South Asian Journal of Management Sciences
Vol: 16(2): 188-201, 2022
DOI: 10.21621/sajms.2022162.04

Sectoral Output and Income Inequality Nexus in G7 Countries: A Panel ARDL Approach

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Abstract: *The sectoral output and income inequality nexus has attracted the attention of economists in recent years. The present study contributes to the existing literature on the sectoral output and income inequality nexus in G7 economies. To serve this purpose, the study uses panel autoregressive distributed lag (PARDL) methodology. The PARDL methodology suggests the long-run and short-run relationship among all variables except the inflation rate. The positive impact of the industrial sector on income inequality outweighs the negative impact of the agriculture and service sectors. The impact of sectoral per capita output on income inequality is different from the overall per capita output suggested by Wald test statistics. However, industrialization is a catalytic factor causing income inequality in highly developed countries. The study suggests different interventions at sector level(s) for G7 countries to make income distribution more equal.*

Keywords: *Sectoral output, Agriculture Output, Service Sector, Income inequality, Panel ARDL, G7.*

Introduction

The G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) contribute almost 30 percent of the global GDP. The G20 countries (excluding G7 countries) contribute 42.87 percent of world GDP and the rest of the world accounts for 26.57 percent of the global GDP in 2017 [1]. One-third of the world output is supplied by the group of major seven countries. Sectoral contribution to per capita output is very high in G7 countries as compared to other countries except for G20 countries. High per capita income leads to a higher level of per capita income and consumption. Although, there may be a marginal segment of the society where an increase in sectoral output leads to unequal distribution of resources. This causes inequality and poverty in society.

Poverty eradication was a major target for poor countries around the World as per UNDP Millennium Development Goals. Although the G7 countries were not prone to this

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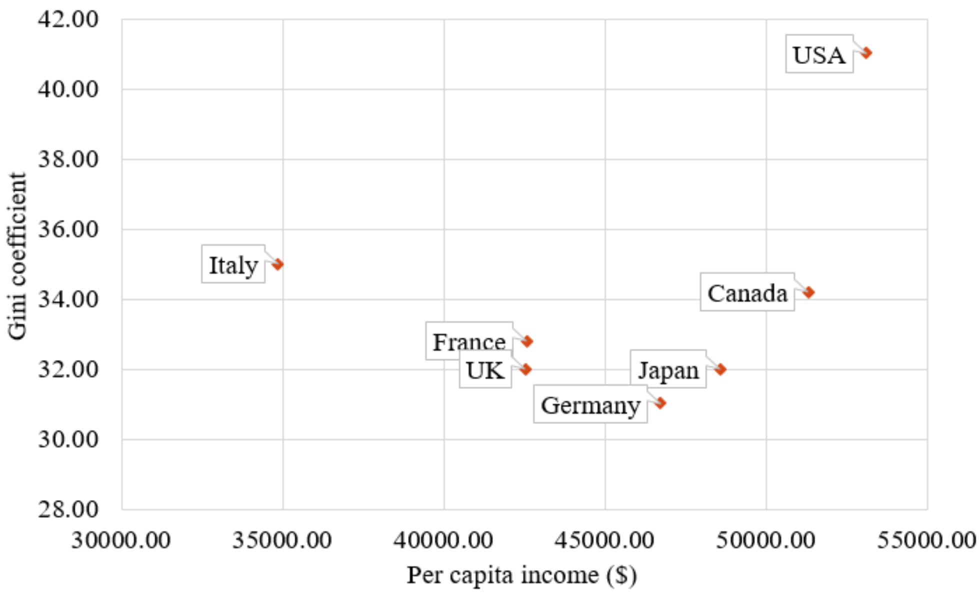
[1] https://www.statista.com/statistics/722962/g20-share-of-global-gdp/

target due to their sound economic position and industrial base. But the extent of relative poverty and income inequality is scorching due to industrialization. Income inequality is increasing over time among all countries of the World including G7 countries (Alvaredo, Chancel, Piketty, Saez, & Zucman, 2018). But the speed of increase is different for different regions and within the regions also. The lowest increase is observed in Europe and the highest increase observed in the Middle East. The IMF study (Ostry et al., 2014) concludes that income inequality raised by 11 percent from 1990 to 2010 within emerging economies even after adjusting for the size effect of the population.

A closer look at data of GDP per capita and income inequality of G7 economies unveils that economies with higher per capita income have a higher rate of income inequality (Figure 1). The highest income inequality is observed in the USA as compared to other pair countries. So, we can hypothesize that in the case of G7 countries increasing per capita income cause income inequality to rise. However, our main emphasis is whether income inequality is due to industrialization (manufacturing sector) as compared to overall per capita output. Figure 1 well explains the extent of current income inequality and per capita output.

Figure 1
Gini Coefficient and Per Capita Income for G7 Countries (WDI & WIID, 2017)



During the last two decades, sectoral output growth for the industrial sector, agriculture sector, and service sector showed different growth compositions. The sectors growing at a higher rate caused the per capita income and consumption to grow at a different rate in similar countries. This differential was augmented by the rising price level which affected the marginal class badly. The price level is very important and plays a greater role in the determination of real wages. Almost 16 percentage point wage differential in G7 countries is observed due to the gender gap [2]. The wage differential is even higher in Japan, the USA, and the UK. Italy has the lowest wage differential gap which is almost 6 percentage points in the region. The wage differential between the sectors may also lead to unequal distribution of resources in society.

Apart from the gender wage gap, the distribution of wealth is also skewed in OECD countries including G7 countries. About 1 percent of the population holds 20 percent of the total wealth. Half of the wealth is possessed by the richest 10 percent population while the poorest 40 percent just owns 3 percent of it. The skewed distribution of the resources greatly affected the living standard of the marginal class in almost all countries. This is not limited to regional, national, or sub-national levels but even between urban and rural areas of the cities. On average, people living in city areas are earning 18 percent higher than counterpart rural areas residents in OECD countries. So we can say that income inequality is also exacerbated with regional disparity too (OECD, 2017).

In literature, different studies showed mixed results regarding the impact of sectoral output on income inequality. In case of developing countries, the findings of Ivanic and Martin (2018) shows that agricultural productivity becomes less effective in the reduction of global inequality as compared to service and industrial sector. In another study (Siami-Namini & Hudson, 2019), agricultural growth at earlier stages of growth and then the industrial sector has a significant negative impact on the reduction of income inequality. However, the service sector has a positive impact and inflation has a nonlinear impact on the income inequality. There are some contrary findings as well in the literature. For example in India, (Aneja, Barkha, & Banday, 2021) empirically found that the agriculture sector has an off-setting impact on income inequality while the industrial and service sector causing income inequality to rise. In the case of the European Union, the regions are converging to a higher level of income inequality and they are becoming more unequal. The extent of absolute poverty is very minimum in G7 countries and it is not a matter of institutions to make some policy imperatives. However, relative poverty matters for each nation because relative poverty is an outcome of income inequality. Some studies discussed the possible impact of a particular sector on income inequality. However, the impact on income inequality needs to be further analyzed with the dis-aggregate data of all major sectors of the G7 countries.

The review of the existing literature shows that most of the studies focused in growth-income inequality relationship in developing economies. In reference to developed economies, very few studies addressed the correlates of income inequality. For instance, Fang, Miller, Yeh, et al. (2015) examined the impact of long run growth volatility on income inequality in 28 states in the US. The study showed that larger growth volatility were significantly correlated with higher levels of income inequality. Balan, Torun, and Kilic (2015) focused on globalization and income inequality in G7 economies. In another study, Zhang, Liu, Xu, and Wang (2017) addressed the impact of military spending on income inequality in BRICS and G7 countries. The existing literature provides the authors strong reason to believe that various studies primarily focused on the growth-income inequality relationship in developing economies. These studies have shown inclusive results regarding growth-income inequality association. However, there is dire need to assess the growth and income

[2] https://blogs.imf.org/2018/08/06/chart-of-the-week-equal-pay-remains-a-global-issue/

inequality relationship in the context of developed economies. The objective of the current study is to examine the impact of sectoral growth on income inequality in G7 countries. The findings of the study would provide profound insight into the sectorial growth and income inequality relationship and would help to generalize the results in the case developed economies as well. For this purpose to serve, the study explores the impact of sectoral output on income inequality in G7 economies to examine whether sectoral growth (manufacturing growth) causes the latter. In economic literature, Kuznets hypothesis (Kuznets, 2019) provides the basis for growth-inequality relationship. The authors chooses to solely investigate the impact of sectoral output on income inequality to pin down the dilemma as suggested by the existing literature. It becomes imperative to explore empirically whether the sectoral output growth has a similar or different impact as compared to overall per capita output on income inequality in G7 economies.

Literature Review

The relationship between income inequality and economic growth is broadly discussed in the literature. The studies such as Bourguignon (1990); Forbes (2000) suggested a positive relationship, and some studies like Alesina and Rodrik (1994); Perotti (1996); Sukiassyan (2007) found a negative relationship between economic growth and income inequality. Some studies (Amos Jr, 1988; Banerjee & Duflo, 2003; Barro, 1999) showed inconclusive results. While Chen (2003) found an inverted relationship supporting the inverted U hypothesis; the Kuznets cure proposition. Shin (2012) discussed the theoretical aspects of the issue and conclude that both positive and negative relationships can exist. These findings were based on the aggregate growth rate of out and GDP per capita.

Janvry and Sadoulet (2000) discussed the relationship between income inequality and poverty in 12 Latin American countries. They found that an increase in income reduces poverty but not income inequality. The impact of growth in income on income inequality turned to be asymmetrical instead of following any specific pattern. The growth effects were more effective during the years of low inequality. Ravallion and Datt (2002) discussed the linkages between growth, inequality, and poverty. They analyzed the household primary data of 50 developing countries. Per capita, private consumption expenditures, income per person, and the data of the Gini coefficient show that the share of income to the poor does not change as an average growth rate increases. It means that richer is benefited more with incremental national income growth as compared to that of the poor (Dollar, Kleineberg, & Kraay, 2016). So, the Ravallion claimed that distribution corrected rate of growth which reduces income inequality is a very important determinant of poverty in the developing world.

Li, Lai, Wang, and Zhao (2016) analyzed the panel data of 24 Chinese provinces. The estimates from the panel ARDL suggests the positive relationship between income inequality and growth during the post reforms era. They found that private capital is the main factor causing income inequality. The rate of income inequality was even higher as compared to a counter study for the US. Andersson and Palacio (2017) analyzed the data on income inequality, agriculture development, and inter-sectoral duality. They observed that development in the agriculture sector reduces income inequality. The gap between rural and urban income lowered to too much extent. They termed them productivity growth due to farm mechanization and other development initiatives in the agriculture sector. They also observed the Kuznets curve generated by a fall in income inequality due to the lower income gap between urban and rural peoples.

The sectoral growth nexus puzzle was resolved using the district-level panel data of Indonesia from 2000 to 2010. They considered four sectors: manufacturing, mining, agriculture, and services. The results show that the manufacturing, mining, and service sector have a positive impact on income inequality. However, the agriculture sector has a negative impact on income inequality. There is sufficient literature on the impact of output on income inequality. These research studies have focused mainly on emerging economies, developing and underdeveloped countries. Even world development organizations extensively discussed this issue for such countries. However, there are very few studies about OECD, G20, and some individual countries of the European Union and Latin America that addressed particularly a little segment of the economy. Many studies presented inconclusive and controversial results to generalize the findings. The present research study is an attempt to resolve the dilemma of inconclusiveness and positive addition to literature related to G7 countries regarding sectoral per capita output and inequality nexus.

Modeling Income Inequality and Sectoral Growth

The theory of sectoral composition towards income inequality and poverty reduction is naive but how data is treated makes it a little different. The Kuznets curve preposition (Kuznets, 2019) explains the relationship between economic growth and income inequality while studies such as Ivanic and Martin (2018); Loayza and Raddatz (2010) and many other studies established the links between poverty, income inequality, and sectoral growth. In this study, the theoretical reasoning of a variable used in the empirical model is based on previous studies (Montalvo & Ravallion, 2010; Ravallion & Datt, 2002). These studies portrayed the basic framework for developing countries. To empirically verify the preposition for G7 countries data, the model as follows:

$$LnGini_{it} = \alpha + \sum_{k=1}^{3} \beta_k LnS_{k,it} + \gamma LnY_{pc,it} + \lambda Ln\pi_{it} + \mu_{it} \tag{1}$$

In equation (1), i represents the country and t represents the year. $Gini_{it}$ is the Gini coefficient used to measure income inequality calculated from the Lorenz curve based on income instead of expenditures. $S_{k,it}$ is the per capita sectoral output produced by the sector k in the country i in a year t. It is calculated by $\bar{Y}_{kit}/\bar{Y}_{it}$ of which $\bar{Y}_{kit}$ is the per capita output of sector k in the country i in a year t and $\bar{Y}_{it}$ is the per capita output in the country i in a year t. Y_{pcit} is the per capita income in dollars for the country i in a year t. π_{it} is the inflation rate calculated from the consumer price index for the country i in a year t. Inflation is taken as the control variable in the model, an important determinant of income inequality.

Assuming three sectors in the economy, the researchers determine the relationship between income inequality and sectoral growth by constructing the following null.

$$H_0 : \beta_1 = \beta_2 = \beta_3 = 0 \tag{2}$$

It shows that the impact of per capita sectoral output on income inequality is independent of overall per capita output. If the null hypothesis is rejected, we test another null hypothesis.

$$H_0 : \beta_1 = \beta_2 = \beta_3 \tag{3}$$

It means that the impact of each sector's per capita output on income inequality is the same. After testing this hypothesis, the next step is to compare the relevance of the sectoral share of per capita output to aggregate per capita output.

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \gamma \tag{4}$$

If the null is not rejected, it means that sectoral output produced by sector impact on income inequality is the same as the aggregate per capita output. The estimation of equation (1) will help to explain the impact of sectoral per capita output on income inequality.

Methodology and Data Issues

As per the nature of data, many statistical techniques are suitable and estimate the model precisely. The choice of the statistical technique must comply with the nature of the data. If data of all variables is a combination of I(0) and I(1); the ARDL approach is superior and gives efficient estimates as suggested by Pesaran, Shin, et al. (1995). Therefore, for empirical verification of the preposition, the researcher opted panel autoregressive distributed lag method proposed by Pesaran and Shin (2002); Pesaran, Shin, and Smith (2001).

Once the data stationarity properties are confirmed, one can estimate the unrestricted ECM (Pesaran et al., 2001). The equation for conditional ECM is written as;

$$\Delta LnGini_{it} = \mu + \sum_{j=1}^{n-1} \sigma \Delta LnGini_{it-j} + \sum_{j-0}^{m-1} (\sum_{k=1}^{3} \theta_k \Delta LnS_{kit-j}) + \sum_{j=0}^{k-1} \rho \Delta LnY_{pc_(it-j)} +$$
$$\sum_{j=0}^{p-1} \psi \Delta Ln\pi_{it-j} + \alpha LnGini_{it-1} + \sum_{k=1}^{3} \beta_k LnS_{kit-1} + \gamma LnY_{pc_(it-1)} + \lambda Ln\pi_{it-1} + \nu_{it} \tag{5}$$

The Akaike information criteria are used for optimal lag length. The short-run coefficient is estimated by differenced variables while long-run coefficients are estimated by the variables in the level form in equation 5. Wald test statistics is used to justify our argument of the long-run relationship supposed in equation (1) to equation (3).

To test whether the variables are converting to their long-run equilibrium values or not, the researcher must estimate the short-run elasticity. To estimate the short-run elasticities, equation 1 is estimated with error correction term (ECM) suggested by Pesaran et al. (2001). For this purpose, the normalized long-run coefficients are used to calculate the error correction term in equation 3.

$$\Delta LnGini_{it} = \mu + \sum_{j=1}^{n-1} \sigma \Delta LnGini_{it-j} + \sum_{j-0}^{m-1} (\sum_{k=1}^{3} \theta_k \Delta LnS_{kit-j}) + \sum_{j=0}^{k-1} \rho \Delta LnY_{pc_(it-j)} + \sum_{j=0}^{p-1} \psi \Delta Ln\pi_{it-j} + \lambda ECM_{it-1} + e_{it} \quad (6)$$

The formulation of the error correction term is given in equation 6. The coefficient attached with the error correction term describes the speed of adjustment towards equilibrium per period and is expected to be negative. Any value is closer to minus one describes a higher speed of adjustment.

$$ECM_{it} = LnGini_{it} - \sum_{k=1}^{3} \frac{\beta_k}{\alpha} LnS_{kit} - \frac{\gamma}{\alpha} LnY_{pc_(it)} - \frac{\lambda}{\alpha} Ln\pi_{it} \quad (7)$$

The abbreviation used for various variables denomination is well defined in the income and inequality modeling section. All variables data have been extracted from the World Bank Database (WDI, 2019) except the data of income inequality (Gini coefficient) which is extracted from the WIID. The data has been taken at constant prices of the year 2010 in the US dollar. The log of the data has been taken to make the interpretation easy and more meaningful. The sample size consists of fiscal years 2000 to 2017.

Empirical Estimation and Results Discussion

The stationarity test shows that all variables are stationary at their first difference form except the inflation rate which is stationary at level form. The literature suggest that if the variables are a combination of I(0) and I(1) form, the most suitable statistical technique may be the ARDL. The empirical results of various panel data stationarity tests are given in table 1.

The long-run estimates of panel ARDL (1, 2, 2, 2, 2, 2) are given in equation 5. The results show that all variables are significant except for the inflation rate. The sectoral share of per capita output of the agriculture sector and service sector is negatively associated with income inequality. As compared to the agriculture sector, service sector has stronger negative impact on income inequality. It shows that a one percent increase in per capita of service sector would lessens the income inequality by 0.18 percent.

Table 1
Data Stationarity Statistics

Variable	Test statistics	At level Form: With Intercept	At level Form: Intercept & Trend	Decision
LGINI	Levin, Lin & Chu	-3.72942 (0.0001)	-3.01082 (0.0013)	I(1)
	Im, Pesaran and Shin W-stat	-2.88800 (0.0019)	-0.92443 (0.1776)	
	PP - Fisher Chi-square	29.5124 (0.0089)	19.7481 (0.1383)	
LSA	Levin, Lin & Chu	-2.32406 (0.0101)	-5.09646 (0.0000)	I(1)
	Im, Pesaran and Shin W-stat	-1.32353 (0.0928)	2.53545 (0.0056)	
	PP - Fisher Chi-square	18.8177 (0.1720)	26.1650 (0.0247)	
LSI	Levin, Lin & Chu	-1.59127 (0.0558)	-0.56999 (0.2843)	I(1)
	Im, Pesaran and Shin W-stat	-1.1143 (0.01326)	-0.22606 (0.4106)	
	PP - Fisher Chi-square	13.9400 (0.4542)	10.8865 (0.6949)	
LSS	Levin, Lin & Chu	-0.78979 (0.2148)	-1.61441 (0.0532)	I(1)
	Im, Pesaran and Shin W-stat	-0.35702 (0.3605)	-0.51166 (0.3044)	
	PP - Fisher Chi-square	18.3493 (0.1913)	13.6944 (0.4727)	
LYPC	Levin, Lin & Chu	-0.47806 (0.3163)	-2.09054 (0.0183)	I(1)
	Im, Pesaran and Shin W-stat	1.71389 (0.9567)	-1.53036 (0.0630)	
	PP - Fisher Chi-square	4.53292 (0.9913)	15.8017 (0.3256)	
LINF	Levin, Lin & Chu	-5.72728 (0.0000)	-5.79462 (0.0000)	I(0)
	Im, Pesaran and Shin W-stat	-4.10428 (0.0000)	-4.19642 (0.0000)	
	PP - Fisher Chi-square	37.6874 (0.0006)	48.9866 (0.0000)	

Note: P-values are in parenthesis.

The industrial sector and overall per capita output causes income inequality to rise. One percent increase in per capita output of the industrial sector causes income equality to rise by 0.528 percent. The positive impact of industrial sector per capita output on income inequality outweighs the negative impact of the agriculture and service sector and turns the coefficient of per capita output to be positive. It means that G7 countries are highly industrialized causing a more skewed capitalist society. As compared to overall per capita output, per capita output of the industrial sector is a major factor escalating income inequality further (Li et al., 2016; Shin, 2012). The long-run equation suggests a strong relationship between income inequality and sectoral growth variables as shown by respective p-values given in parenthesis.

$$LGINI = -0.0828LSA + 0.528LSI - 0.18LSS + 0.136LYPC - 0.0003LINF$$

$$(0.0000) \qquad (0.0000) \qquad (0.0013) \qquad (0.0000) \qquad (0.6295) \tag{8}$$

Furthermore, it is required to verify whether the proposed null hypothesis of sectoral per capita output is statistically different from aggregate per capita output or not. Out of three null hypotheses, the first hypothesis is the impact of all sectoral per capita output on income inequality is the same. The F-statistics and Chi-square value of Wald test statistics strongly rejected the null at a 1 percent level of significance. It means that the impact of all three sub-sectors is statistically different from each other.

Table 2
Wald Test: Long Run Coefficients Linear Restrictions

Null Hypothesis	Test Statistics	Value	df	Probability
$\beta_1 = \beta_2 = \beta_3$	F-statistic	415.4942	(2, 37)	0.0000
	Chi-square	830.9883	2	0.0000
$\beta_1 = \beta_2 = \beta_3 = 0$	F-statistic	619.1217	(2, 37)	0.0000
	Chi-square	1857.365	3	0.0000
$\beta_1 = \beta_2 = \beta_3 = \gamma$	F-statistic	301.2944	(3, 37)	0.0000
	Chi-square	903.8833	3	0.0000

The second null was to verify whether the impact of all individual sectoral per capita output on income inequality is zero i.e. they do not affect income inequality at all. But again, the Wald test statistics show that the null is rejected. The third and last null is to justify whether the impact of per capita output for each sector is equal to the aggregate per capita output. The findings of Wald test statistics reject the null hypothesis showing that the individual sector's per capita output affects the income inequality statistically different from aggregate per capita output. Therefore, it is concluded that each sector impact differently income equality as compared to the overall impact of per capita output. The findings of the Wald test statistics justify the estimates of the long-run equation.

The short-run analysis shows that the error correction term is significant at a 6 percent level of significance and shows a 100 percent adjustment per period towards equilibrium. All other explanatory variables are statistically insignificant during the short run. This shows that these variables have a lasting impact in the long run as compared to the short run. The significance of the error correction term may imply that the short-run coefficients of some individual countries may be different for each country causing the short-run coefficient statistically insignificant. The estimates of the short-run equation are given in table 3.

Table 3
Short Run Equation [Dependent Variable: D(LGINI)]

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COINTEQ01	-1.014803	0.519614	-1.952995	0.0584
D(LSA)	0.029034	0.105985	0.27394	0.7857
D(LSA(-1))	0.146008	0.076796	1.901237	0.0651
D(LSI)	0.370822	0.312177	1.187861	0.2425
D(LSI(-1))	-0.169754	0.399849	-0.424547	0.6736
D(LSS)	1.422748	0.948417	1.500129	0.1421
D(LSS(-1))	-0.795835	1.885135	-0.422164	0.6753
D(LYPC)	0.939193	0.706985	1.328449	0.1922
D(LYPC(-1))	0.092136	0.83747	0.110018	0.913
D(LINF)	-0.001632	0.005979	-0.273041	0.7863
D(LINF(-1))	-0.007264	0.008104	-0.896302	0.3759
C	1.745015	0.868751	2.008647	0.0519
Mean dependent var	0.001307	S.D. dependent var		0.038764
S.E. of regression	0.027197	Akaike info criterion		-4.20337
Sum squared resid	0.027369	Schwarz criterion		-2.199964
Log likelihood	353.8123	Hannan-Quinn criter.		-3.389449

To remove this ambiguity, the researcher tried disaggregating analysis further for the short run and estimated the cross-section short-run coefficients. The estimates of cross-section short-run coefficients are given in table 4. The error correction term is significant for all countries and the sign of ECM for Germany is not according to the underlying theory. This shows that the system is not converging to equilibrium in the short run. The sectoral share of the agriculture sector per capita output is significant for all countries but statistically insignificant for Canada. The sectoral share of the industrial sector is significant for all countries except Japan. It shows that the industrial sector of Japan is fully saturated and does not impact income inequality during the short run. The service sector per capita output for France, Japan, and the United Kingdom is statistically insignificant. The overall per capita output for Japan and the UK is statistically insignificant while all other countries' coefficients are statistically significant. However, the mixed impact is observed during the short run for all variables, agriculture sector, industrial sector, service sector, and inflation rate.

Table 4
Cross Section Short Run Coefficients

Variable	Coefficient (P-Value)						
	Canada	France	Italy	Japan	Germany	UK	USA
COINTEQ01	-0.24092 (0.0001)*	-0.09462 (0.0167)*	-1.92017 (0.0000)*	-0.64145 (0.0007)*	0.22060 (0.0030)*	-0.70767 (0.0263)*	-3.71937 (0.0000)*
D(LSA)	0.01195 (0.1599)	0.08816 (0.0000)*	0.22589 (0.0000)*	0.37630 (0.0004)*	-0.01523 (0.0000)*	0.04076 (0.054)**	-0.52462 (0.0000)*
D(LSA(-1))	0.00272 (0.7456)	-0.01164 (0.0427)*	0.52873 (0.0000)*	0.17986 (0.0212)*	0.01187 (0.0000)*	0.02009 (0.2364)	0.29040 (0.0000)*
D(LSI)	-0.29310 (0.068)**	-0.71862 (0.0116)*	0.92775 (0.0000)*	0.53979 (0.1893)	-0.11935 (0.0077)*	0.52353 (0.0284)*	1.73576 (0.0000)*
D(LSI(-1))	0.63874 (0.0041)*	-0.53399 (0.0162)*	0.56989 (0.0000)*	0.67615 (0.2935)	0.23467 (0.0001)*	-0.50949 (0.0186)*	-2.26425 (0.0000)*
D(LSS)	-1.86417 (0.0285)*	-0.37292 (0.2442)	2.07020 (0.0000)*	1.89661 (0.5694)	0.60017 (0.0086)*	1.47079 (0.7544)	6.15854 (0.0055)*
D(LSS(-1))	2.11905 (0.0117)*	-0.48573 (0.061)**	2.33852 (0.0000)*	2.36241 (0.5936)	0.95767 (0.0097)*	-1.22219 (0.1983)	-11.6405 (0.0003)*
D(LYPC)	-1.77515 (0.0275)*	1.46339 (0.0152)*	0.21577 (0.0009)*	1.16307 (0.3957)	0.56909 (0.0190)*	0.47424 (0.8037)	4.46391 (0.0063)*
D(LYPC(-1))	2.19953 (0.0134)*	-1.64005 (0.0042)*	2.50661 (0.0000)*	1.06704 (0.1728)	0.11612 (0.1332)	0.20508 (0.5009)	-3.80938 (0.0002)*
D(LINF)	-0.01138 (0.0000)*	-0.01098 (0.0000)*	-0.02347 (0.0000)*	0.00673 (0.0000)*	-0.00070 (0.0001)*	0.00258 (0.0000)*	0.02580 (0.0000)*
D(LINF(-1))	-0.01288 (0.0000)*	0.00783 (0.0000)*	-0.01986 (0.0000)*	0.02102 (0.0000)*	0.00562 (0.0000)*	-0.00826 (0.0000)*	-0.04431 (0.0000)*
C	0.41516 (0.0009)*	0.18097 (0.073)**	-1.92017 (0.0003)*	1.07586 (0.0049)*	-0.36136 (0.0164)*	1.22714 (0.1064)	6.10156 (0.0024)*

