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Industrialization Dynamics in Organization of Islamic Cooperation (OIC) Countries: Evidence from the Club Convergence Approach

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Abstract: The primary objective of this study is to scrutinize the industrialization patterns across 36 member states of the Organization of Islamic Cooperation (OIC) spanning from 1990 to 2021, adopting a club convergence approach. This study employed the Competitive Industrial Performance (CIP) index developed by the United Nations Industrial Development Organization. The CIP index serves as a yardstick for assessing countries' effectiveness in manufacturing and exporting industrial goods, facilitating comparisons of industrial competitiveness across nations. The empirical findings derived from the convergence methodology established by Phillips & Sul (2007, 2009) unveiled the absence of convergence in CIP among OIC countries yet delineate the existence of four distinct convergence clusters. Notably, the CIP scores of countries exerted a significant influence on the formation of these clusters, with member states within the same cluster exhibiting comparable CIP performances. This outcome underscored the persistent dual structure characterizing the OIC panel, wherein nations with lower CIP standings failed to converge toward those with higher performance levels.

Keywords: Convergence, Club Convergence, Competitive Industrial Performance Index, Manufacturing Industry, Organization of Islamic Cooperation

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Introduction

The Industrial Revolution, an 18th-century phenomenon that transformed the economic landscape of Western countries, led to a remarkable increase in their overall welfare by unprecedented productivity gains. Accordingly, the industrial sector has historically been called the "engine of growth" due to its contribution to productivity, trade, employment, and innovation (Kaldor, 1966, 1967; Tregenna, 2008). Manufacturing activity remains cornerstone of development, driving economies, technological progress, and societal transition. Hence, industrial development is a means of increasing productive capacity and an effective way of improving living standards and ensuring environmental sustainability (United Nations Industrial Development Organization-UNIDO, 2020a). In addition, the industrial sector generates tradable goods and can swiftly join global production networks, facilitating the transfer of technology. Even if certain countries' industrial sectors focus solely on domestic markets, they face competition from proficient foreign suppliers, compelling them to enhance operations and bolster production efficiency. Therefore, increasing competitiveness in the industrial sector is one of the top priorities on the development agenda of many countries. In 2015, the United Nations (UN) adopted the resolution "Transforming our world; the 2030 Agenda for Sustainable Development," which covers 17 Sustainable Development Goals (SDGs) to be accomplished by 2030 (UN, 2015). Among the 17 SDGs, SDG-9 on "*industry, innovation, and infrastructure, which aims to build resilient infrastructure, promote inclusive and sustainable industrialization, and strengthen innovation*" is one of the most significant objectives regarding interaction with other goals. Indeed, SDG-9 plays a pivotal role in advancing various other objectives, encompassing socio-economic targets (such as SDG-1 "End Poverty," SDG-2 "Zero Hunger," SDG-5 "Gender Equality," SDG-8 "Decent Work and Economic Growth," and SDG-10 "Reduced Inequalities"), as well as environmental aspirations (including SDG-7 "Affordable and Clean Energy," SDG-11 "Sustainable Cities and Communities," SDG-12 "Responsible Production and Consumption," SDG-13 "Climate Action"). Beyond its profound effects on economic advancement and its role in facilitating the achievement of the SDGs, the industrial sector serves as a bastion of resilience, mitigating the detrimental effects of crises on national economies. The COVID-19 has disproportionately impacted countries with the least developed industrial infrastructure (UNIDO, 2022).

Another pivotal attribute of the industrial sector is elucidated within the context of the convergence concept, a fundamental tenet of neo-classical growth theory. It is widely recognized that the industrial sector fosters productivity enhancement in a more systematic manner than other sectors. This is evidenced by the diminishing cross-country disparities in labor productivity within the manufacturing industry over time, a trend not mirrored in other sectors. For example, approximately half of the decline in cross-country productivity differentials can be attributed to substantial productivity advancements in the manufacturing industry (Rodrik, 2013; Duarte & Restuccia, 2010). The present study aims to assess the convergence dynamics in industrial performance among the member nations of the Organization of Islamic Cooperation (OIC). Following the United Nations, the OIC currently stands as the world's second-largest international organization, boasting a membership of 57 nations. Encompassing 24.3 percent of the Earth's landmass and approximately 25.1 percent of the global population, the member nations of the OIC wield significant influence. Their collective economic output accounts for 9.2 percent of the world's GDP, bolstered by extensive reserves of oil and natural gas. With a per capita GDP of $4,550, the organization endeavors to foster trade and economic collaboration among its members, with the ultimate goal of achieving economic integration and establishing an Islamic common market. Through these efforts, the OIC seeks to ensure sustainable human development and foster economic prosperity across its member nations. Moreover, the organization's ten-year action plan, initiated in 2015, endeavors to enhance the local production and export capabilities of OIC economies by concentrating on value-added sectors, such as "a*griculture, manufacturing, maritime, and services*." The execution strategy of this action plan encompasses various initiatives aimed at achieving these objectives, including fostering investments and pioneering solutions for the advancement of modern and cost-effective technologies adaptable to industry and local contexts. Additionally, it entails forging strategic alliances with a diverse array of stakeholders, encompassing the private sector, academia, and other research institutions and foundations, to bolster industrialization and innovation efforts (OIC, 2016a; OIC, 2016b).

The present study contributes to existing literature in two ways. First, the paper is the first to investigate the industrial convergence dynamics in OIC nations by employing the competitive industrial performance (CIP) index as a proxy for industrial performance. The CIP Index, introduced by UNIDO, consists of three dimensions and six key indicators aligned with these dimensions. It gauges the success of a country's industries in manufacturing and marketing goods both domestically and internationally as their technological sophistication advances. The first dimension encompasses sub-indicators reflecting production and export capacity, specifically manufacturing industry value added per capita and manufacturing industry exports per capita. The second dimension comprises indicators about the level of technological advancement and progression, including industrialization intensity and export quality. The third dimension assesses a country's impact on the global manufacturing industry, as indicated by its share in the world manufacturing industry value added and exports. These six indicators are equally weighted to derive the Competitive Industrial Performance Index (UNIDO, 2017). The CIP index provides robust policy signals by pointing to obstacles in countries' industrial development processes and enables cross-country comparisons of industrial competitiveness (UNIDO, 2020a). There is also a close connection between industrial competitiveness and the SDGs (UNIDO 2017; UNIDO, 2018; UNIDO, 2019; UNIDO, 2020a; UNIDO, 2020b). This relationship is demonstrated by the overlap of production capacity, export capacity, and technology-deepening indicators measuring competitiveness with SDG 9.2.1, SDG 17.11.1, and SDG 9.B.1, respectively (UNIDO, 2020a). Second, this study investigates the convergence dynamics of the OIC nations based on the Club Convergence Hypothesis using the Phillips & Sul (PS hereafter) (2007, 2009) approach. This technique provides a novel framework for evaluating both the club convergence hypothesis and general convergence while also considering heterogeneities in technological advancement and convergence speed.

The remainder of this study proceeds as follows: Section 2 summarizes the theoretical background and empirical literature. Section 3 assesses the OIC nations based on the value added, employment, and competitive industrial performance. Section 4 explains the methodology and dataset. Section 5 discusses the empirical findings, and section 6 concludes with policy implications specific to OIC nations.

Theoretical Background and Literature Review

The convergence theory, the most prominent implication of Solow's (1956) Neo-classical Growth Model, contends that the lower a country's or region's per capita income level compared to other countries or regions, the greater its growth potential and thus convergence to rich countries or regions. The primary reason for the development of this process is that, under closed-economy conditions, impoverished nations' low capital stock has a slower decreasing marginal return than affluent countries.

The convergence hypothesis proposes the existence of absolute, conditional, and club convergence approaches. Conditional convergence refers to the convergence that depends on countries having similar characteristics. In contrast, absolute convergence refers to the convergence of the countries or units analyzed in the long term, regardless of initial conditions. The club convergence approach conceptualized by Baumol (1986), Durlauf and Johnson (1995), and Galor (1996), which has a multiple equilibrium approach, argues that "*a set of economies with similar conditions and structural characteristics (such as technology, preferences, political systems) will tend to converge towards the same steady state*" (Islam, 2003). Quah (1996) and Galor (1996) have also made notable contributions to formulating this type of convergence.

However, PS introduces a new approach to test the club convergence hypothesis and the general convergence hypothesis. This approach is based on the Solow growth model but considers heterogeneities in technical progress and convergence rate. The PS approach has a wide range of applications, including examining basic macroeconomic indicators and analyzing convergence dynamics in fields, such as "*ecology, energy, agriculture, tourism, security, demography, digital infrastructure, education, health, and accounting*" (Tomal, 2023).

The empirical literature on the dynamics of convergence in the industrial sector is quite limited. Duarte and Restuccia (2010) analyze how sectoral labor productivity influences the process of structural transformation and the trajectory of overall productivity across nations throughout time. Their findings indicate that approximately half of the narrowing productivity gaps between countries can be attributed to significant productivity increases within the manufacturing sector. Rodrik (2013) examines the patterns of unconditional convergence within the industrial (manufacturing) sector across 118 countries from 1965 to 2005. Based on the panel regression approach, the study finds compelling evidence supporting unconditional convergence in labor productivity within the manufacturing industry. The study suggests that this outcome is attributed to the inherent characteristics of the manufacturing sector. Erten and Schwank (2021) investigate unconditional convergence within the manufacturing sector, emphasizing variations in technology intensity among industries. Utilizing the panel regression approach, the authors indicate that low and medium-technology-intensive industries in Sub-Saharan African and Latin American countries exhibit a slower convergence pace than their counterparts in high-technology-intensive nations. The study's empirical results, which reveal the absence of a notable gap in the convergence of low-technology sectors across Asian economies, indicate that medium-technology-intensive sectors undergo swifter convergence compared to high-technology ones. Furthermore, in developed economies, low-technology sectors exhibit a comparatively slower convergence, while medium-technology sectors tend to converge at similar rates to high-technology sectors. The study's conclusions indicate that the variances observed among countries are attributed to the growing interconnectedness on a global scale, wherein this global integration offers developing nations the chance to participate in competition within the international market. Dong et al. (2021) explore the influence of industrial convergence on energy efficiency within the manufacturing sector of newly industrializing countries. Based on the spatial autoregressive joint model, the research reveals that industrial convergence enhances the energy efficiency of the manufacturing sector by fostering spillover effects derived from imitation and learning. Furthermore, the study asserts that technological innovation serves as a potent avenue for the emergence of industrial convergence dynamics. Additionally, it is assessed that industrial convergence not only directly impacts technological innovation but also indirectly influences it through the expansion of industrial scale and optimization of factor structure, thereby enhancing energy efficiency. Lastly, Saba and Ngepah (2023) examine the convergence trends within the industrial sector across 183 countries spanning from 2000 to 2018. Employing the log-t convergence test method devised by PS (2007; 2009), the study's empirical results demonstrate the absence of convergence behavior in the industrial sector across the entire dataset. However, the analysis identifies six distinct convergence clusters. The study highlights the significant role of economic, demographic, governance, and geographical factors in shaping the composition of these convergence clubs.

It is worth noting that there is a scarcity of studies addressing the convergence hypothesis, specifically within the OIC nations. Most of these studies utilize diverse indicators and primarily focus on countries in the MENA region, which has remained under-researched. However, they typically test the convergence hypothesis solely concerning income (Guetat & Serranito, 2007; Erlat, 2007; Tunali & Yilanci, 2010), ecological footprint (Arogundade et al. 2023), and military burdens (Yilanci et al. 2020). The OIC countries intend to construct an Islamic unified market in the future. To achieve this aim, income convergence is a critical component of the economic integration process. However, only two studies have explored the income convergence hypothesis for the OIC group (Gunduz et al., 2021; SESRIC, 2013). To our knowledge, no study has been conducted on industrial convergence. Moreover, empirical studies utilizing the CIP Index have investigated its effects on environmental quality (Caglar & Askin, 2023; Caglar et al., 2023a; Caglar et al., 2023b). In this context, this study is anticipated to enrich the current body of literature concerning the variables utilized and the econometric methodology employed.

Manufacturing Sector in the OIC Nations

The proportion of value-added within the overall industry and manufacturing sectors offers valuable insights into the economic structure of the OIC nations. As is seen in Table 1, 9.2 percent of global value-added comes from the OIC nations. Upon evaluating the distribution of total value-added within the OIC between the overall industry and manufacturing sectors, the industrial sector accounts for 22.7 percent as of 2021. Meanwhile, the manufacturing sector, known for its higher potential for productivity and competitiveness gains, stands at 17 percent. At the national level, this sector contributes to 35% of the total value-added in Turkmenistan and between 20-24% in Bangladesh, Indonesia, Malaysia, Suriname, and Türkiye (SESRIC, 2022; SESRIC, 2023).

Table 1

Total Value Added in OIC

	Total Value Added (Current Prices-Billion USD)		Share in Total Value-Added (Current Prices) (%)			
			Industry		Manufacturing	
	OIC	% of World	OIC	World	OIC	World
2000	1,648	5.1	35.1	23.5	15.6	17.3
2005	2,895	6.4	37.7	23.1	14.5	17.0
2010	5,454	8.6	35.5	27.7	13.8	16.7
2015	6,419	8.9	28.4	22.4	14.3	17.0
2020	7,168	8.7	28.4	21.5	16.0	16.5
2021	8,599	9.2	31.0	22.7	16.1	17.0

Source: SESRIC (2023)

Another significant indicator that reveals the OIC's structural transformation process is employment's sectoral distribution. Table 2 indicates that the shares of agriculture, industry, and services sectors in total employment in 2021 are 31.7 percent, 21.1 percent, and 47.2 percent, respectively. Table 2 also depicts that the employment share of the industrial sector increased from 16.9% to 21.1% from 2000 to 2021.

Table 2

Distribution of Sectoral Employment in OIC Countries

	Total Value-Added (Current Prices-Billion USD)		Share in Total Value-Added (Current Prices) (%)			
			Industry		Manufacturing	
	OIC	% of World	OIC	World	OIC	World
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Source: SESRIC (2023)

The performance of the industrial sector in the OIC nations can be assessed comprehensively by focusing on the CIP Index, which has three dimensions with six leading indicators. The first dimension of the index consists of the sub-indicators for manufacturing industry value added and manufacturing industry exports per capita. These sub-indicators demonstrate the production and export capacity. The second dimension includes indicators related to technological deepening and progress. The sub-indicators of this dimension are industrialization intensity and export quality. In the third dimension, the effect of the country on the world manufacturing industry is assessed by its proportion in the world manufacturing industry value-added and exports. The CIP index, therefore, is obtained by combining these six indicators with the same weight.

Table 3

Dimensions and Indicators of the CIP Index

1st Dimension:	Capacity to Produce and Export
1.	Manufacturing Value Added Per Capita
2.	Manufacturing Exports Per Capita
2nd Dimension:	Technological Deepening and Upgrading
3.	Industrialization Intensity
4.	Export Quality
3rd Dimension:	World impact
5.	Country-specific Impact on World Manufacturing Value Added
6.	Country-specific Impact on World Manufacturing Exports

Source: UNIDO (2017).

Table 4 presents the ranking of the OIC economies based on the average CIP Indexes between 1990-2021. As shown in the table, Malaysia is the best-performing country, followed by Türkiye, Saudi Arabia, Indonesia, and the United Arab Emirates. At the same time, Albania, Tajikistan, Uganda, Niger, and Mozambique are the lowest performers.

Table 4

Competitive Industrial Performance Index Ranking in OIC Countries

Rank	Country	CIP	Rank	Country	CIP
1	Malaysia	0.167	19	Lebanon	0.021
2	Turkiye	0.109	20	Uzbekistan	0.018
3	Saudi Arabia	0.084	21	Cote d'Ivoire	0.017
4	Indonesia	0.080	22	Libya	0.017
5	United Arab Emirates	0.069	23	Algeria	0.017
6	Qatar	0.064	24	Syrian Arab Republic	0.014
7	Bahrain	0.063	25	Senegal	0.014
8	Kuwait	0.057	26	Azerbaijan	0.012
9	Tunisia	0.040	27	Suriname	0.010
10	Iran	0.038	28	State of Palestine	0.010
11	Morocco	0.037	29	Gabon	0.010
12	Kazakhstan	0.036	30	Cameroon	0.009
13	Egypt	0.035	31	Kyrgyzstan	0.009
14	Oman	0.035	32	Albania	0.008
15	Jordan	0.030	33	Tajikistan	0.008
16	Pakistan	0.027	34	Uganda	0.005
17	Bangladesh	0.026	35	Niger	0.004
18	Brunei Darussalam	0.026	36	Mozambique	0.004

Note: The table covers 36 of 57 OIC nations because of data availability for the examination period, 1990-2021.

Data and Methodology

The present study explores the convergence dynamics of competitive industrial performance in OIC nations. The study focuses on 57 of 36 OIC nations because of data availability and covers the period spanning from 1990 to 2021, as the CIP index values are available for this period. The CIP indexes of selected countries are gathered from the UNIDO database. In the empirical investigation, this study utilizes the club convergence approach introduced by PS to determine the convergence dynamics of the CIP index series of the OIC countries. The convergency hypothesis can be explained by the following equation (PS, 2007):

$$X_{it} = g_{it} + \alpha_{it} \qquad (1)$$

where $X_{it}X_{it}$ representing the variable of interest (in our case, CIP index in OIC nations) consists of two dimensions ($g_{it}g_{it}$ and $\alpha_{it}\alpha_{it}$). $g_{it}g_{it}$ shows the systematic components and $\alpha_{it}\alpha_{it}$ shows transitory components. ii and tt show cross-sectional dimensions and time, respectively. Since the systematic and transitory components in equation 1 are assumed to include both common and idiosyncratic elements, the following transformation can be applied (PS, 2007):

$$X_{it} = \left(\frac{g_{it+}\alpha_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t, \quad \textit{for all } i \textit{ and } t, \qquad (2)$$

Equation 2 above presents the dynamic factor model, wherein $X_{it}X_{it}$ is decomposed into two time-varying components. The first component is the common trend function with deterministic or stochastic behavior, i.e., the common factor component in the panel ($\mu_t\mu_t$), while the second component is the idiosyncratic component (δit), which measures the relative share of country *i* in $\mu_t\mu_t$ at time *t*, i.e., the unit gap between the common trend component $\mu_t\mu_t$ and $X_{it}X_{it}$. In this context, it can be argued that the $\mu\mu$ factor is common across countries, whereas the transition dynamics of countries are represented by the $\delta_{it}\delta_{it}$ components that allow for heterogeneity across time and units.

The main purpose of the club convergence approach of PS (2007, 2009) is to investigate whether the variable $X_{it}X_{it}$ exhibits a single equilibrium state convergence for $t \to \infty$ under the assumption that convergence is a dynamic process (Apergis et al., 2013). In this context, the estimation of $\delta_{it}\delta_{it}$ holds significant importance in investigating the existence of convergence since the transition paths to the equilibrium state may differ significantly across countries. Since it is not possible to estimate the relevant component without applying additional structural constraints and assumptions, the following alternative approach to modeling transit routes is suggested (PS, 2007, 2009):

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}} \qquad (3)$$

$h_{it}h_{it}$, known as the relative transition path in the equation, measures the transition path for country *i* relative to the average of the panel at time *t* by removing the common trend factor and can be calculated directly using the data in the panel. In other words, $h_{it} h_{it}$ captures the behavior of individual countries in relation to other countries and measures the relative deviation of each country in the panel from the common trend or long-run equilibrium state path, $\mu_t \mu_t$. Here, as $t \to \infty$, when all countries in the panel move towards the same transition path ($\delta_{it} \delta_{it} \to \delta$), i.e., in the presence of convergence, the relative transition parameter converges towards $h_{it} h_{it} \to 1$ and the cross-sectional variance of $h_{it} h_{it}$ converges towards $H_{it} = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2 \ \to 0 H_{it} = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2 \ \to 0$ (PS, 2007, 2009). In this regard, relative transit path plays an important role in determining the divergence and assessing whether this divergence is temporary.

To examine whether the club convergence hypothesis is valid in the panel data set, a semi-parametric model is applied to the transition coefficients, $\delta_{it} \delta_{it}$, allowing for heterogeneity across time and units as follows:

$$\delta_{it} = \delta_i + \delta_{it} \xi_{it,} \quad \sigma_{it} = \frac{\sigma_i}{L(t) t^{\alpha}}, \quad t \geq 1, \qquad \delta_i > 0 \quad for\ all\ i, \tag{4}$$

Here, $\delta_i \delta_i$ is the time-invariant part of the countries' unique factor loadings ($\delta_{it} \delta_{it}$), $\sigma_{it} \sigma_{it}$ is the unique scale parameter, $L(t L(t)$ is a gradually expanding and diverging function at infinity ($t \to \infty$ while $L(t L(t) \to \infty$), α is the speed of convergence and $\xi_{it} \xi_{it}$ represents a random variable with an independent identical distribution with zero mean and constant variance. Considering the equation 4, the null hypothesis expressing the presence of convergence for $i=1,2,..,N$ is $H0$: $\delta i=\delta$ and $\alpha \geq 0$; The alternative hypothesis is established as $H1$: $\delta i \neq \delta$ and $\alpha < 0$ (PS, 2007; 2009).

The log-t test equation used to test the presence of convergence between countries and to determine convergence clubs is shown in equation 5 below:

$$log \frac{H_1}{H_t} - 2log[\log(t)] = \alpha + \beta \log(t) + u_t, \quad t = [rT] + 1, \dots, T \tag{5}$$

Here $H_1 H_1$ is the change at the beginning of the sample ($t=1$); $H_t H_t$ indicates the change at every point in time ($t=1,2,\dots,T$). In addition, $L(t)= \log(t+1) \log(t+1)$ and $\beta\ \beta$ parameter represents the convergence speed ($\hat{\beta} = 2\hat{\alpha} \hat{\beta} = 2\hat{\alpha}$). The $r r$ in the equation corresponds to a positive value in the range (0,1] and is used to remove the first observation block from the prediction before the log-t test equation is estimated. This data generation process allows focusing on the transition dynamics of the next period in relation to the intended asymptotic properties of the test. For the results of Monte Carlo simulations, it is recommended to take r = 0.3 for small samples and r = 0.2 for large samples. The null hypothesis expressing the existence of convergence is tested with a one-sided t-test based on consistent standard errors against heteroskedasticity and autocorrelation. If the calculated log-t test statistic is less than the critical value ($t\hat{\beta}t\hat{\beta} < -1.65$) at the 5% significance level, the null hypothesis is rejected, and it is concluded that there is no convergence in the entire panel considered.

If convergence is not observed across the entire panel, a clustering algorithm is employed to investigate the presence of different convergence clubs, with the determination of sub-clubs that converge to each other (PS, 2007; 2009). In cases where convergence is rejected, PS (2007) proposes a four-stage algorithm to identify convergence clubs within a panel. The flow chart outlining this algorithm is depicted in Figure 1. In the initial stage of the PS (2007) approach, panel data are sorted in descending order based on the latest observations. Subsequently, in the second stage, commencing with the highest-ranked country, neighboring states are sequentially added from the ordered list, and the model outlined in equation 5 is estimated. In the next stage, the core group, $G_k G_k$, is identified by maximizing the convergence t-statistic value, ensuring it exceeds -1.65. Moving on to the third phase of the algorithm in question, the remaining countries are incorporated into the core group one by one, and the model articulated in equation number 3 is recalculated for each addition. The sign criterion (t-statistic >0) is employed to determine whether a country is eligible to join the core group. In the concluding stage, the second and third steps of the algorithm are reiterated iteratively for the remaining countries. This iterative process continues until no further clubs can be formed. Ultimately, if the final group obtained does not conform to a convergence model, it is inferred that its members exhibit divergence.

