan

	LJCUK	TFPG	GLOB	LEMP	LOERH	LNPR	LRMW
Mean	-0.13477	0.802433	55.21163	3.353418	0.641577	2.259075	9.887854
Median	-0.17607	0.822522	52.96435	3.367028	0.639661	2.271454	9.905313
Maximum	0.897664	1.868843	64.66513	3.465126	0.783445	2.284081	10.13143
Minimum	-0.84134	0.040243	45.29981	3.225449	0.499772	2.213058	9.687379
Std. Dev.	0.411578	0.473207	5.508913	0.07604	0.073946	0.023344	0.128351
Skewness	0.896036	0.441797	0.193283	-0.18558	0.312301	-0.95828	0.397152
Kurtosis	3.260367	2.356959	1.932326	1.792269	2.541996	2.34183	2.06368
Jarque-Bera	4.23578	1.54256	1.665425	2.061985	0.774866	5.304044	1.947337
Probability	0.120285	0.462421	0.434868	0.356653	0.678797	0.070509	0.377695
Sum	-4.17773	24.87543	1711.561	103.9559	19.88887	70.03133	306.5235
Sum Sq. Dev.	5.081903	6.717737	910.4437	0.173462	0.164039	0.016348	0.494217
Observations	31	31	31	31	31	31	31

Table A3: Descriptive Statistics for Variables Based on Job Concentration in Oman Relative to Pakistan

	LJCOM	TFPG	LGLOB	LEMP	LWOP	LNPR	LPOP
Mean	-0.0499	0.082749	4.533205	1.285625	5.547356	21.93767	2.976999
Median	-0.02525	0.074077	4.542402	0.822864	5.617059	21.7486	2.582991
Maximum	0.279256	0.263183	4.723337	2.539751	6.554475	23.12033	4.636262
Minimum	-0.61149	0.004427	4.353997	0.473216	4.381764	20.62926	1.893771
Std. Dev.	0.140631	0.066334	0.101824	0.723013	0.684651	0.869028	0.896005
Skewness	-1.87031	1.242362	-0.13895	0.56366	-0.0753	0.112745	0.61842
Kurtosis	3.260367	2.156959	2.172039	1.629518	1.620219	1.300507	1.804856
Jarque-Bera	4.53578	1.24256	0.985216	4.06755	2.488368	3.796364	3.820936
Probability	0.130285	0.662421	0.611031	0.130841	0.288176	0.149841	0.148011
Sum	-1.54681	2.565221	140.5294	39.85437	171.968	680.0678	92.28696
Sum Sq. Dev.	0.593309	0.132006	0.311041	15.68242	14.0624	22.6563	24.08472
Observations	31	31	31	31	31	31	31

Table A4: Stationarity test for the variable used in the model based on job concentration in the UK relative to Pakistan

	ADF		**PP**		**KPSS**	
Variable	**Level**	**First Difference**	**Level**	**First Difference**	**Level**	**First Difference**
LJCUK	no	0.000***	no	0.000***	no	no
TFPG	0.000***	0.000***	0.000***	0.000***	0.140*	0.500**
GLOB	no	0.001***	no	0.000***	no	0.452*
LEMP	0.080*	0.004***	no	0.004***	no	no
LOERH	No	0.049**	no	0.031**	0.142*	no
LNPR	No	0.000***	no	0.000***	0.161**	no

LRMW	No	0.000***	no	0.002***	0.125*	no
Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant						

Table A5: Stationarity test for the variable used in the model based on job concentration in Oman relative to Pakistan

	ADF		**PP**		**KPSS**	
Variable	**Level**	**First Difference**	**Level**	**First Difference**	**Level**	**First Difference**
LJCOM	0.094*	0.000***	0.029**	0.000***	no	0.274***
TFPG	0.000***	0.000***	0.000***	0.000***	0.134*	0.215**
GLOB	No	0.000***	no	0.000***	0.176**	0.483***
LEMP	No	0.004***	no	0.004***	0.152**	no
LWOP	No	0.000***	no	0.000***	0.131*	no
LNPR	No	0.023**	no	0.017**	no	0.124*
LPOP	0.014**	0.0032***	no	0.002***	0.155**	n0
Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant						