Income Inequality, Innovation and Human Capital Nexus: A Comparative Analysis of Asia-Pacific Countries

Lakhwinder Singh and Zemed Degu Mengesha

Global economy has shown a rising income inequality as well as increasing the influence of innovations. Economic theory of income inequality-innovation nexus and empirical evidence are counter intuitive. Therefore, the present study attempts to examine a comparative analysis of income inequality, innovation and human capital relationship among the 15 Asia-Pacific countries using time-series data from 1990 to 2020. The study employs the Augmented Dickey-Fuller and Phillips-Perron unit root test methods to examine the stationarity of variables and the ARDL bounds co-integration approach to estimate the long run relationship between income inequality, innovation and human capital development. Results of the bounds co-integration test indicated that there is a long run equilibrium relationship between income inequality, innovation and human capital in both models with interaction term and without interaction term for all the 15 countries. With human capital as a mediating variable, findings of the long run ARDL model indicated that innovation variable adversely affects income inequality across countries and over time in majority of the sampled countries. This study examined the innovation-inequality connection over time and unraveled the puzzle why innovations generate income inequality in some countries but not in others. Therefore, it is suggested that there is a dire need to relook at the innovation system that should use both bottom-up and top-down approach with a right mix to have an impact on the reduction of income inequality in the long run.

Keywords: Income Inequality, Innovation, Human Capital, Cointegration, Asia-Pacific, Comparative Analysis.

JEL Classification: O3, O15, O57, C32, I24

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I. Introduction

Innovation and economic policy have come to the public scrutiny during the Covid-19 pandemic (Jain and Singh, 2020: Lee, 2020). Covid-19 shock has not only devastating impact on the global economy but also brought to the surface of the high degree of multidimensional inequities that are prevailing across and within countries (World Bank, 2022; UNDP, 2021). Income inequalities turned out to be most glaring which is being caused by several processes generated within the economic system. Capitalist economic system has remained dynamic over time due to innovations and technological progress (Kuznets, 1966: Schumpeter, 1934; Marx, 1887; Smith, 1776). The evolution of the structure of a modern capitalist economy examined by Kuznets (1966) has been determined by the productivity differentials across and within sectors. Income inequality emerged due to innovations and application of technological progress across economic activities but shown to have a general tendency to decline even in the absence of the public policy to reduce it. This generalized tendency of rise and fall of income inequality popularly known as inverted 'U' shape relationship between income inequality and per capita income (Kuznets, 1955). These trends of income inequality reversed in the last two decades of 20th century and the first two decades of 21st century with a continuously rising trends (Cornia, Addison and Kiiski, 2003; Cinagano, 2014; WIL, 2022). It is argued that the recent phase of hyper-globalization was largely responsible in the resultant high degree of economic inequalities across (within) countries and over time (Rodrik, 2019). However, the endogenous theory of economic growth has underlined the factors that determine the long run economic growth and a tendency of widening income inequalities (Romer 1986; and Lucas, 1988). Both the versions of endogenous growth theory have argued the existence of increasing returns to scale due to long term investment in R&D for new knowledge (Romer, 1986) and accumulation of human capital (Lucas, 1988). An implication that emerged from endogenous growth theory is that so long as innovations/new knowledge and human capital accumulation differs across countries and economic activities, it continues to generate income differentials.

It is amply clear that innovation and human capital plays a central role in determining the long run economic growth and income inequalities. Moreover, the hyper-globalization phase has also witnessed an emergence of fourth industrialization revolution innovations and technologies such as artificial intelligence, internet of things, 3D printing, robotics, genetic engineering and quantum computing that have developed new possibilities of income inequalities to worsen (UNDP, 2001; Holzer, 2022). The new technologies have been dramatically changing the nature of work, organization of production, social interaction and skill base of the workforce. Recent studies that surged during the hyper-globalization phase have empirically examined the relationship between innovation and economic inequalities reached to the conclusion that innovation increases income inequality (Aghion, Akcigit, Bergeaud, Blundell and Hemous, 2019). The fourth industrial revolution innovation studies have argued that the large number of unskilled and semi-skilled jobs are being displaced at a higher scale. However, these studies have underlined the skill mismatches and emphasized on the need for accumulation of human capital that is to make human beings as a lifelong learner (Singh, 2019). It is amply clear that there is a strong relationship among innovations, human capital and income inequality. The nexus of income inequality, innovation and human capital has remained relatively under researched, but the studies pooling data to increase observations have obscured the country wide process of impact of innovations on income inequality (Aghion and Griffith, 2022). The present study strives to fill this gap in literature, while analyzing processes of innovation and income inequality. For this we have developed econometric model and collected relevant indicators to examine the relationship among the income inequality, human capital and innovations. The empirical evidence covering the period of three decades and a sample of 15 Asia-Pacific countries showed that innovations and human capital explains why income inequality increases across countries and over time. The rest of paper is organized into five sections. The review of literature relating to innovation, human capital and income inequality is presented in section two. The model specification and method of econometric estimation used to estimate the long run relationship among income inequality, innovation and human capital is outlined in the sections three and four respectively. Results and discussion of the empirical evidence are presented in section five. The concluding remarks are presented in the last section of the paper.

II. Review of Literature

The determinants of income inequality across countries and over time examined by various studies have underlined the factors such as skill-biased technological change, education and health, globalization and international trade, institutions, immigration, and gender that have played an important role in generating inequities (Kierzenkowski and Koske, 2013; Lemieux, 2008). Recently, the studies conducted on impact of innovations on inequality has assigned prominent role to innovations as a main cause of income inequality (Aghion and Griffith, 2022; Cozzens, 2008). The relationship between inequality and technology is complex and multifaceted. Technology has enhanced productivity, accelerated economic growth, enabled knowledge and information sharing and increased access to basic services. Together with the opportunities provided by trade and investment for capital accumulation and productive transformation, it has helped to achieve an unprecedented level of economic growth, enabling several countries to catch up with developed nations (Antonelli and Gehringer, 2017). However, it has also been the cause of inequalities because of its skill-bias nature and due to monopoly rents.

Traditionally, a new technology increases productivity and wages for both low-skilled and high-skilled labor, so it may either increase or decrease income inequalities in the economy. Skill-biased technological change or innovation increases inequalities, but it also increases the relative demand for high-skilled workers creating incentives to achieve higher educational attainment. In general, greater supply of high-skilled workers translates into the reduction of income inequalities in the economy. This supply and demand approach of high-skilled workers was effective in explaining the wage structure changes in the US economy until the 1990s (Katz and Murphy, 1992), but unsuccessful to explain other developments such as wage polarization, declining real wages at the lower end of income distribution and substitution of domestic labor either by capital (computers or machines) or by foreign labor due to offshoring (Acemoglu and Autor, 2010). In this context, Autor *et al.* (2003) underscored the role of tasks performed in a distinguished routine task that can be substituted by computers or machines and non-routine tasks that are usually complemented by new technologies. They indicated that when computerization displaces medium-skilled workers that cannot substitute high-skilled workers, wage polarization is likely to increase.

Furthermore, several studies indicated that income inequalities may result from the implementation of new technologies in the economy. Implementation of new technologies can be usually done by skilled workers only, so that skilled labor find employment in new sectors and earn higher wages, while unskilled workers remain at old sectors with prevailing wages. Some workers can adapt faster to leading-edge technologies several periods in a row and thus obtain an additional premium in the economy (Aghion, 2002). However, as suggested by Antonelli and Gehringer (2017), based on the Schumpeterian growth theory, if new vintages of technological innovation destroy the competitive advantage of incumbents and reduce the duration of monopolistic rents, the faster is the rate of technological change, and the faster would be the reduction of income inequalities in the economy. Using quantile regressions, they tested the Schumpeterian hypothesis with a large dataset on advanced and industrializing economies. The result revealed that the inequality-diminishing effect of technological change holds along the entire income inequality distribution but has larger effects in countries where the concentration of wealth and, consequently, income asymmetry are stronger. The Schumpeterian concept of creative destruction (Schumpeter, 1947) can be also useful in explaining top income inequality in the economy. Particularly, Jones and Kim (2017) argued that numerous entrepreneurs exert high effort to generate exponential growth in their incomes, but creative destruction by outside innovators hinders this expansion which leads to the logic of Pareto distribution in top incomes.

Although the slowing pace of innovation is one source of income inequality, in another study, Perera-Tallo (2017) argues that biased technological change may lead to increasing income inequality in the economy. The author presents a growth model in which technological change raises the income share of reproducible factors at the expense of non-reproducible ones and agents are heterogeneous in wealth and preferences, indicating that the savings rate increases with wealth. Hence, assets (reproducible factor) less equally distributed than raw labor (non-reproducible factor) in the economy which indicated that technological change or innovation raises the share of the less-equally distributed factor, increasing inequality along a permanent growth path. This suggests that when reproducible factors and the state of know-how are low, adopting new technologies is not feasible and profitable, and learning-by-doing and technological change or innovation stop, which could increase unproductive activities in the economy. Pouresmaeilia *et al.* (2018) indicated that innovation plays a significant role in mediating the knowledge management system and performance nexus. On the other hand, in accelerating labor productivity in the Middle East and North African region, Samargandi (2018) revealed that innovation is found to be a significant factor.

On the contrary to the Schumpeterian growth hypothesis, some researchers argued that the rate of technological change or innovation significantly influences the reduction of income inequality in the economy. Using data on Japanese trunk route airlines over the period from 1977 to 1993, Kinugasa (1998) explores the structure of firm productivity and the Schumpeterian hypothesis. Empirical studies of this hypothesis have traditionally tested the relationship between some measure of innovative activity and firm size. In the study, the rate of technical change is used to measure the innovative activity using some innovative inputs and outputs and the total factor productivity decomposed into technical change and changes in the economies of scale, thus the shift in the cost function is associated with these two changes. To this end, empirical results of the study rejected the Schumpeterian hypothesis.

Although numerous studies indicated the influential role of technological change or innovation in influencing income inequality, yet Cuaresma *et al.* (2013) demonstrated that human capital also plays an important role in reducing income inequality and income convergence in the economy. In a similar vein, Shahpari and Davoudi (2014) argue that increasing human capital can reduce income inequality and, hence, make more equal distribution of income in the economy. To ensure the realization of technological change or innovation activities, better human capital is a crucial component in how innovation influences income inequality across countries. The wider the distribution of human capital is, the greater is the chance of fostering the pace of technological change and reducing income inequality.

The human capital theory on income distribution stated human capital as one of the major factors affecting income distribution in the long run (Shultz, 1961; Becker, 1962; Becker and Chiswick, 1966; Mincer (1958, 1974). They argued that a rise in the level of education would tend to decrease the dispersion of income distribution when educational expansion and returns to education have an inverse relationship implying that an increase in the level of human capital accumulation will lead to a more equal distribution of income given those in the bottom income group earn relatively more income from human capital accumulation (Psacharopoulos and Patrinos, 2002; Coady and Dizioli, 2017). This assumes that human capital accumulation will increase the skill and productivity of the bottom group thereby income as compared to high skilled and high-income group of the society (Psacharopoulos and Patrinos, 2002; Cram, 2017). Becker (1962) indicated that the competencies and productivity of individuals will increase through educational attainment and will bring a higher wage to the workers in a competitive labor market indicating that the worker's lifetime earnings can be a function of the level of educational attainment embodied in the worker (Becker, 1962; Lee and Lee, 2018).

De Gregorio and Lee (2002) and Lin (2007) indicated inequality of educational distribution and income inequality has a positive relationship whereas, for a given level of educational attainment, the effect of an increase in the level of schooling may either be negative or positive. Similarly, Knight and Sabot (1983) indicated two different effects of human capital accumulation on the distribution of income in the economy. First is the *composition effect*, which tends to increase unequal distribution of income due to the relative sheer size of educated people. The second is the *wage compression effect*, which reduces the difference in earnings between the more and less highly educated people due to an increase in the relative supply of educated workers (Tilak, 1989).

Studies conducted by Knight and Sabot (1983), Park (1996), Checchi (2001), and De Gregorio and Lee (2002) have found a positive significant relationship between dispersion of human capital distribution and wider dispersion of income distribution indicating that a lower level of human capital inequality is associated with a lower level of inequality of income distribution. On the contrary, Fields (1980) indicated that human capital development, measured in terms of average years of education, has a positive association with wider dispersion of income distribution.

On the other hand, Ram (1984) and Digdowiseiso (2009) pointed out that the impact of human capital development on the inequality of income distribution was insignificant indicating that the increase or decrease in the level of human capital nothing to do with the level of income distribution. Similarly, Castello-Climent and Domenech (2014) pointed out that most developing countries, in the last few decades, registered a remarkable achievement by reducing the level of human capital inequality distribution by more than 50 percent through expansion of education. Despite such reduction in the dispersion of human capital distribution, the dispersion level of income distribution remained stable in these countries (Castello-Climent and Domenech, 2014; Lee and Lee, 2018) indicating that the exact contribution of human capital development to the distribution of income is empirically different from what the theory expects.

From the foregoing discussion, it is safely concluded that the studies examined the relationship between innovation and income inequality, human development and income inequality are inconclusive and sometimes contradictory. However, the innovation mediated human development studies are almost scanty. Therefore, there exists a gap in the literature in examining the relationship between innovation and inequality. This study attempts to fill this gap.

III. Model Specification and Methodology

This study employs the Schumpeterian concept of creative destruction hypothesis that the rate of technological change has a significant effect on narrowing income distribution. Because of the powerful effects of creative destruction, the rate of technological change engenders a reduction in wealth and rent inequality, which are highly skewed and, consequently, limit income inequality (Schumpeter, 1947). Furthermore, we employed the basic tenets of the human capital theory of income distribution which states that there are two effects human capital accumulation on distribution of income (Knight and Sabot, 1983). The first is the *composition effect*, which tend to increase unequal distribution of income due to the relative sheer size of educated labor force. The second is the *wage compression effect*, which reduces the difference in earnings between the more and less highly educated people due to an increase in the relative supply of educated labor force, thereby reducing the dispersion of income distribution. In analyzing the effects of innovation and human capital on income inequality for the select 15 Asia-Pacific countries, the present study specifies the following equation:

$$INIE_t = \beta + \theta_1 INOV_t + \theta_2 X_t + \theta_3 Z_t + \mu_t, \tag{1}$$

where *INIE* is income inequality (proxied by the Gini coefficient of Standardized World Income Inequality Database, which measures the degree with which the distribution of income among households/individuals within a country diverges from a perfect equal distribution), *INOV* is the innovation variable (proxied by the average score of Knowledge and Technology Output and Creative Output Scores), *X* is a vector of mediating variables that affect income inequality, *Z* is a vector of other control variables that affect income inequality, *t* is the time in year, μ_t is an error term. The group of control variables (Z) consists of Gross National Income per capita (*GNIPC*), Institutional Quality (*INST*), Infrastructure (*INFR*), and Market Sophistication (*MKTS*). Institutional Quality variable score is the average scores of Political, Regulatory and Business Environment whereas Infrastructure value is the mean score of information and technology communications and general infrastructure. Human capital measured by Education capital (*ECAP*), proxied by Mean Years of Schooling and health capital (*HCAP*), proxied by Life Expectancy at Birth are the mediating variables (*X*) employed in the nexus between innovation and income inequality. All the relevant variables of the income inequality model are transformed into natural logarithms.

A. Interaction Effect Model Specification:

To examine the moderating roles of human capital (proxied by human capital index-HCI) with innovation in influencing income inequality, equation (1) is extended to include the interaction term between these respective variables in the model specification as follows:

$$INIE_t = \rho + \alpha_1 INOV_t + \alpha_2 HCI_t + \alpha_3 (HCI \cdot INOV)_t + \alpha_4 Z_t + \mu_t, \tag{2}$$

Equation (2) provides the basis for the empirical model by interaction between innovation and human capital mediator or indirect effect in influencing income inequality. *Z* refers to the control variables as shown in Equation (1), namely *GNIPC, INST*, *INFR*, and *BUSS*. *HCI* is computed as the average score of educational and health indices.

It is inappropriate to interpret the individual terms α_1 and α_2 in equation (2) if the income inequality model contains an interaction term. For instance, the coefficient of α_1 on *INOV* captures only the effect of innovation on income inequality when *HCI* is zero. Similarly, α_2 captures only the effect of *HCI* on income distribution when *INOV* does not exist. Therefore, it is incorrect to indicate that negative and significant coefficients of α_1 and α_2 imply that an increase in innovation (human capital) is expected to lead to reduce income inequality. Thus, *human capital variable (HCI)* as the mediator is expected to buffer the effect of innovation on income inequality, thus, whether α_3 is expected to be marginally positive or negative depends on the influence of innovation on income inequality.

IV. Method of Econometric Estimation

In examining the long run effect of innovation and human capital variables on income inequality for the 15 Asia-Pacific countries from 1990 to 2020, the Autoregressive Distributed Lag (ARDL) Bounds Co-integration Approach, which was first proposed by Pesaran and Shin (1999) and later extended by Pesaran, Shin, and Smith (2001), is employed. This is precisely because of several reasons. *First*, the ARDL framework can be employed for a different orders of integration of time series variables with purely I(0) or purely I(1) or a mixture of both orders of integration (Pesaran *et al.*, 2001). *Second*, while other conventional methods of co-integration are sensitive to sample size, the ARDL approach can yield significant and valid results for a small sample of data set (Narayan, 2005). *Third*, the ARDL co-integration approach recognizes and also permits different lag lengths for time-series variables, but it is not possible in the other conventional co-integration approaches (Pesaran and Shin 1999; Narayan and Smyth, 2004). *Fourth*, in examining both the long-run and short-run impact relationships simultaneously, the ARDL bounds co-integration approach overcomes the endogeneity problem of explanatory variables (Pesaran *et al.*, 2001; Narayan 2005). The present study specified the following unrestricted error correction models of the ARDL co-integration equations for equations 1 and 2, respectively.

$$\begin{aligned}
\Delta INIE_t &= \lambda_0 + \theta_1 INIE_{t-1} + \theta_2 INOV_{t-1} + \theta_3 ECAP_{t-1} + \theta_4 HCAP_{t-1} \\
&+\theta_5 INST_{t-1} + \theta_6 INFR_{t-1} + \theta_7 MKTS_{t-1} + \theta_8 GNIPC_{t-1} + \lambda_1 \sum_{i=1}^{a} \Delta INIE_{t-i} + \lambda_2 \sum_{i=0}^{b} \Delta INOV_{t-i} \\
&+\lambda_3 \sum_{i=0}^{c} \Delta ECAP_{t-i} + \lambda_4 \sum_{i=0}^{d} \Delta HCAP_{t-i} + \lambda_5 \sum_{i=0}^{e} \Delta INST_{t-i} + \lambda_6 \sum_{i=0}^{f} \Delta INFR_{t-i} \\
&+\lambda_7 \sum_{i=0}^{g} \Delta MKTS_{t-i} + \lambda_8 \sum_{i=0}^{h} \Delta GNIPC_{t-i} + \varepsilon_t,
\end{aligned} \tag{3}$$

$$\begin{aligned}
\Delta INIE_t &= \gamma_0 + \beta_1 INIE_{t-1} + \beta_2 INOV_{t-1} + \beta_3 HCI_{t-1} + \beta_4 (HCI \cdot INOV)_{t-1} + \beta_5 INST_{t-1} \\
&+\beta_6 INFR_{t-1} + \beta_7 MKTS_{t-1} + \beta_8 GNIPC_{t-1} + \gamma_1 \sum_{i=1}^{a} \Delta INIE_{t-i} + \gamma_2 \sum_{i=0}^{b} \Delta INOV_{t-i} \\
&+\gamma_3 \sum_{i=0}^{c} \Delta HCI_{t-i} + \gamma_4 \sum_{i=0}^{d} \Delta (HCI \cdot INOV)_{t-i} + \gamma_5 \sum_{i=0}^{e} \Delta INST_{t-i} + \gamma_6 \sum_{i=0}^{f} \Delta INFR_{t-i} \\
&+\gamma_7 \sum_{i=0}^{g} \Delta MKTS_{t-i} + \gamma_8 \sum_{i=0}^{h} \Delta GNIPC_{t-i} + \varepsilon_t,
\end{aligned} \tag{4}$$

Where INIE is income inequality (proxied by Gini coefficient) is the dependent variable, *INOV* is the innovation variable (proxied by the average score of Knowledge and Technology Output and Creative Output Scores), ECAP is education capital (proxied by Mean Years of Schooling), HCAP is health capital (proxied by Life Expectancy at Birth), *HCI* is human capital index which is computed as the average score of educational and health indices, GNIPC is Gross National Income per capita, INST is Institutional Quality, INFR is Infrastructure, and MKTS is Market Sophistication are the explanatory variables, $\in_t$ is the random error term, t is the time in years and a, b, c, d, e, f, g, and h are optimum lag lengths. To test the long run relationship among income inequality, innovation and human capital variables, the null hypothesis of no co-integration (θ_1=θ_2=θ_3=θ_4=θ_5=θ_6=θ_7=θ_8=0) and (β_1=β_2=β_3=β_4=β_5=β_6=β_7=β_8=0) are tested against the alternative hypothesis of co-integration (θ_1≠θ_2≠θ_3≠θ_4≠θ_5≠θ_6≠θ_7≠θ_8≠0) and (β_1≠β_2≠β_3≠β_4≠β_5≠β_6≠β_7≠β_8≠0), respectively using the F statistics of the ARDL bounds test. When the F-statistics is greater than the upper critical bound critical values, the null hypothesis is rejected and concluded that there is a long run relationship among the variables in the model.

Once the existence of long run relationship among income inequality, innovation and human capital variables is confirmed, the following long-run equations (equation 5) and (equation 6) are estimated for income inequality model without interaction and with interaction term, respectively.

$$INIE_t = \phi_1 + \lambda_{11}\sum_{i=1}^{a} INIE_{t-i} + \lambda_{21}\sum_{i=0}^{b} INOV_{t-i} + \lambda_{31}\sum_{i=0}^{c} ECAP_{t-i} + \lambda_{41}\sum_{i=0}^{d} HCAP_{t-i} + \lambda_{51}\sum_{i=0}^{e} INST_{t-i} + \lambda_{61}\sum_{i=0}^{f} INFR_{t-i} + \lambda_{71}\sum_{i=0}^{g} MKTS_{t-i} + \lambda_{81}\sum_{i=0}^{h} GNIPC_{t-i} + \varepsilon_{1t}, \tag{5}$$

$$INIE_t = \pi_1 + \gamma_{11}\sum_{i=1}^{j} INIE_{t-i} + \gamma_{21}\sum_{i=0}^{k} INOV_{t-i} + \gamma_{31}\sum_{i=0}^{l} HCI_{t-i} + \gamma_{41}\sum_{i=0}^{m} (HCI \cdot INOV)_{t-i} + \gamma_{51}\sum_{i=0}^{n} INST_{t-i} + \gamma_{61}\sum_{i=0}^{o} INFR_{t-i} + \gamma_{71}\sum_{i=0}^{p} MKTS_{t-i} + \gamma_{81}\sum_{i=0}^{q} GNIPC_{t-i} + \varepsilon_{2t}, \tag{6}$$

A. Sources of Data and Description of Variables

The data for Gini coefficient is obtained from the Standardized World Income Inequality Database (*SWIID*). Knowledge and Technology Output, Creative Output, Institutional Quality, Infrastructure and Market Sophistication scores are obtained from the World Intellectual Property Organization (*WIPO*) and World Economic Forum (*WEF*). Mean years of schooling, expected years of schooling, Life expectancy at birth, educational and health indices are collected from United Nations Development Program (*UNDP*), while Gross national income per capita data are obtained from the World Bank's World Development Indicators (*WDI*) database. Furthermore, the interpolation method is used to fill the missing values for few years to complete the time-series data. The descriptions of the variables used in the econometric estimations are as follows:

Income Inequality: In the absence of comprehensive annual time-series data on other indicators of income inequality such as income share of top earners, income share of middle earners and income share of bottom earners of the population for some countries, the Gini coefficient of Standardized World Income Inequality Database is used as a proxy measure of income inequality for all countries under investigation. It measures the degree with which the distribution of income among households/individuals within a country diverges from a perfect equal distribution. Its value ranges from 0 to 100 percent with low values of the Gini index indicate a more equal distribution of income whereas high values show the existence of a high level of income inequality in the economy.

Innovation: The innovation variable is proxied by the average score of knowledge and technology output and creative output scores. The knowledge and technology output pillar is a composite measure of number of resident patent applications filled, number of patent cooperation treaty applications, number of scientific and technical journal articles, number of ISO 9001 quality certificates issued, total computer software spending as a percentage of GDP, intellectual property receipts, high-tech exports, and ICT services exports as a percentage of total trade indicators. On the other hand, the score of creative outputs is measured as a composite measure of indicators such as trademarks by origin, cultural and creative services exports as a percentage of total trade, number of national feature films produced per million population, creative goods exports as a percentage of total trade, and mobile app creations.

In the first step, normalization was made for all the variables/ indicators in such away that the range is between 0 to 100 with the higher scores representing better outcomes. The normalization formula for each variable/indicator is given as:

$$Normalization\ \ Index = \frac{Actual\ \ Value - Minimum\ \ Value}{Maximum\ \ Value - Minimum\ \ Value} * 100, \qquad (7)$$

Secondly, the knowledge and technology output and creative output pillar scores are calculated as the arithmetic average of its respective individual indicator scores with equal weights. Finally, the innovation index is computed by the average score of knowledge and technology output and creative output scores with each value being assigned as equal importance.

Human Capital: The *human capital* is computed as the average score of educational and health indices. Educational and health indices are computed using the dimensional index of minimum-maximum values of respective indicators. Two steps are used in computing the educational index; *first*, the expected years of schooling index and mean years of schooling index are computed separately using the “dimension index” method. *Secondly*, the average values of these two indices are considered as the educational index of the economy. Using the same formula, the health capital index is also computed based on the life expectancy at birth. The dimensional index formula is given as:

$$Dimension\ \ Index = \frac{Actual\ \ Value - Minimum\ \ Value}{Maximum\ \ Value - Minimum\ \ Value}, \tag{8}$$

Finally, the *human capital index* is computed as the simple average score of educational and health indices.

Institutional and Governance Quality: This study employs the average scores of political, regulatory and business environment pillars as proxy measure of Institutional and Governance Quality variable score to evaluate its effect on the income distribution among the 15 Asia-Pacific countries. Its value ranges from 0 to 100 percent with low values indicate a poor institutional and governance quality whereas high values show the existence of a high level of institutional and governance quality in the economy. To this end, political environment score measures the likelihood and severity of political, legal, operational risks affecting business operations as well as the perceptions of public services and the degree of its independence from political pressures whereas Regulatory environment score measures the effectiveness of the rule of law and the perception of the ability of the government to formulate and implement sound policies and regulations that promote private-sector development. The index of business environment measures the ease of doing business in the economy.

Then, normalization was made for all the variables/indicators in such a way that the range is between 0 to 100 with the higher scores representing better outcomes. The normalization formula for each variable/indicator is given as:

$$Normalization\ \ Index = \frac{Actual\ \ Value - Minimum\ \ Value}{Maximum\ \ Value - Minimum\ \ Value} * 100,$$

Each three pillar scores are calculated as the average of its individual indicators. Finally, Institutional and Governance Quality Index is computed as the average value of political, regulatory and business environment pillars.

Infrastructure: It includes indicators of information and technology communications and general infrastructure pillars. In this regard, information and technology communication index is a composite score of ICT access, ICT use and Government's online service indices whereas the general infrastructure score measured in terms of the level of electricity production scaled by population, logistics performance and gross capital formation as percentage of GDP in the economy. Then, normalization was made into the (0, 100) range, based on the minimum-maximum method, with higher scores representing better outcomes.

Finally, the Infrastructure index is computed as the average value of information and technology communications and general infrastructure pillars.

Market Sophistication: It is a composite measure of ease of getting credit, domestic credit to the private sector as a percentage of GDP, microfinance gross loans as a percentage of GDP, ease of protecting minority investors, market capitalization (market value) of listed domestic companies as a percentage of GDP, weighted average applied tariff rate, domestic industry diversification based on manufacturing output and domestic market size. Then, normalization was made into the (0, 100) range, based on the minimum-maximum method, with higher scores representing better outcomes. Finally, the market sophistication score is calculated as the average value of its individual indicators.

Gross National Income per capita: It is computed by dividing the gross national income of the economy by the total population in a given country.

V. Empirical Findings and Discussion

A. Descriptive Analysis of Income Inequality, Innovation and Human Capital

Descriptive results of the study, as shown in Table 1, indicated that the average income inequality of the 15 Asia-Pacific countries was about 38.026 percent with a standard deviation of 5.548 during the period of study. Among these economies, Japan, Australia and Korea have registered the lowest Gini coefficients of 30.35, 31.46 and 31.87 percent on average, respectively whereas Sri Lanka, India and Indonesia have come on the top three list with highest average Gini coefficient of 46.5, 44.92 and 44.11 percent, respectively. Figure 1 shows a wide variations of income inequality across countries. There is a secular trend of rise of income inequality over time.

With respect to innovation variable, which is computed as the average score of knowledge and technology output and creative output, the 15 Asia-Pacific countries that have an average score of 31.64 with the bottom three countries with average lowest scores are 15.67, 17.28 and 18.75 for Sri Lanka, Bangladesh and Pakistan, respectively. The top three countries with average scores of innovations of 54.57, 48.38 and

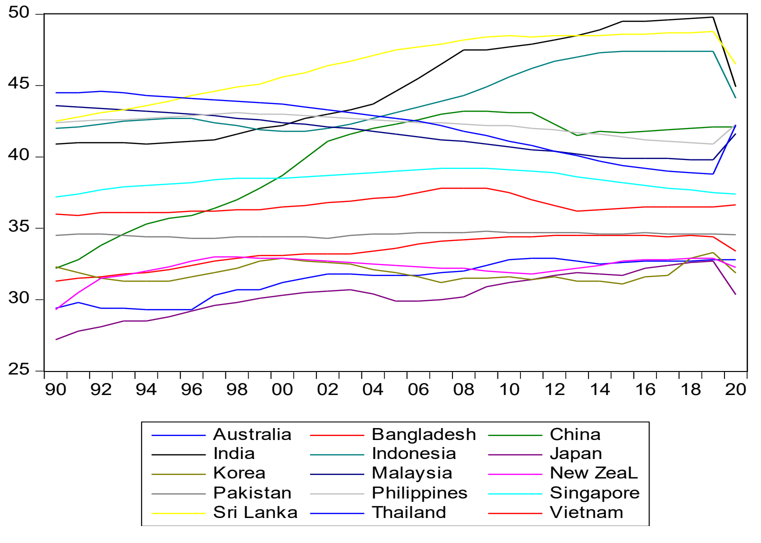

Figure 1
Trends of Income Inequality among the 15 Asia-Pacific Countries

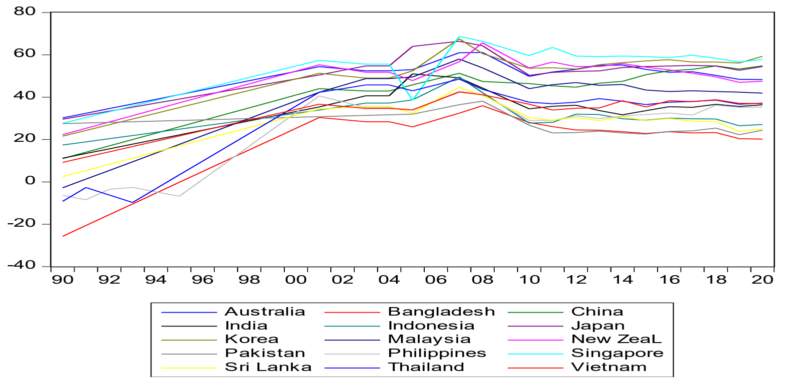

Figure 2
Trends of Global Innovation Index among the 15 Asia-Pacific Countries

45.69 for Korea, Japan and China, respectively. Concerning the human capital variable, the recent trends for the past 10 years indicated an increase in the human development index of these economies. Figure 2 points out the rising trend of innovation index across countries and over time.

The average human capital index of these countries is about 0.7036 which is categorized under high human development during the period of study. Similarly, the average human capital index of Pakistan (0.488) and Bangladesh (0.508) is categorized under low human development. Whereas the eight countries in our sample such as India (0.538), Vietnam (0.609), Indonesia (0.629), China (0.645), Philippines (0.647),

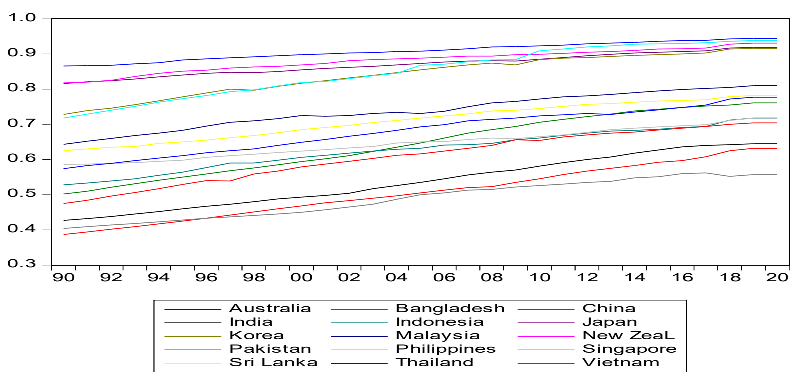

Figure 3
Trends of Human Capital Index among the 15 Asia-Pacific Countries

TABLE 1
DESCRIPTIVE STATISTICS

Variables	*Unit of Measurement*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Income Inequality	Percent	38.026	5.548	27.200	49.800
Innovation@	Scale (1 – 100)	31.644	15.974	-4.750	93.754
Knowledge & Technology Output	Scale (1 – 100)	29.115	21.413	-8.607	98.841
Creative Output	Scale (1 – 100)	34.173	14.751	-9.821	98.547
Education Capital	Mean Years of Schooling	8.170	2.894	2.300	12.900
Health Capital	Life Expectancy at Birth	73.128	6.369	57.900	84.600
Gross National Income per capita	US$ (2015 constant price)	14080.73	15269.21	1152.56	88155.00
Institutional Quality	Scale (1 – 100)	57.288	20.692	-8.690	96.785
Infrastructures	Scale (1 – 100)	47.729	21.127	-3.619	98.595
Market Sophistication	Scale (1 – 100)	49.697	14.695	2.166	78.700
Global Innovation Index	Scale (1 – 100)	36.311	16.020	-25.700	68.710
Human Capital Index	Scale (0 – 1)	0.7036	0.1478	0.3870	0.9440

Note: Innovation@ = average score of knowledge and technology output and creative output scores; Std. Dev. = *Standard Deviation*; Min. = *Minimum*; Max. = *Maximum.*

Thailand (0.682), Sri Lanka (0.711) and Malaysia (0.739) are classified under medium human development category countries. On the other hand, the average human capital index of Korea (0.841), Singapore (0.851), Japan (0.871), New Zealand (0.882), and Australia (0.909) comes out to be under the category of high human development level countries. The upward trend is visible over time across countries (Figure 3).

The summary of descriptive statistics further indicated that the relevant variables included in the econometric model using income inequality as dependent variable in the equations of each country showed a normal distribution. This confirms the suitability of the variables used in the study.

B. Unit Root Test Results

Due to the non-stationary nature of time series variables, theoretical and empirical literature have indicated that the use of time-series data directly in any empirical analysis might create the problem of spurious

TABLE 2

AUGMENTED-DICKEY-FULLER (ADF) UNIT ROOT TEST ANALYSIS

1^{st} *Row*→	*INIE*	*INOV*	*ECAP*	*HCAP*	*INST*	*INFR*	*MKTS*	*GNIPC*
2_{nd} Row→	*ΔINIE*	*ΔINOV*	*ΔECAP*	*ΔHCAP*	*ΔINST*	*ΔINFR*	*ΔMKTS*	*ΔGNIPC*
Australia	-1.27	-0.94	-0.39	-5.74***	-1.91	-1.06	-3.85*	-0.31
	(0.631)	(0.760)	(0.898)	(0.000)	(0.325)	(0.717)	(0.006)	(0.912)
	-4.37***	-4.22***	-4.50***	-0.71	-2.31	-4.35***	-5.96***	-5.54***
	(0.002)	(0.003)	(0.001)	(0.828)	(0.176)	(0.002)	(0.000)	(0.001)
Bangladesh	-3.07**	-0.11	-1.57	-7.63***	-14.07***	2.73*	-3.08**	0.41
	(0.041)	(0.938)	(0.486)	(0.000)	(0.000)	(0.083)	(0.039)	(0.979)
	-5.33***	-2.84*	-4.43***	0.49	-3.97***	-5.53***	-4.98***	-4.00***
	(0.001)	(0.067)	(0.005)	(0.983)	(0.005)	(0.001)	(0.004)	(0.005)
China	-8.94***	-1.41	-5.31***	-1.41	-1.52	-1.85	-3.07**	-1.01
	(0.000)	(0.563)	(0.001)	(0.566)	(0.510)	(0.350)	(0.041)	(0.736)
	-3.61**	-8.50***	-1.74	-4.06***	4.92***	-4.09***	-5.36***	-4.31***
	(0.013)	(0.000)	(0.400)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)
India	-1.21	-1.36	-1.93	-5.61***	-1.79	-1.77	-2.36	-0.17
	(0.656)	(0.586)	(0.314)	(0.001)	(0.378)	(0.385)	(0.161)	(0.932)
	-3.51**	-3.68**	-5.51***	-1.26	-5.42***	-2.07	-1.41	-5.84***
	(0.015)	(0.011)	(0.001)	(0.634)	(0.001)	(0.257)	(0.559)	(0.000)
Indonesia	-1.15	-2.69*	-3.82***	-0.04	-6.22***	-1.46	-2.25	-0.14
	(0.682)	(0.089)	(0.007)	(0.947)	(0.000)	(0.538)	(0.194)	(0.935)
	-4.90***	3.15**	-3.38**	-5.27***	-4.07***	-5.46***	-6.10***	-4.64***
	(0.005)	(0.034)	(0.019)	(0.002)	(0.004)	(0.001)	(0.000)	(0.001)
Japan	-1.81	-1.28	-0.30	-1.43	-1.09	-1.13	-9.58***	-0.47
	(0.367)	(0.627)	(0.912)	(0.553)	(0.705)	(0.691)	(0.000)	(0.883)
	-3.34**	-4.15***	-2.45	-5.37***	-2.71*	-4.29***	-2.71*	-5.06***
	(0.022)	(0.003)	(0.139)	(0.001)	(0.086)	(0.002)	(0.085)	(0.003)
Korea	-2.88*	-1.14	-3.36**	-3.09**	-1.34	-0.93	-2.23	-0.55
	(0.060)	(0.685)	(0.021)	(0.038)	(0.596)	(0.763)	(0.200)	(0.866)
	-3.43**	-4.69***	-7.70***	-0.28	-2.61	-4.96***	-4.13***	-5.62****
	(0.018)	(0.008)	(0.000)	(0.972)	(0.103)	(0.004)	(0.004)	(0.001)
Malaysia	-3.58**	-15.02***	-1.15	-0.83	-3.31**	-2.18	-1.93	-0.31
	(0.013)	(0.000)	(0.681)	(0.796)	(0.023)	(0.217)	(0.314)	(0.911)
	3.07	-4.76***	-4.63***	-4.25***	-4.67***	-4.83***	-1.24	-5.48***
	(1.000)	(0.009)	(0.001)	(0.003)	(0.001)	(0.006)	(0.638)	(0.001)
New Zealand	-2.36	-2.02	2.27	-6.74***	-1.71	-2.52	-2.97**	0.10
	(0.162)	(0.275)	(0.999)	(0.000)	(0.414)	(0.121)	(0.049)	(0.960)
	-3.45**	-1.08	-1.20	-0.41	-2.53	-3.59**	-3.19**	-5.78***
	(0.017)	(0.708)	(0.657)	(0.894)	(0.121)	(0.012)	(0.031)	(0.000)
Pakistan	-1.50	0.63	-4.22***	-2.67*	-2.48	-2.45	-2.47	-0.25
	(0.517)	(0.988)	(0.003)	(0.091)	(0.129)	(0.137)	(0.133)	(0.921)
	-5.63***	-6.37***	-5.78***	-3.88***	-5.11***	-3.82***	-3.19**	-5.12***
	(0.001)	(0.000)	(0.000)	(0.006)	(0.003)	(0.007)	(0.031)	(0.003)
Philippines	-0.59	-2.46	-2.09	2.90	-2.97**	-2.41	-2.91*	0.01
	(0.857)	(0.133)	(0.249)	(1.000)	(0.049)	(0.147)	(0.057)	(0.952)
	-2.17	5.82***	-4.43***	-5.57***	-4.87***	-4.48***	-4.18***	-4.26***
	(0.219)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.003)	(0.002)
Singapore	-1.40	-2.29	-5.48***	-1.08	0.29	-2.16	-7.25***	-0.34
	(0.568)	(0.182)	(0.001)	(0.710)	(0.974)	(0.224)	(0.000)	(0.907)
	-5.78***	-6.58***	-1.04	-5.75***	-4.51***	-4.40***	-1.81	-5.41***
	(0.000)	(0.000)	(0.722)	(0.000)	(0.002)	(0.002)	(0.365)	(0.001)
Sri Lanka	-1.67	-1.55	-3.58**	-0.57	-2.10	-9.93***	-2.57	0.21
	(0.437)	(0.143)	(0.012)	(0.894)	(0.243)	(0.000)	(0.111)	(0.969)
	-3.49**	-5.99***	-4.57***	-4.15***	-4.73***	-6.42***	-3.87***	-5.34***
	(0.016)	(0.000)	(0.001)	(0.012)	(0.001)	(0.000)	(0.007)	(0.001)
Thailand	0.46	-3.24**	-2.63*	2.23	-1.29	-1.63	-3.24**	-0.32
	(0.982)	(0.028)	(0.097)	(0.999)	(0.620)	(0.453)	(0.027)	(0.909)
	-4.62***	-2.06	-1.83	-3.92***	-5.07***	-4.11***	-4.47***	-5.58***
	(0.001)	(0.260)	(0.357)	(0.005)	(0.001)	(0.004)	(0.002)	(0.001)
Vietnam	-1.95	-1.64	-2.31	-2.76*	-1.06	-2.23	-1.72	0.06
	(0.305)	(0.449)	(0.176)	(0.075)	(0.715)	(0.201)	(0.408)	(0.957)
	-3.74***	-8.20***	-6.79***	-4.69***	-5.28***	-4.05***	-8.01***	-5.18***
	(0.009)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.000)	(0.001)

Note: *1st row* = ADF test statistics at level; 2^{nd} *row* = ADF test statistics after first differencing; *numbers in bracket* are p-values; *, **, and *** denote statistical significance at 10%, 5%, and 1% level of significance.

Table 3

PHILLIPS-PHERRON (PP) UNIT ROOT TEST ANALYSIS

1^{st} *Row*→	*INIE*	*INOV*	*ECAP*	*HCAP*	*INST*	*INFR*	*MKTS*	*GNIPC*
2^{nd} Row→	*ΔINIE*	*ΔINOV*	*ΔECAP*	*ΔHCAP*	*ΔINST*	*ΔINFR*	*ΔMKTS*	*ΔGNIPC*
Australia	-1.26	-1.13	-0.53	-5.49***	-8.87***	-1.12	-3.82*	-0.08
	(0.636)	(0.692)	(0.871)	(0.000)	(0.000)	(0.694)	(0.007)	(0.943)
	-4.41***	-4.26***	-4.50***	-2.17	-2.31	-4.33***	-6.95***	-5.91***
	(0.002)	(0.002)	(0.001)	(0.222)	(0.177)	(0.002)	(0.000)	(0.000)
Bangladesh	-3.04**	-3.84***	-1.56	-6.93***	-13.29***	-2.98**	-8.59***	0.45
	(0.042)	(0.007)	(0.491)	(0.000)	(0.000)	(0.048)	(0.000)	(0.982)
	-5.29***	-3.31**	-4.44***	-1.64	-6.73***	-5.53***	-5.63***	-3.52**
	(0.002)	(0.024)	(0.002)	(0.450)	(0.000)	(0.001)	(0.001)	(0.015)
China	-1.39	-1.21	-5.31***	-1.41	-1.65	-1.78	-3.16**	-1.03
	(0.573)	(0.658)	(0.000)	(0.563)	(0.446)	(0.380)	(0.033)	(0.729)
	-4.33***	-8.43***	-3.95***	-4.06***	-4.92***	-4.11***	-6.38***	-4.19***
	(0.002)	(0.000)	(0.005)	(0.004)	(0.000)	(0.003)	(0.000)	(0.003)
India	-1.22	-11.89***	-2.01	-9.86***	-1.85	-1.75	-1.97	-0.03
	(0.651)	(0.000)	(0.279)	(0.000)	(0.352)	(0.398)	(0.297)	(0.948)
	-3.40**	-6.09***	-5.55***	-1.59	-5.43***	-5.25***	-4.17***	-5.91***
	(0.019)	(0.000)	(0.000)	(0.475)	(0.001)	(0.002)	(0.003)	(0.000)
Indonesia	-1.25	-5.60***	-3.32**	0.07	-5.97***	-1.64	-3.92***	-0.18
	(0.641)	(0.001)	(0.023)	(0.957)	(0.000)	(0.449)	(0.005)	(0.930)
	4.91***	-3.13**	-3.52**	-5.28***	-4.18***	-5.46***	-10.28***	-4.60***
	(0.004)	(0.035)	(0.014)	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)
Japan	-1.81	-1.29	-0.81	-1.50	-1.09	-1.19	-10.53***	-0.45
	(0.366)	(0.621)	(0.803)	(0.517)	(0.705)	(0.665)	(0.000)	(0.888)
	-3.477**	-4.15***	-4.54***	-5.37***	-5.40***	-4.41***	-3.44**	-5.75***
	(0.016)	(0.003)	(0.001)	(0.000)	(0.001)	(0.002)	(0.017)	(0.001)
Korea	-2.32	-1.15	-3.93***	-4.38***	-1.63	-1.03	-2.03	-0.79
	(0.173)	(0.684)	(0.005)	(0.002)	(0.457)	(0.730)	(0.274)	(0.807)
	-3.04**	-4.69***	-7.63***	-0.20	-3.47**	-4.56***	-8.17***	-10.49***
	(0.043)	(0.000)	(0.000)	(0.928)	(0.016)	(0.001)	(0.000)	(0.000)
Malaysia	-1.53	-12.85***	-1.64	-0.82	-5.36***	-1.83	-2.12	-0.17
	(0.505)	(0.000)	(0.450)	(0.797)	(0.000)	(0.359)	(0.237)	(0.932)
	6.38***	-6.64***	-4.63***	-4.06***	-4.66***	-4.61***	-3.24**	-5.81***
	(0.000)	(0.000)	(0.001)	(0.004)	(0.001)	(0.001)	(0.028)	(0.000)
N. Zealand	-5.74***	-2.16	2.70	-6.80***	-8.95***	-2.87*	-6.03***	0.94
	(0.000)	(0.224)	(1.000)	(0.000)	(0.000)	(0.061)	(0.000)	(0.995)
	-3.51**	-2.75*	-4.86***	-2.11	-3.01**	-3.49**	-3.19**	-6.43***
	(0.015)	(0.078)	(0.005)	(0.243)	(0.046)	(0.015)	(0.031)	(0.000)
Pakistan	-0.63	-0.62	-2.267	-3.55**	-2.49	-2.40	-6.03***	-0.22
	(0.477)	(0.849)	(0.188)	(0.013)	(0.126)	(0.149)	(0.000)	(0.926)
	-7.39***	-7.38***	-5.77***	-5.02***	-5.11***	-3.82***	-3.19**	-5.12***
	(0.001)	(0.000)	(0.000)	(0.003)	(0.003)	(0.007)	(0.031)	(0.003)
Philippines	0.76	-5.26***	-1.98	0.59	-2.26	-1.62	-2.10	-0.22
	(0.991)	(0.002)	(0.295)	(0.986)	(0.191)	(0.458)	(0.246)	(0.926)
	-4.08***	-5.82***	-4.53***	-5.57***	-5.79***	-3.92***	-8.31***	-3.56**
	(0.004)	(0.000)	(0.001)	(0.000)	(0.000)	(0.006)	(0.000)	(0.013)
Singapore	-1.41	-1.65	-5.82***	-1.16	0.27	-1.53	-5.90***	-0.33
	(0.564)	(0.446)	(0.000)	(0.676)	(0.972)	(0.502)	(0.000)	(0.909)
	-6.78***	-6.58***	-3.51**	-5.75***	-4.46***	-4.19***	-2.35	-5.41***
	(0.000)	(0.000)	(0.015)	(0.000)	(0.001)	(0.003)	(0.164)	(0.001)
Sri Lanka	-1.67	-1.55	-3.98***	-0.09	-2.12	-8.53***	-2.78*	0.30
	(0.437)	(0.524)	(0.004)	(0.941)	(0.239)	(0.000)	(0.072)	(0.975)
	-3.49**	-5.63***	-4.62***	-3.56**	-4.73***	-6.91***	-4.19***	-5.34***
	(0.015)	(0.000)	(0.001)	(0.013)	(0.001)	(0.000)	(0.003)	(0.001)
Thailand	0.31	-5.77***	-2.27	2.14	-1.29	-1.64	-2.05	-0.26
	(0.975)	(0.000)	(0.187)	(0.999)	(0.620)	(0.453)	(0.263)	(0.919)
	-4.63***	-13.27***	-4.23***	-3.91***	-4.83***	-4.01***	-4.72***	-5.58***
	(0.001)	(0.000)	(0.003)	(0.006)	(0.001)	(0.004)	(0.001)	(0.001)
Vietnam	-1.56	-1.71	-2.65*	-2.83*	-0.77	-2.31	-1.86	0.36
	(0.490)	(0.416)	(0.093)	(0.066)	(0.813)	(0.175)	(0.347)	(0.978)
	-3.78***	-8.78***	-6.71***	-4.71***	-7.28***	-3.99***	-8.38***	-5.29***
	(0.008)	(0.000)	(0.000)	(0.001)	(0.000)	(0.005)	(0.000)	(0.001)

Note: 1^{st} *row* = PP test statistics at level; 2^{nd} *row* = PP test statistics after first differencing; *numbers in bracket* are p-values; *, **, and *** refer statistical significance at 10%, 5%, and 1% level of significance.

regression which leads to biased and invalid decision and interpretation (Harris and Solis, 2003). As a result of spurious regression, Granger and Newbold (1974) and Stock and Watson (1988) indicated that t-values of regression coefficients become highly significant, coefficient of determination become highly inflated and close to one and the statistical value of Durbin-Watson become very low which results in a high probability to commit Type I error. To avoid the problem of spurious regression in time-series analysis, the present study examined the extent of stationarity of the time-series variables at level and first difference. For this purpose and as a pre-condition for the ARDL co-integration test approach, the study employs the popular and widely used methods of Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) unit root tests. These tests indicate that a unit problem exists if the time series variables are non-stationary at level while the problem of unit root does not exist when the time series variables are stationary after first differencing. Thus, the null hypothesis (H0) *"There is a unit root problem in the time-series variables" is tested against the alternative hypothesis (H1) "There is no unit problem in the time-series variables."*

As presented in Table 2, the Augmented Dickey-Fuller (ADF) unit root test results indicated that income inequality (*INIE*), health capital (*HCAP*), and gross national income per capita (*GNIPC*) for all countries are stationary at level or after first differencing. Similarly, education capital (*ECAP*) except Japan, innovation (*INOV*) except New Zealand, institutions (*INST*) except Korea, infrastructure (*INFR*) except India, and market sophistication (MKTS) except India and Malaysia are all stationary at level or after first differencing.

On the other hand, the Phillips-Perron (PP) unit root tests results, as presented in Table 3, indicated that all the relevant variables of the income inequality equations for the 15 Asia-Pacific countries are either stationary at level or after first differencing. Thus, we can conclude that some of the time-series variables are integrated at order zero I[0] while others are integrated at order one I[1] implying that the ARDL bounds co-integration mechanism is best fit to analyze the effect of innovation and human capital variables on income inequality of the 15 Asia-Pacific countries.

C. Co-integration Test Results

After examining the extent of stationary of the relevant time-series variables of income inequality equation via unit root testing, co-integration test is employed in order to ascertain the existence of long-run equilibrium relationship (steady-state equilibrium) among the variables included in the selected ARDL model. The null hypothesis of "all coefficients of explanatory variables are zero indicating that there is no co-integration (no long-run relationship)" is tested against the alternative hypothesis of "all coefficients of explanatory variables are

Table 4
ARDL Bounds Test Analysis

Country	*Co-integration Function*	*Optimal Lag*	*F-Statistics*
Australia	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 1, 0, 2, 2, 2, 0)	6.0947****
Bangladesh	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 1, 0, 0, 2, 2, 2, 2)	14.512****
China	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 1, 2, 2, 2, 2, 1, 2)	9.4569****
India	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 2, 2, 2, 0)	7.9293****
Indonesia	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 1, 2, 2, 0, 2)	16.5461****
Japan	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 1, 2, 0, 0, 1, 2, 2)	8.5366****
Korea	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 1, 0, 0, 0)	4.1618***
Malaysia	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(1, 2, 2, 2, 2, 2, 2, 2)	21.0184***
N. Zealand	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 1, 2, 2, 2, 0)	6.1232*****
Pakistan	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(1, 2, 0, 1, 1, 1, 2, 1)	5.7076****
Philippines	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 1, 2, 2, 2)	4.6382****
Singapore	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(1, 1, 2, 2, 2, 2, 1, 2)	7.4464****
Sri Lanka	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 0, 0, 2, 2, 2, 2)	7.3867***
Thailand	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 1, 2, 2, 2, 2, 0)	14.6356****
Vietnam	F(INIE|INOV, EDCAP, HCAP, INST, INFR, MKTS, GNIPC)	ARDL(2, 1, 1, 2, 2, 2, 1, 1)	15.4543****

Note: *, **, *** and **** denote statistical significance at 10%, 5%, 2.5% and 1% level of significance.

not equal to zero indicating for the existence of long-run relationship" among income inequality, innovation, human capital and other explanatory variables of the model. This means, appropriate lag length selection is important. The present study used a maximum lag order of two for both dependent variable and dynamic regressors based on the recommendation of Pesaran and Shin (1999), Pesaran *et al.* (2001) and Narayan (2004) for annual time series data. In line with this, Akaike Information Criterion (AIC), the appropriate method for a relatively small number of observations, is used to determine the optimum lag length

TABLE 5

ARDL BOUNDS TEST ANALYSIS; WITH INTERACTION TERM (*HCI*INOV*)

Country	*Co-integration Function*	*Optimal Lag*	*F-Statistics*
Australia	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 0, 0, 2, 2)	15.6184****
Bangladesh	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 0, 0, 1, 1, 2, 2, 2)	5.3931****
China	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 1, 2, 1, 2, 2)	7.9161****
India	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 2, 2, 2, 2)	16.4849****
Indonesia	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 1, 2, 2, 2, 2, 2)	6.9401****
Japan	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(1, 2, 2, 2, 1, 2, 1, 1)	7.1009****
Korea	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(1, 1, 2, 0, 2, 0, 2, 1)	7.2551****
Malaysia	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 1, 2, 2, 1, 2, 2)	6.8721****
N. Zealand	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 0, 2, 2, 2)	13.373*****
Pakistan	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(1, 1, 2, 1, 2, 2, 2, 0)	7.1586****
Philippines	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 1, 1, 1, 2, 2, 2)	5.5141****
Singapore	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 0, 2, 0, 2)	9.0845****
Sri Lanka	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 0, 2, 2, 2, 2, 2, 2)	13.9763****
Thailand	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 0, 1, 1, 0)	13.2818****
Vietnam	F(INIE|INOV, HCI, HCI*INOV, INST, INFR, MKTS, GNIPC)	ARDL(2, 2, 2, 2, 2, 2, 2, 2)	9.7428****

Note: *, **, *** and **** denote statistical significance at 10%, 5%, 2.5% and 1% level of significance.

Table 6
Critical Values of ARDL Bounds Test

Significance Level	*Lower Bound, I(0)*	*Upper Bound, I(1)*
10%	(2.03)	(3.13)
5%	(2.32)	(3.50)
2.5%	(2.60)	(3.84)
1%	(2.96)	(4.26)

Note: I(0) is *integrated at order zero*; I(1) is *integrated at order 1*.

of the dependent and explanatory variables of the model. Optimal lag of income inequality, innovation and human capital as well as other conditional variables for each country are presented in Tables 4 and 5 (Appendix A, Figures A1-A15).

Following the optimum lag length determination for the relevant variables in the income inequality equations, the ARDL bounds test for co-integration was performed for each country. As presented in Tables 4 and 5, the Autoregressive Distributed Lag (ARDL) bounds test resulted in F-statistic values greater than the upper bound critical values of 5% significance level (3.50) and 1% level of significance (4.26). Table 6 presents the critical values of ARDL bounds test. These results indicate the evidence that the null hypothesis of no co-integration among the relevant variables in the income inequality model is rejected implying that there is a significant long-run equilibrium relationship between income inequality, innovation and human capital as well as other control variables in the 15 Asia-Pacific countries during the period of study.

D. Estimation Results of the Selected ARDL Model

After confirming the existence of long-run equilibrium relationships between income inequality, innovation and human capital variables via the ARDL bounds co-integration approach, estimation of long-run parameters of the selected ARDL models of income inequality were carried out for the 15 Asia-Pacific countries. As indicated in Table 7, innovation variable (measured in terms of the average score of technology, knowledge and creative output) has a significant and positive effect on the income inequality of most of the Asia-Pacific countries including Australia, Bangladesh, China, Indonesia, Korea, Malaysia, Pakistan, Singapore and Sri Lanka. Similarly, the impact of knowledge, technology and creative output on income inequality in India, New Zealand, Philippines and Thailand is positive but insignificant at conventional level of significance. This finding is consistent with recent studies that surged during the hyper-globalization phase have empirically examined the relationship between innovation and economic inequalities reached to the conclusion that innovation increases income inequality (Aghion, Akcigit, Bergeaud, Blundell and Hemous, 2019). Furthermore, it confirms the proposition that technological innovation adversely affects income distribution of the economy through the composition and nature of work available for which automation and robotic technologies tend to favor non-routine cognitive tasks while they are reducing the demand for manual work as well as the generation of economic rents and rent-seeking behavior of skill and capital biased technologies owned by individuals and corporations. The significant and positive effect of innovation on income inequality is consistent with findings of Kinugasa (1998), Aghion (2002), and Perera-Tallo (2017). On the contrary to these findings, the study pointed out that income inequality and innovation variables have an inverse relationship in the economies of Japan and Vietnam. Only for two countries, the Schumpeterian hypothesis of creative destructive innovations reduces inequality stands vindicated.

With respect to the impact of human capital variables on income inequality of the Asia-Pacific region, education capital (proxied by mean years of schooling) has a significant income equalizing effect in India, Korea, Malaysia, Sri Lanka and Thailand whereas it has an insignificant inverse relationship with income inequality in Australia, Indonesia, New Zealand, and Philippines. These findings are in line with Shultz (1961) proposition which suggested that the deterioration in distribution of income can be improved through human capital development in which public education expansion mainly at primary level plays an important role. Similarly, Mohan and Sabot (1988) and Lecaillon, Paukert, Morrisson and Germidis (1984) have argued that the expansion of education capital could lead to an increase in the supply of educated workers which tend to reduce the dispersion of income distribution for which the compression effect dominates the composition effect thereby reducing the gap of wage differentials in the long run. The negative impact of education capital on income inequality is consistent with the empirical findings of Park (1998, 2017), De Gregorio and Lee (2002); Sylwester (2003) and Lin (2007) for which wide range of marginalized and disadvantaged section of the society in the country have been highly benefited from the expansion of education that has led to raise their income share and resulted in a decline in the income gap and improved the distribution of income during the study period. On the contrary to this, the empirical results indicate that education capital has a significant income disequalizing effect on the economies of China, Japan, Singapore, and Vietnam. This finding is in line with the argument proposed by Becker (1962), Becker and Chiswick (1966), Mincer (1958), and Gylfason and Zoega (2003) that the inequality in distribution of income is affected by the supply and demand of educated people in the economy in such a way that a shift in labor demand from unskilled workers to skilled workers would lead to a decrease in the demand for low-educated workers whereas the demand for better educated workers increase leading to a larger inequality in the distribution of income of the economy across the population.

On the other hand, concerning the effect of health capital variable in income distribution, it has a significant and positive relationship with income inequality in Bangladesh, China, Japan, Korea, Malaysia, and Pakistan. This is in line with Acemogulu and Johnson (2007) who argued that the existence of more investment in healthcare and improved health condition could lead to an increase in population size as well as lower distribution of current resources over enormous population size that eventually results in a depressing effect on distribution of income in the economy. On the contrary to this finding, health capital has an equalizing effect in Indonesia, New Zealand, Thailand, and Vietnam during the period of study. Existence of healthy work force in the economy is expected to enhance productivity growth of the economy due to the fact that they have physical strength, stamina and endurance as well they are mentally strong and less likely absent from their workplace and use their time appropriately (Bloom and Canning, 2000; Gupta, 2006). In addition, a worker having a longer life expectancy could help to raise his/her productivity by accumulating more and more experience (Mincer, 1974). Health economics scholars also argued that existence of improved health condition of the workforce is also expected to make effective and productive use of advanced technologies, equipment and machineries in the economy (Suhrcke *et al.*, 2005). Similarly, individuals and society at large with increased longevity are usually capable to increase the propensity to save thereby investment in physical and intellectual capital accumulation leading

Table 7

Results of Relationship between Income Inequality, Innovation and Human Capital

Country	*INOV*	*ECAP*	*HCAP*	*INST*	*INFR*	*MKTS*	*GNIPC*
Australia	0.0625**	-0.2256	-0.3523	-0.3895**	-0.0295	-0.1188***	-0.0325
	(0.0259)	(0.2154)	(0.7045)	(0.1713)	(0.0369)	(0.0335)	(0.0387)
Bangladesh	0.1499**	0.1032	0.9569***	0.4431***	0.1487	0.1341*	-0.0369
	(0.0477)	(0.0903)	(0.2703)	(0.1326)	(0.0845)	(0.0675)	(0.0442)
China	0.2396***	0.2439*	2.1284*	0.15278**	0.0915**	0.0956	-0.0473*
	(0.0479)	(0.1111)	(1.0424)	(0.0482)	(0.0392)	(0.0527)	(0.0235)
India	0.0551	-0.2220**	0.3197	-0.9386***	0.1387*	0.5516*	0.1876**
	(0.0483)	(0.1016)	(1.1433)	(0.2107)	(0.0754)	(0.2960)	(0.0889)
Indonesia	0.0725*	-0.0423	-2.8816**	0.0166	-0.4429***	-0.0114	0.2456***
	(0.0362)	(0.0785)	(0.8636)	(0.0092)	(0.0817)	(0.0140)	(0.0379)
Japan	-0.1486**	0.7255***	1.4282*	0.0001	-0.0112	-0.1576**	-0.1888**
	(0.0609)	(0.1559)	(0.6502)	(0.0089)	(0.0271)	(0.0526)	(0.0674)
Korea	0.2805**	-0.7789*	2.3824*	-0.0718	-0.0755	0.4177**	0.0516
	(0.1014)	(0.4104)	(1.1389)	(0.1680)	(0.0671)	(0.1764)	(0.0461)
Malaysia	0.0025*	-0.0945*	4.1904**	-0.0706	0.0511	0.1594**	-0.0161
	(0.0011)	(0.0424)	(1.4351)	(0.0594)	(0.0312)	(0.0573)	(0.0142)
New Zealand	0.1463	-0.1964	-3.2308***	-0.4021**	0.2494**	0.1034**	0.0042
	(0.0925)	(0.4001)	(0.8104)	(0.1749)	(0.0860)	(0.0411)	(0.0204)
Pakistan	0.1025***	-0.0203	0.6018***	0.0022	0.0654***	-0.0351***	0.0194***
	(0.0186)	(0.0115)	(0.1310)	(0.0031)	(0.0099)	(0.0047)	(0.0057)
Philippines	0.0225	-0.1077	-0.3928	0.0853	-0.0688**	-0.0376*	0.0294
	(0.0249)	(0.0599)	(0.4171)	(0.0559)	(0.0265)	(0.0173)	(0.0202)
Singapore	0.1758***	0.3447	-0.4924	-1.0315*	-0.1497**	-0.3191**	0.0126
	(0.0514)	(0.2049)	(0.6942)	(0.5511)	(0.0463)	(0.1163)	(0.0348)
Sri Lanka	0.0082*	-0.3166**	0.0270	0.1470***	0.1409***	-0.0343**	-0.0301**
	(0.0037)	(0.0960)	(0.2016)	(0.0233)	(0.0142)	(0.0113)	(0.0091)
Thailand	0.0209	-0.1127*	-0.7059**	-0.0760	-0.0162	0.2207***	-0.0026
	(0.0278)	(0.0583)	(0.2523)	(0.0761)	(0.0256)	(0.0455)	(0.0153)
Vietnam	-0.1103	0.7679**	-0.5486***	0.6829*	0.1633**	0.2343**	-0.1942**
	(0.1442)	(0.2656)	(0.1069)	(0.3419)	(0.0649)	(0.0946)	(0.0700)

Note: Standard errors in parenthesis; *, **, and *** refer statistical significance at 10%, 5%, and 1% level of significance.

to create more investment opportunities thereby results more equal distribution of income in the long run (Bloom and Canning, 2000; Bhargava *et al.*, 2001; Weil, 2007).

Institutional quality variable in the economies of Australia, India, New Zealand, and Singapore has a significant and more income equalizing effect. This result is consistent with the empirical findings of Chong and Gradstein (2007) who pointed out better institutional quality is associated with more equal distribution of income indicating that income inequality is found to be correlated with low institutional quality in terms of poor political, regulatory and business environments. On the contrary, it has adversely affected the income distribution of Bangladesh, China, Sri Lanka and Vietnam significantly. Regarding the effect on infrastructure variable on income inequality of the Asia-Pacific region, the study pointed out that it hurts income distribution of China, India, New Zealand, Pakistan, Sri Lanka and Vietnam whereas it has significantly contributed to reduce the rate of income inequality in the economies of Indonesia, Philippines, Singapore and Thailand. However, the empirical evidence indicated that the expansion and enhancement of market sophistication variable has a significant and positive relationship with income inequality in Bangladesh, India, Philippines, and Vietnam. Contrary to this result, market sophistication variable has a significant and more income equalizing effect on the economies of China, Japan, Pakistan, and Sri Lanka. Gross National Income per capita has a disequalizing effect on income in India, Indonesia, Pakistan, Korea, Philippines and Singapore whereas it reduces income inequality in China, Japan, Sri Lanka, and Vietnam.

While introducing the interaction term, as indicated in Table 8, a multiple of human capital index and innovation index, the results of the ARDL approach indicated that it has an income equalizing effect in Japan, New Zealand, and Vietnam at conventional level of significance. This indicates that the expansion of human capital development in the presence of better innovation has an inverse relationship with income inequality in these economies. On the contrary, as presented in Table 8, the study points out that the interaction term has an increasing effect on income inequality in Australia, China, India, Malaysia, Philippines, Pakistan, Singapore, Thailand and Sri Lanka during the period of the study. This finding is consistent with the skill biased technological change-income inequality hypothesis which states that the relative demand for highly educated workers increased in an economy characterized by innovative technology and creative output which eventually leads to a larger inequality in the distribution of income in the economy. This indicates that the income inequality-innovation nexus in majority of the Asia-Pacific economies is subject to the country's level of human capital development via the so-called skill premium during the period of study.

Table 8

Results of Long-Run Model of Income Inequality Equation: With Interaction (*HCI*INOV*)

Country	*INOV*	*HCI*	*HCI*INOV*	*INST*	*INFR*	*MKTS*	*GNIPC*
Australia	0.0012 (0.0009)	3.6635*** (0.0796)	1.0782*** (0.0139)	-0.0077*** (0.0008)	0.0020** (0.0008)	-0.0011 (0.0008)	-0.0100*** (0.0027)
Bangladesh	0.2614 (0.4558)	1.9786 (2.9525)	0.0083 (0.6393)	0.9365** (0.3333)	0.2684** (0.0974)	0.43055** (0.1508)	-0.1522* (0.0776)
China	0.1642** (0.0642)	-1.9632 (2.9141)	1.8612*** (0.4567)	0.0357 (0.0287)	-0.0030 (0.0536)	-0.2481*** (0.0544)	0.0463** (0.0182)
India	0.3104* (0.1528)	-0.7798 (0.9749)	0.7437** (0.2968)	1.3642** (0.4362)	-1.0547** (0.3345)	0.4576* (0.2270)	0.0682 (0.0419)
Indonesia	0.3223 (0.2487)	-0.1248** (0.0491)	0.6502** (0.2371)	0.0684 (0.0657)	0.0970 (0.0548)	0.0164 (0.0134)	-0.0458* (0.0191)
Japan	0.64135*** (0.1937)	-0.72704*** (0.1655)	-0. 5944* (0.3001)	-0.0445* (0.0209)	-0.1234* (0.0614)	-0.1024* (0.0538)	-0.1185 (0.0797)
Korea	0.2290*** (0.0519)	-0.2707 (0.5267)	-0.4986 (0.6581)	-0.2013** (0.0854)	-0.2275*** (0.0476)	-0.0445 (0.2375)	-0.0719* (0.0337)
Malaysia	0.1977*** (0.0181)	0.7724*** (0.0956)	0.3044*** (0.0283)	-0.0109 (0.0364)	0.0038 (0.0038)	0.0098 (0.0223)	-0.0197*** (0.0040)
N. Zealand	-0.2712** (0.1025)	0.1124 (0.6811)	-0.7103*** (0.1371)	-0.3908** (0.1441)	0.2419** (0.0796)	0.0714 (0.0380)	0.0119 (0.0359)
Pakistan	0.2622 (0.2160)	0.7772*** (0.2543)	0.9308** (0.4088)	0.0063 (0.0052)	0.0398*** (0.0109)	-0.0290*** (0.0082)	0.0049 (0.0070)
Philippines	-0.0252** (0.0104)	2.8226** (1.1271)	0.8224* (0.3622)	0.0623*** (0.0131)	-0.0463*** (0.0121)	0.0152** (0.0062)	0.0083 (0.0048)
Singapore	0.1037 (0.0569)	0.5432 (0.3035)	0.1760* (0.0923)	-0.0037 (0.0689)	-0.0108 (0.0078)	-0.0099 (0.0165)	-0.0088** (0.0039)
Sri Lanka	0.1779 (0.1605)	-0.2466 (0.9701)	0.0142* (0.0062)	0.1306*** (0.0280)	-0.0289 (0.0242)	-0.0403** (0.0128)	-0.0185* (0.0086)
Thailand	0.2689** (0.1086)	1.4265** (0.6311)	0.4739*** (0.1691)	-0.0509** (0.0166)	-0.0527*** (0.0061)	0.0926 (0.0132)	-0.0193*** (0.0044)
Vietnam	0.2162 (0.1922)	-0.2953 (0.7983)	-0.45574*** (0.1117)	0.0643* (0.0258)	0.0560** (0.0153)	0.0211* (0.0093)	-0.0217 (0.0113)

Note: Standard errors in parenthesis; *, **, and *** denote to statistical significance at 10%, 5%, and 1% level of significance.

E. Diagnostic and Stability Test Results

To test the reliability, robustness and validity of the empirical estimates can be done through the diagnostic tests of normality, serial correlation, and heteroscedasticity. The diagnostic and stability test results presented in Table 9 and analysis shows that the fitted models of income inequality for each country have passed the diagnostic tests of normality, serial correlation, and heteroscedasticity. This is because the p-values associated with respective test statistics are greater than the standard level of significance in which the null hypotheses specified for each diagnostic test cannot be rejected at 5% level of significance. Moreover, the Jarque-Bera statistical test confirms that the fitted income inequality models are normally distributed. The serial correlation problem was also estimated with the Breusch-Godfrey Serial Correlation LM method and found that the residuals of the fitted

Table 9
Results of Diagnostic Tests

Country	*Normality Test*	*Serial Correlation Test*	*Heteroscedasticity Test*
	J–B Test	*B–G LM Test*	*B–P–G Test*
Australia	1.6497	1.2524	0.7669
	(0.4383)	(0.2921)	(0.7005)
Bangladesh	5.6302	5.5393	0.7832
	(0.0598)	(0.0542)	(0.6848)
China	0.1269	0.5424	0.5066
	(0.9385)	(0.4892)	(0.8922)
India	0.4670	1.4893	1.1236
	(0.7917)	(0.2503)	(0.4330)
Indonesia	2.6468	0.6418	0.2429
	(0.2662)	(0.4594)	(0.9936)
Japan	0.7794	0.0877	1.8620
	(0.6773)	(0.7670)	(0.1481)
Korea	0.4916	2.4432	1.7311
	(0.7820)	(0.1463)	(0.1701)
Malaysia	1.1666	1.0435	0.3354
	(0.5580)	(0.3539)	(0.9724)
New Zealand	2.1740	1.4862	0.6389
	(0.3372)	(0.2623)	(0.8022)
Pakistan	3.0781	1.9206	0.2812
	(0.2145)	(0.1932)	(0.9900)
Philippines	0.4755	0.0017	1.4641
	(0.7883)	(0.9688)	(0.3349)
Singapore	0.0601	5.1277	1.8176
	(0.9704)	(0.0579)	(0.1949)
Sri Lanka	0.1405	0.2003	0.7074
	(0.9321)	(0.6776)	(0.7379)
Thailand	0.7976	1.4909	0.3759
	(0.6711)	(0.2501)	(0.9658)
Vietnam	0.7520	2.0309	0.8809
	(0.6866)	(0.1919)	(0.6132)

Note: *P-values* in parenthesis; J-B = *Jarque-Bera;* B-G = *Breusch-Godfrey;* B-P-G = *Breusch-Pagan-Godfrey.*

ARDL models have no serial correlation problem since the p-values associated with the observed R-squared Chi-square are greater than the conventional significance level. Furthermore, using Breusch-Pagan-Godfrey test, the evidence revealed that the fitted models are free from the problem of heterosedasticity since the p-values associated with observed R-squared Chi-square are greater than the standard critical value.

Furthermore, the parameter stability test shown by CUSUM and CUSUMSQ tests of the fitted models lies within the critical bounds of a standard 5% level of significance (Appendix B, Figures B1-B15). This evidence confirms that the estimated coefficients of the fitted ARDL models of income inequality are stable. Thus, from the foregoing discussion we can conclude that the estimated coefficients have fulfilled all the possible econometric testing requirements and allow us to state that our empirical exercise is in the right direction and interpretation of the fitted models are acceptable.

VI. Conclusion

Income inequality has unprecedently grown in the recent past and its pace has further accelerated. This has alarmed many scholars to reexamine both the widely held wisdom of economic theory of inequality and empirical realities with a view to either reconcile or reject theory for an alternative explanation. The present study posits the relationship between innovation and inequality mediated by the human capital. In this context, it is proposed to examine the long run nexus between income inequality, innovation and human capital for a sample of 15 Asia-Pacific countries. We have employed the ARDL Bounds Co-Integration Approach to estimate the parameters covering the period of hyper-globalization, that is, 1990-2020. To avoid the spurious regression results in time series analysis, the stationarity test was carried out using the Augmented Dickey-Fuller and Phillips-Perron unit root test methods. Indeed, some explanatory variables are stationary at level while others are stationary after first differencing.

The bounds co-integration test revealed a significant long-run equilibrium relationship between income inequality, innovation and human capital variables in all the 15 Asia-Pacific countries. Except Japan and Vietnam, all other countries have a positive relationship between innovation and income inequality. Furthermore, the empirical evidence indicates that the income inequality-innovation nexus in eleven of the Asia-Pacific economies is subject to the countries' level of human capital development via the so-called skill premium during the period of study. The human capital coefficient is positive in eight countries but statistically significant in five countries. This implies that innovation and human capital adversely affected income distribution. The innovation-human capital interaction coefficient implies that technological innovation adversely affects income distribution of an economy through the composition and nature of work reduces the demand for manual work as well as the generation of economic rents and rent-seeking behavior of skill and capital biased technologies. It is important to note that there is a strong negative relationship between gross national income per capita and income inequality. This means that the rise in per capita income improves income distribution. However, the six countries have a growth enhancing income inequality in the case a model estimated without interaction term and five countries in a model estimated with interaction term. An important lesson that comes out of the main finding of the impact of innovation on increase in income equality is that the top-down model of science and technology and increasing investment of private sector in technologies have monopolized the innovations for seeking rents. In this process, the market economy-based innovation system tends to exclude the marginalized section of the society. Therefore, it is suggested that there is a dire need to relook at the innovation system that should use both bottom up and top-down mix to have an impact on reduction of income inequality. Based on these findings, it is important to develop affirmative strategies to improve the education and health services system as well as better opportunities for innovation for those who are marginalized and deprived. In this regard, better quality institutions and infrastructure can play an important role in reducing income inequality in the long run.

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Appendix A

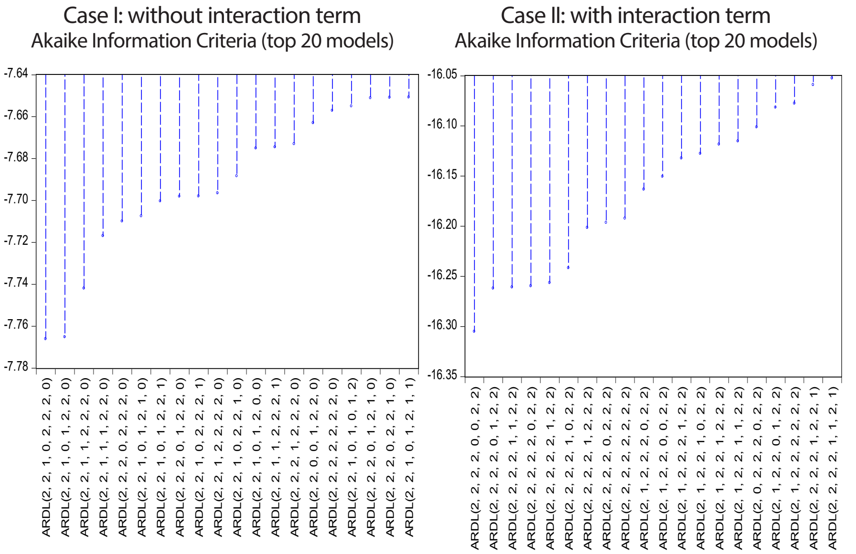

FIGURE A1

OPTIMAL LAG SELECTION FOR AUSTRALIA

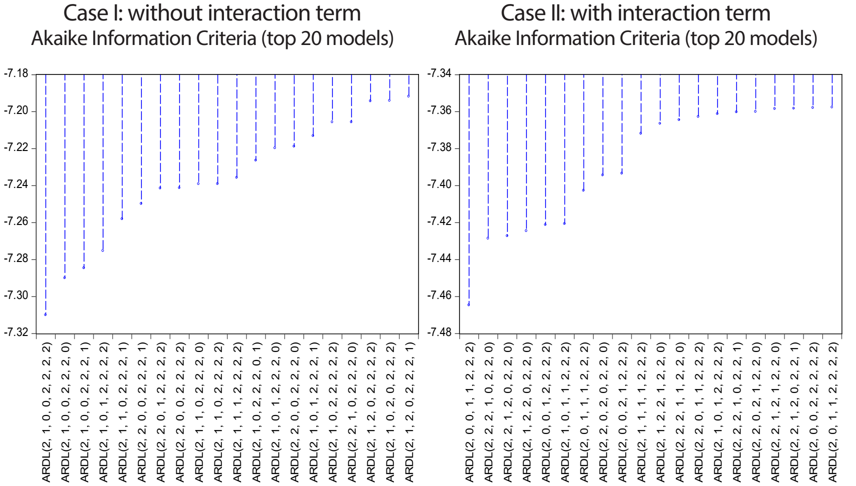

FIGURE A2

OPTIMAL LAG SELECTION FOR BANGLADESH

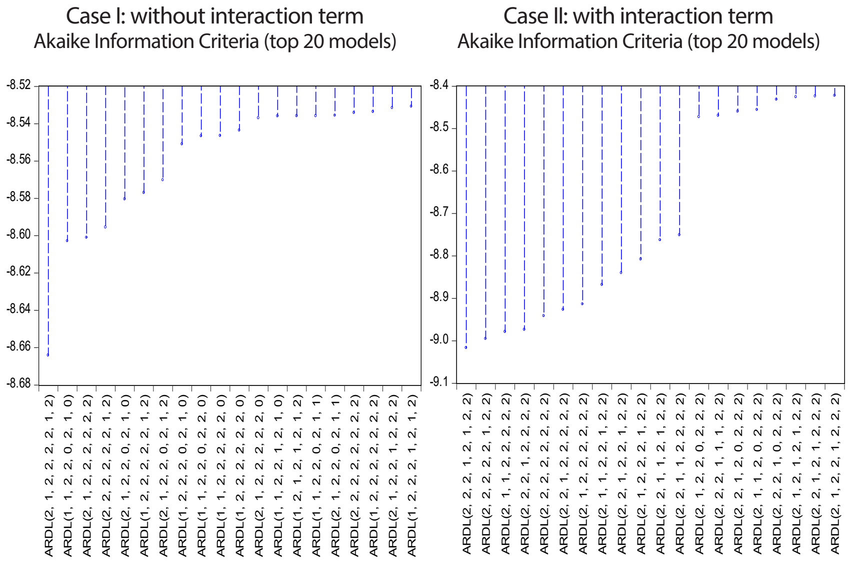

Figure A3

Optimal Lag Selection for China

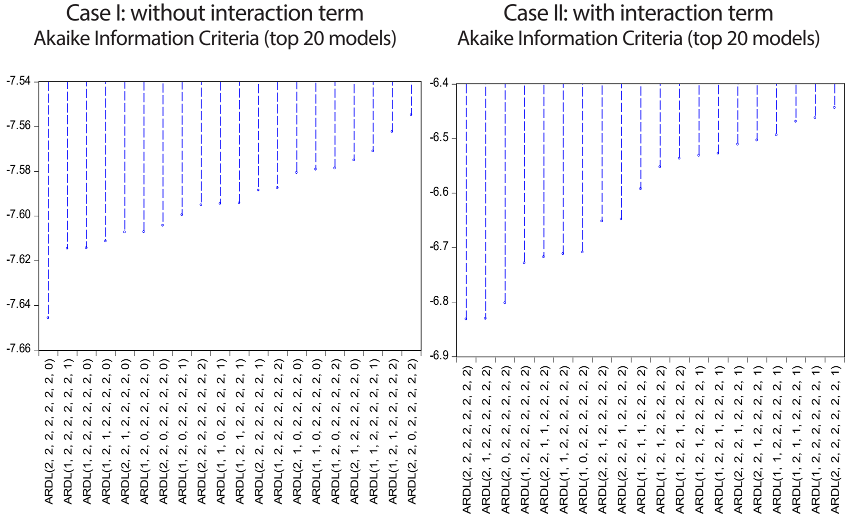

Figure A4

Optimal Lag Selection for India

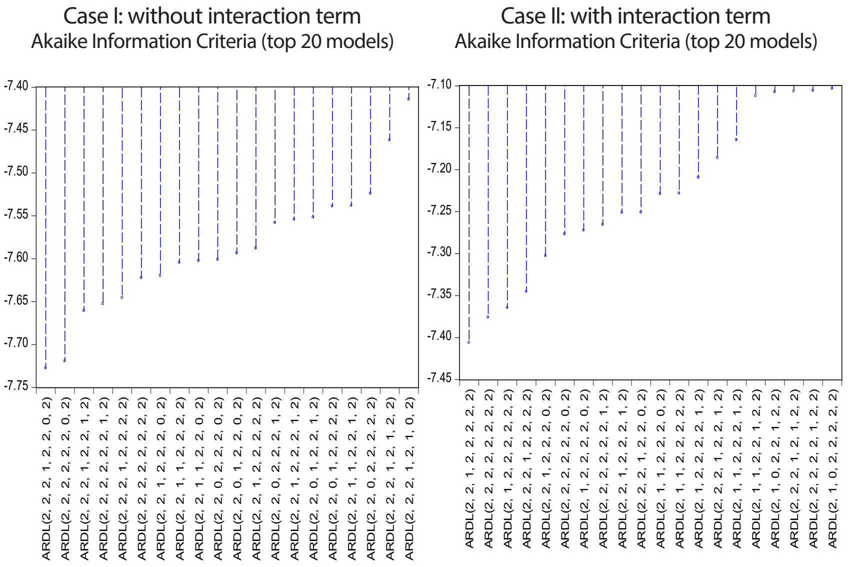

FIGURE A5

OPTIMAL LAG SELECTION FOR INDONESIA

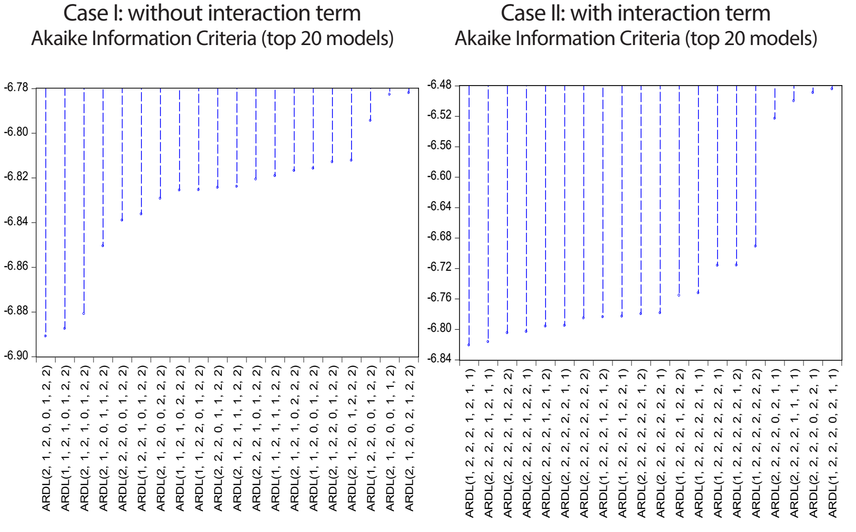

FIGURE A6

OPTIMAL LAG SELECTION FOR JAPAN

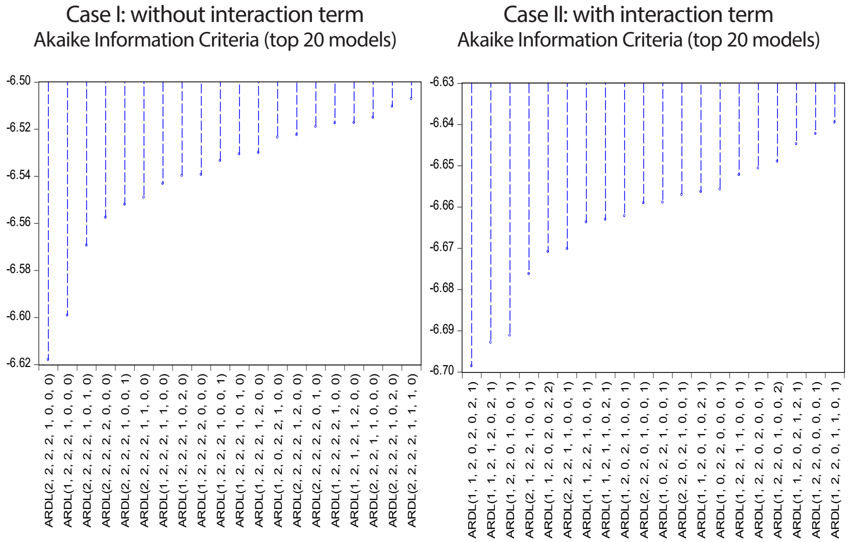

Figure A7

Optimal Lag Selection for Korea

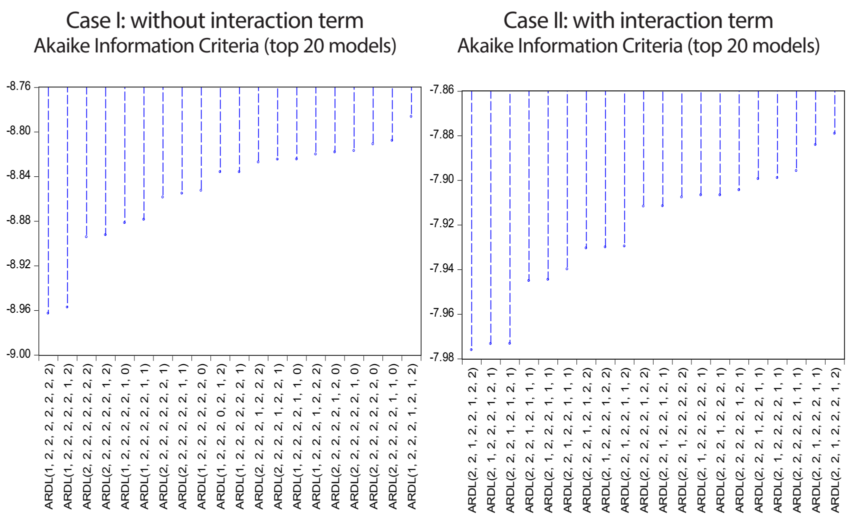

Figure A8

Optimal Lag Selection for Malaysia

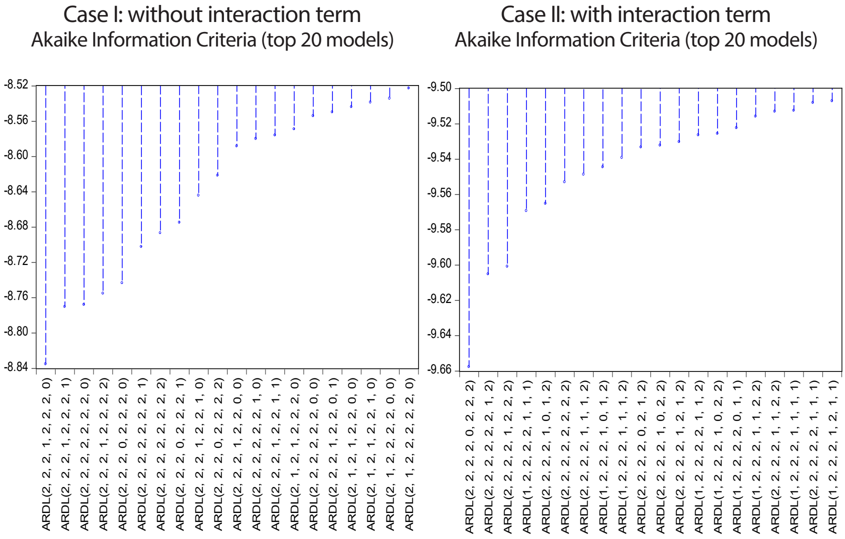

Figure A9

Optimal Lag Selection for New Zealand

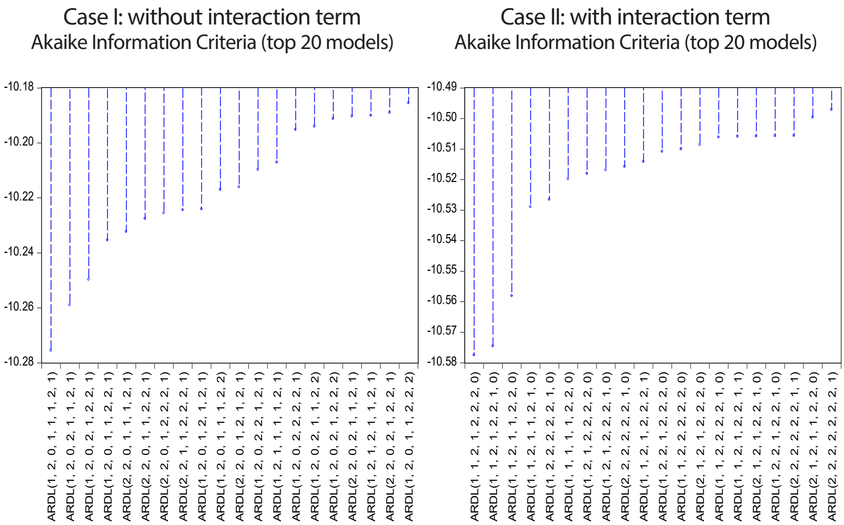

Figure A10

Optimal Lag Selection for Pakistan

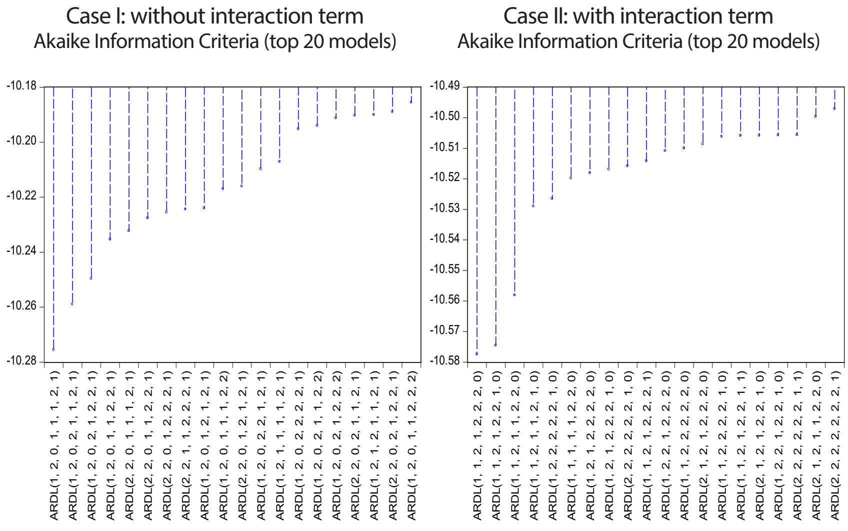

Figure A11

Optimal Lag Selection for Philippines

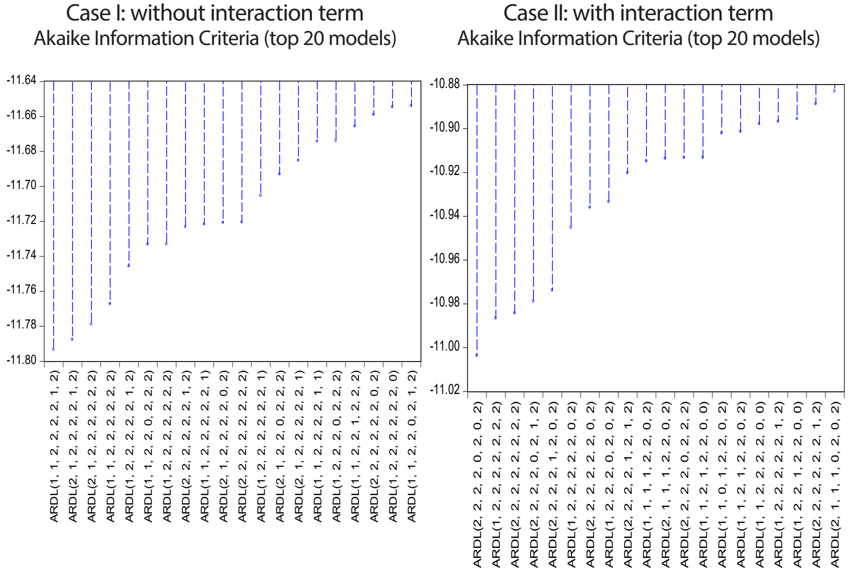

Figure A12

Optimal Lag Selection for Singapore

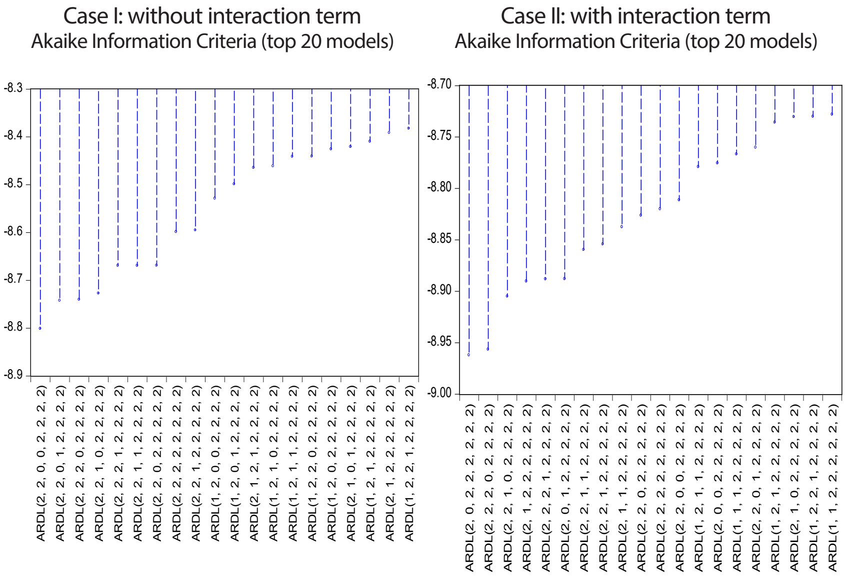

Figure A13

Optimal Lag Selection for Sri Lanka

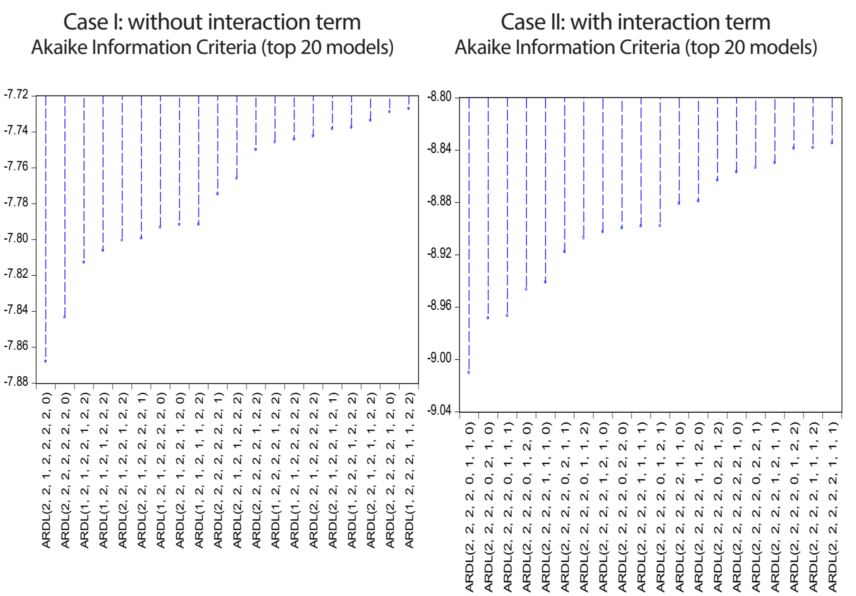

Figure A14

Optimal Lag Selection for Thailand

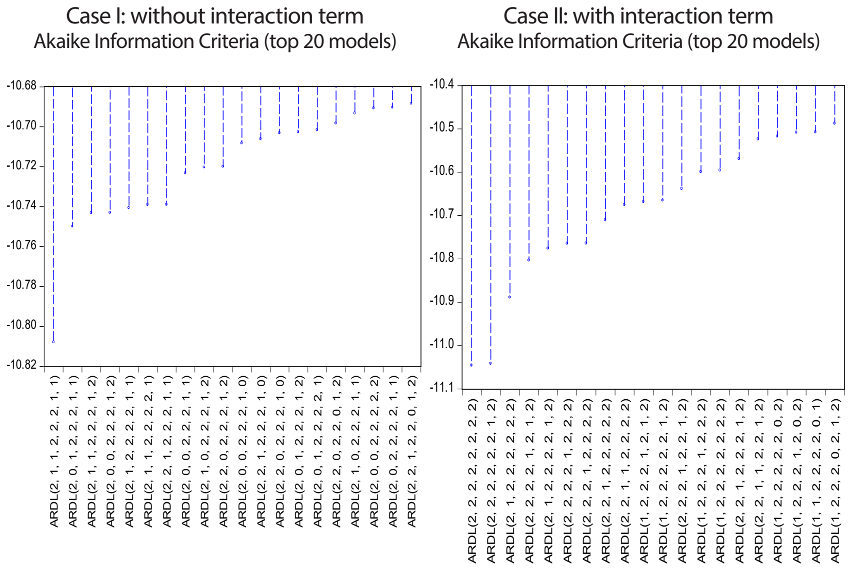

FIGURE A15
OPTIMAL LAG SELECTION FOR VIETNAM

Appendix B

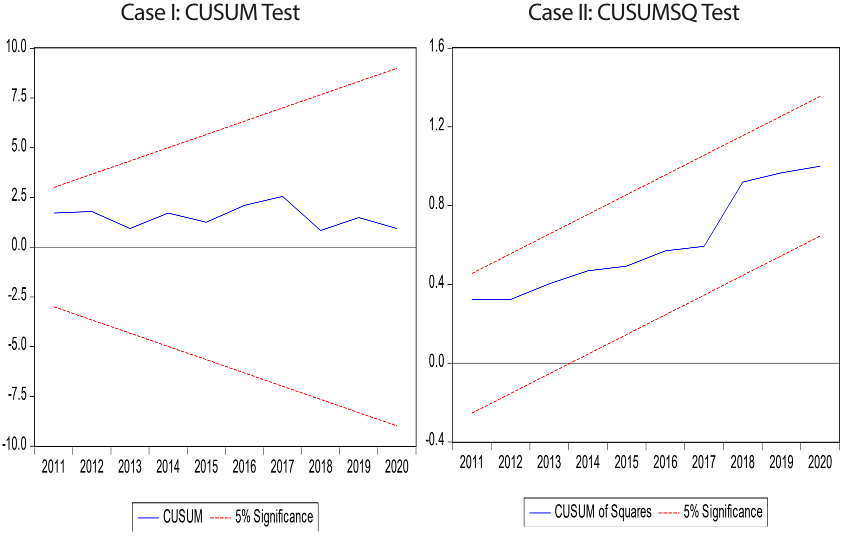

FIGURE B1
STABILITY TESTS OF ARDL MODEL FOR AUSTRALIA

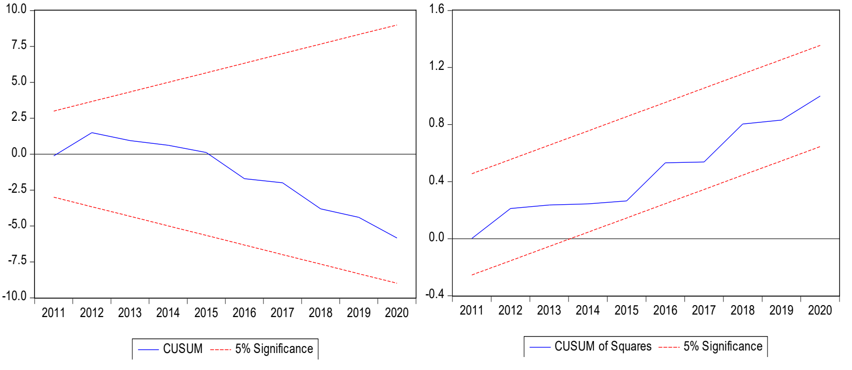

FIGURE B2
STABILITY TESTS OF ARDL MODEL FOR BANGLADESH

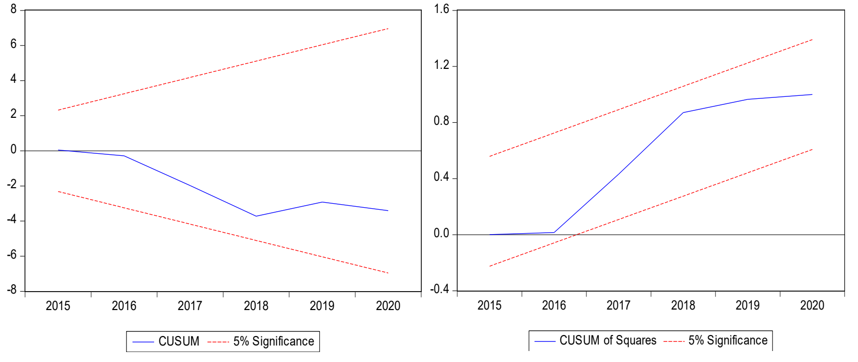

Figure B3

Stability Tests of ARDL Model for China

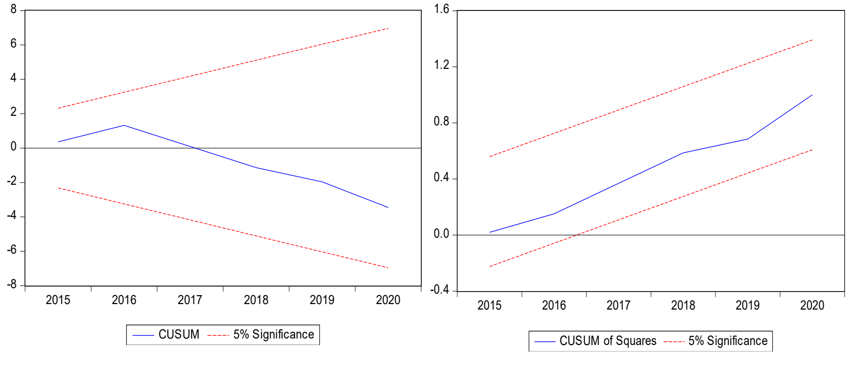

Figure B4

Stability Tests of ARDL Model for India

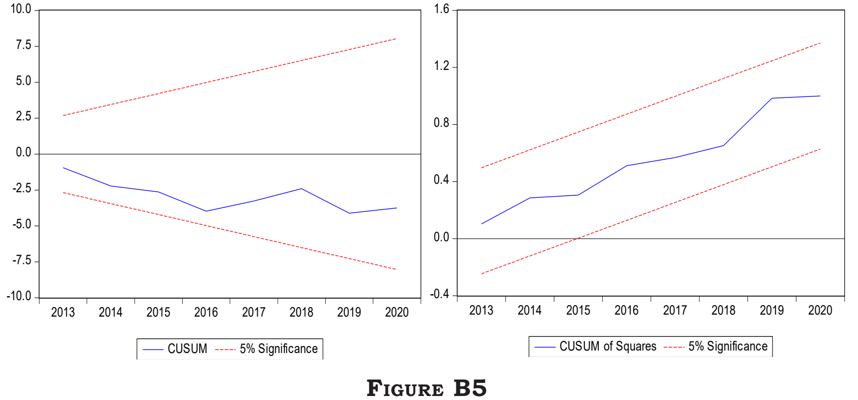

Figure B5

Stability Tests of ARDL Model for Indonesia

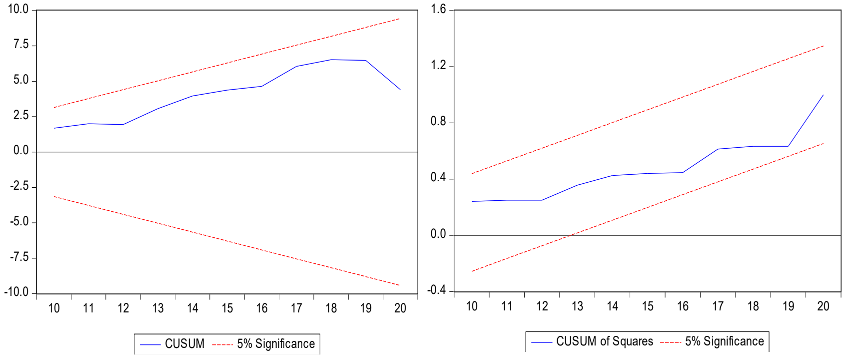

Figure B6

Stability Tests of ARDL Model for Japan

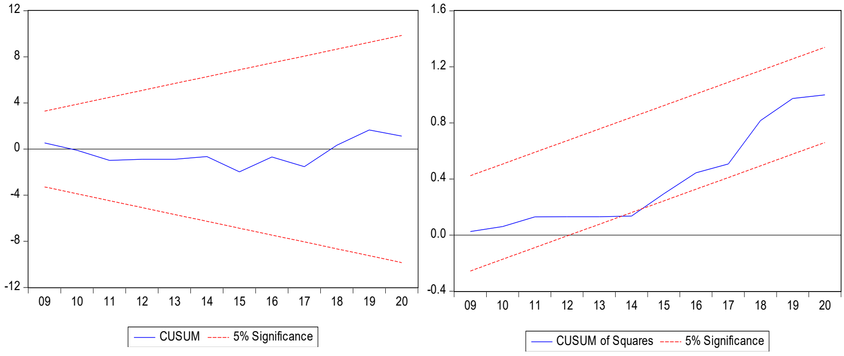

Figure B7

Stability Tests of ARDL Model for Korea

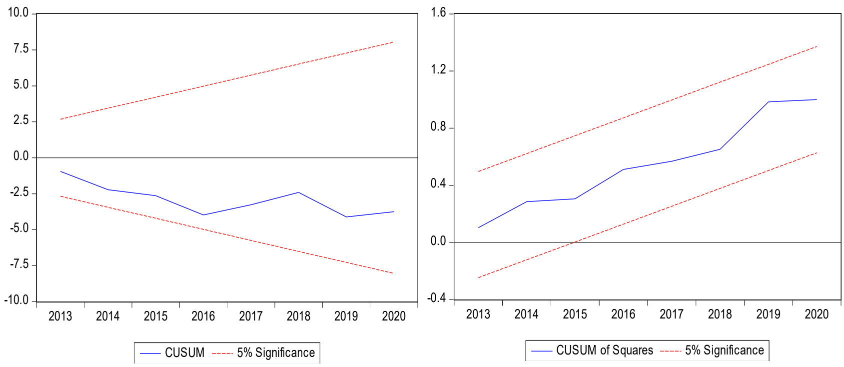

Figure B8

Stability Tests of ARDL Model for Malaysia

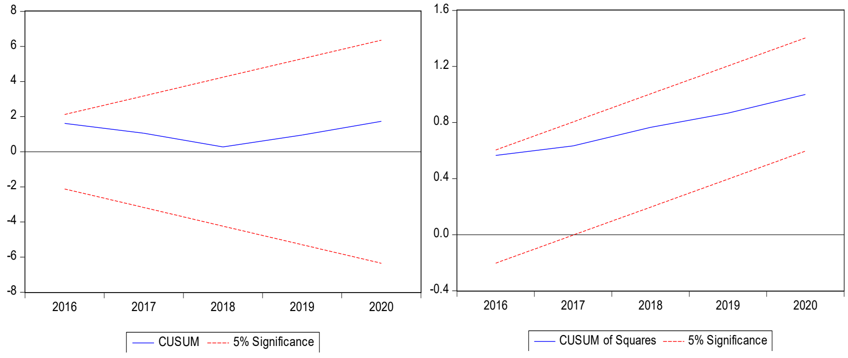

Figure B9
Stability Tests of ARDL Model for New Zealand

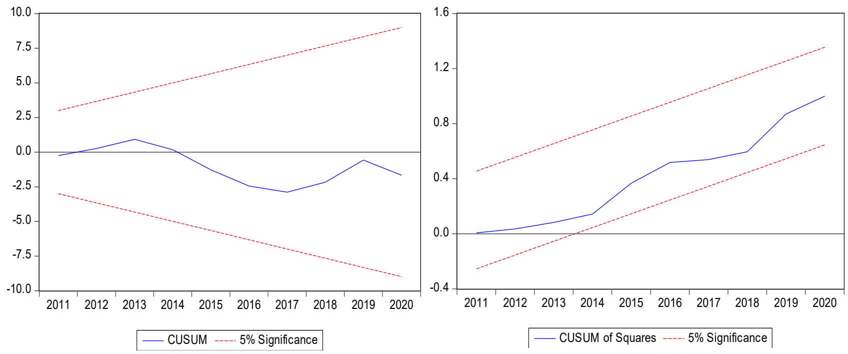

Figure B10
Stability Tests of ARDL Model for Pakistan

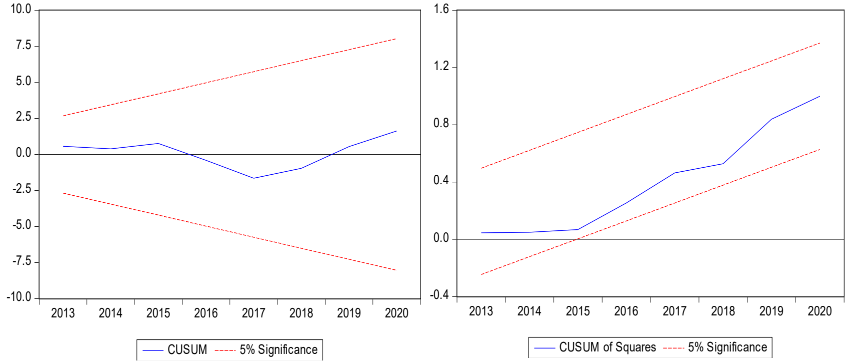

Figure B11
Stability Tests of ARDL Model for Philippines

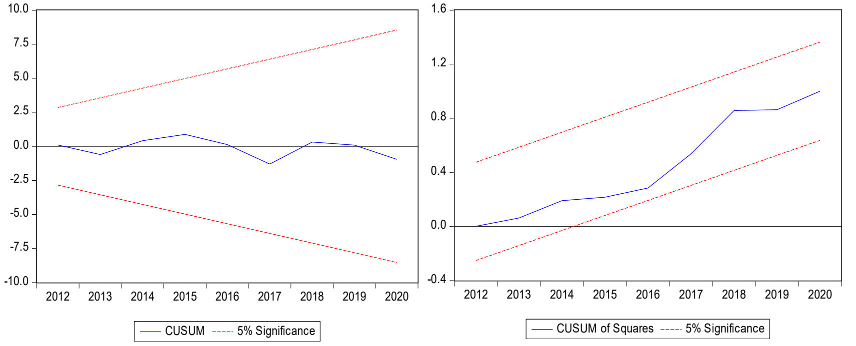

FIGURE B12
STABILITY TESTS OF ARDL MODEL FOR SINGAPORE

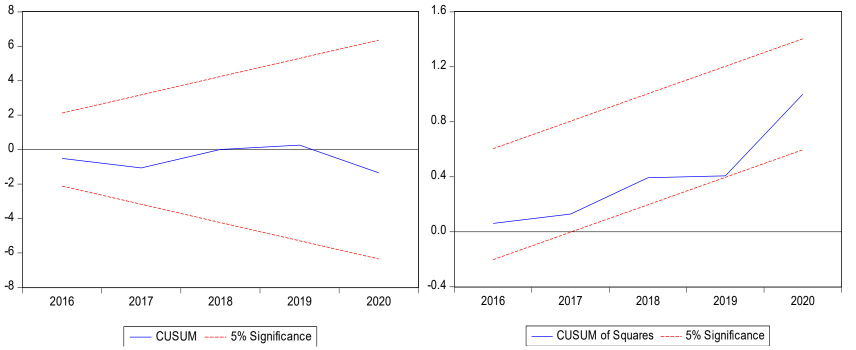

FIGURE B13
STABILITY TESTS OF ARDL MODEL FOR SRI LANKA

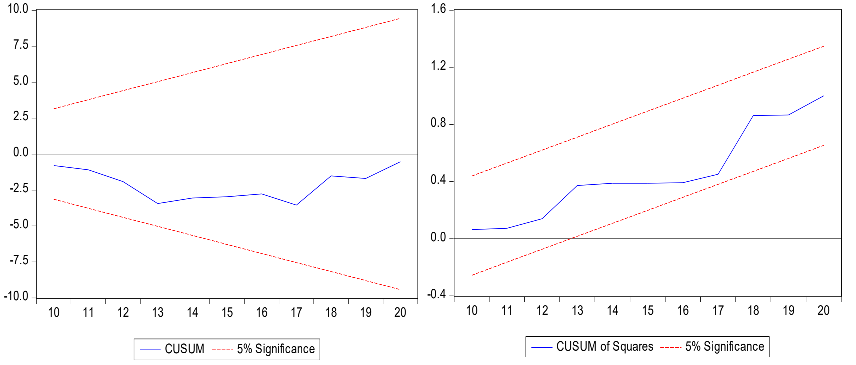

FIGURE B14
STABILITY TESTS OF ARDL MODEL FOR THAILAND

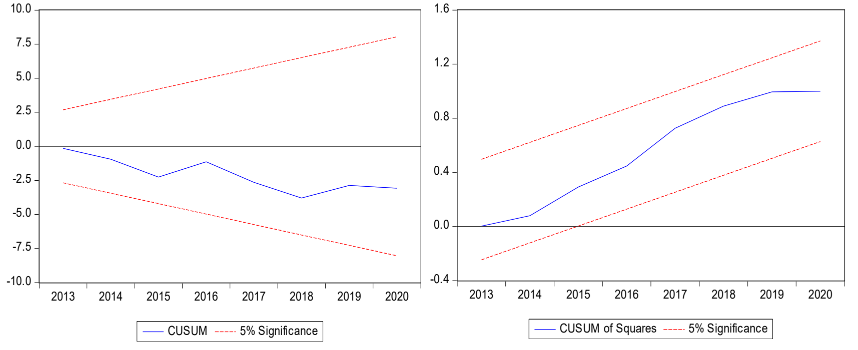

Figure B15
Stability Tests of ARDL Model for Vietnam

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