PS (2009) posits that incorporating the sign requirement during the second phase of the algorithm might lead to an overestimation of the number of clubs. To address this concern, PS (2009) advocate for conducting club merging assessments subsequent to implementing the algorithm using the model delineated in equation 5. In the initial phase of this revised algorithm, the log (t) test is utilized for the first two clubs identified in the primary clustering mechanism. Should the t-statistic surpass -1.65, these groups amalgamate to form a new convergence club. In the subsequent phase, this test is reiterated with the inclusion of the subsequent club, and this process continues until the fundamental criterion (t-statistic > -1.65) is satisfied. If the convergence hypothesis is refuted, it implies that all preceding clubs have converged except for the final one. Consequently, the merging algorithm recommences from the club where the convergence hypothesis is invalidated (Sichera & Pizzuto, 2019).

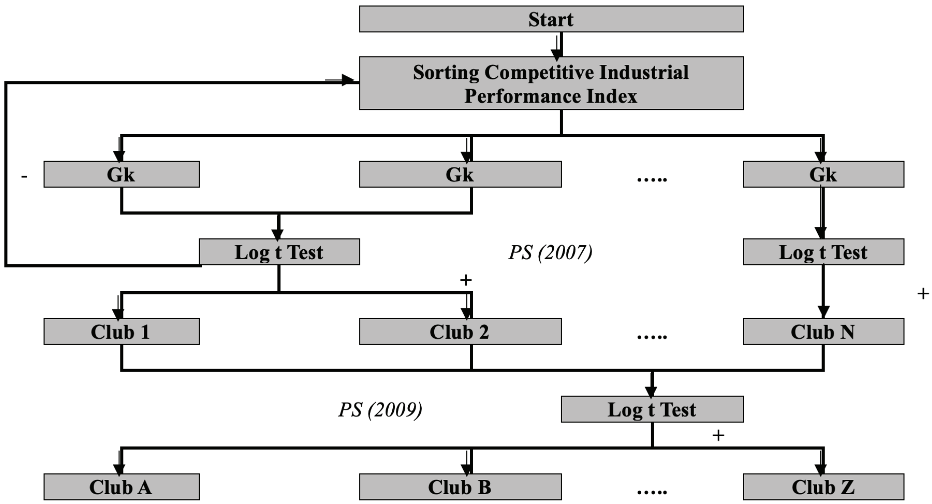

Figure 1: *Club Convergence Test Analysis Flow Chart*

Note: Club convergence test flow chart is adapted from the studies of Bangjun et al. (2023) and He et al. (2023).

Empirical Findings

Club convergence findings of the competitive industrial performances of the OIC countries are presented in Tables 5 and 6. In the framework of the club convergence approach, failing to discover convergence for the entire panel is a requirement for studying whether there is convergence in subgroups or clubs. In this context, as shown in Table 5, the t-statistics for the entire panel of 36 OIC nations is -36.3125. Since the critical value is fewer than -1.65, the null hypothesis stating that there is convergence in the entire sample is rejected. This outcome shows that there is no convergence in the entire panel.

Table 5

Panel Convergence Test Results

Variable	Coefficient	SE	t-stat.
Log (t)	-0.7708	0.0212	-36.3125

In the second stage, the PS (2007) algorithm, based on clustering clubs for the sample of OIC countries, is used to obtain the clubs where the CIP index series differ. It can be seen in the first column of Table 6 that countries are divided into 5 (from Club 1 to Club 5) initial convergence clubs in terms of CIP index values as the t-statistic values of the five clubs in question are greater than -1.65. This result shows that the countries in each initial club meet the convergence hypothesis.

Table 6

Analysis Results of Convergence Club

Initial Club	Coefficient	Test of Club Merging				Final Club
Club 1 {6}	0.102 ***(1.458)***	Club 1+2				**Club A** {6}
Club 2 {8}	0.201 ***(1.832)***	-0.233 *(-5.802)*	Club 2+3			**Club B** {8}
Club 3 {5}	0.231 ***(4.003)***		-0.116 *(-2.523)*	**Club 3+4**		**Club C** {7}
Club 4 {2}	0.029 ***(0.228)***			0.301 ***(5.371)***	Club 4+5	**Club D** {15}
Club 5 {15}	0.098 ***(1.390)***				-0.143 ***(-2.718)***	

Note: The numbers within {} and () in the table represent, respectively, the number of countries in the convergence clubs and the t-statistic values.

The PS (2007) approach tends to overestimate the number of clubs. Thus, the club merging procedure developed by PS (2009) is also applied in this study, and the club merging test results are presented in the third column of Table 2. Comparing the t-statistic values of the club merger test coefficients with the critical value of -1.65 shows whether the initial clubs can be merged or not. In this context, when Table 6 is examined, it is seen that the t-statistic values for Club 1+2, Club 2+3, and Club 4+5 are fewer than the critical value of -1.65. These results show that these clubs cannot be merged and that the starting clubs should be considered their final clubs. On the other hand, it is seen that the t-statistic value for Club 3+4 is greater than the critical value of -1.65. This result means that the starting clubs, Club 3 and Club 4, will be merged. Overall, these results reveal that five initial convergence clubs (Club 1 - Club 5) turned into four final convergence clubs (from Club A to Club D). The countries in these final convergence clubs are presented in Table 7.

Table 7

Countries in Convergence Clubs

Club A	**Club B**	**Club C**	**Club D**	
Bangladesh	Bahrain	Albania	Algeria	Mozambique
Iran	Egypt	Brunei Darussalam	Azerbaijan	Niger
Malaysia	Indonesia	Jordan	Cameroon	Senegal
Saudi Arabia	Kazakhstan	Pakistan	Cote d'Ivoire	State of Palestine
Türkiye	Kuwait	Tunisia	Gabon	Suriname
United Arab Emirates	Morocco	Uganda	Kyrgyzstan	Syria
	Oman	Uzbekistan	Lebanon	Tajikistan
	Qatar		Libya	

When evaluating the countries in the final convergence clubs, the countries' industrial competitiveness scores are influential in forming the clubs. For example, the countries in the Club-A generally have better CIP scores (see, Table 4). This rationale is also valid for the rest of the countries and clubs (i.e., Qatar, Bahrain, Kuwait, Morocco, Kazakhstan, Egypt, and Oman comprise those with the second-best CIP performance following the countries in Club A). This result indicates that the dual structure reflecting high- and low-performing countries in the OIC panel persists, that is, countries with low CIP performance do not converge to high performance countries.

Conclusion

The industrial sector holds immense potential to substantially propel economic development by creating employment opportunities and advancing state-of-the-art technology. Fostering inclusive and sustainable industrialization ranks as a paramount objective within the United Nations' overarching development agenda. Within this framework, it is widely recognized that enhancing competitiveness within the industrial sector stands as a pivotal mechanism for realizing sustainable development goals. From this perspective, the current study delves into the convergence dynamics of competitive industrial performance among 36 OIC member states using yearly data from 1990 to 2021. To achieve this, this study employs the CIP index as a proxy for evaluating competitive industrial performance and adopts

Phillips & Sul's (2007) club convergence approach, which accounts for variations in technical progress and convergence rates. The CIP index directly correlates with SDG-9 and indirectly influences other SDGs. With its capacity to assess industrial competitiveness across nations, appraise the potential for industrialization advancement, and identify areas necessitating industrial policy interventions, the CIP holds substantial promise for conducting comparative research on the selected countries.

CIP scores exhibit notable disparities across OIC nations. For instance, Malaysia demonstrates the highest CIP performance at 0.179, while Mozambique lags behind with the lowest score of 0.04. This variability is duly accounted for in the study's analyses. It has been empirically established that OIC countries do not exhibit convergence. This finding underscores the persistent dual structure observed within the country panel under scrutiny, wherein nations with low CIP performance fail to converge toward those with high-performance levels. Despite the absence of overall convergence, this study reveals the emergence of four distinct convergence clusters. The foundation of these groups is heavily influenced by CIP scores, as countries with comparable scores gravitate toward specific clusters.

Given that attaining long-term development objectives in OIC countries necessitates a higher CIP score, nations with lower CIP scores ought to adopt policies akin to those implemented by countries with higher CIP scores. Such measures are imperative for enhancing the industrial sector and augmenting their competitive prowess.

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