Note: "*" Significant at 5 % level of significance; "**" Significant at 10 % level of significance.

After testing the significance of cross-section short-run coefficients, Pedroni residual cointegration tests and Kao residual cointegration tests of panel cointegration are performed to see whether the variables are cointegrated or not in the long run. The results of panel cointegration are given in table 5. Most of the test statistics of Pedroni and Kao residual cointegration are statistically significant. These tests suggest a strong relationship between income inequality and sectoral growth variables.

Table 5
Panel Cointegration

Residual Cointegration Test	Test Statistics	Statistic	Prob.	Weighted Statistic	Prob.
Pedroni Residual Cointegration Test	Panel v-Statistic	-1.387632	0.9174	-1.623491	0.9478
	Panel rho-Statistic	1.055286	0.8544	0.894682	0.8145
	Panel PP-Statistic	-6.16517	0.0000*	-4.999633	0.0000*
	Panel ADF-Statistic	-4.696882	0.0000*	-4.24652	0.0000*
	Group rho-Statistic	1.895307	0.971	-	-
	Group PP-Statistic	-6.81522	0.0000*	-	-
	Group ADF-Statistic	-4.074646	0.0000*	-	-
Kao Residual Cointegration Test	ADF	-1.793556	0.0364*	-	-

Note: * means the null of no cointegration rejected at 5 % level of significance.

Table 6 presents the vector error correction granger causality/block homogeneity Wald test statistics. The estimation shows that income inequality has a strong causal relationship between the agriculture sector, service sector, industrial sector, inflation, and output in the short run. Although the short-run coefficients showed the mixed results and most of the coefficients were significant at a higher level of significance like 10 percent. The robustness of the PMG/ARDL model is usually assessed by model selection summary, coefficients diagnostic, and residual diagnostic in EViews. The coefficient diagnostics are given in table 2, model selection summary is given in the appendix as model selection criteria, and residual diagnostic is done by normality assumptions of the residuals are given in the appendix. These test statistics validate the estimation of PNG/ARDL model results given in the study.

Table 6
VEC Granger Causality/Block Exogeneity
Wald Tests-DV: D(LGINI)

Excluded	Chi-sq	df	Prob.
D(LSA)	41.07150	8	0.0000
D(LSI)	55.36974	8	0.000
D(LSS)	45.46860	8	0.000
D(LYPC)	51.64140	8	0.000
D(LINF)	42.65143	8	0.000
All	128.0154	40	0.000

Table 7
Model Selection Criteria

Model	LogL	AIC*	BIC	HQ	Specification
2	355.617050	-4.761019	-2.600783	-3.884542	ARDL(1, 2, 2, 2, 2, 2)
1	289.261425	-4.201097	-2.890392	-3.669302	ARDL(1, 1, 1, 1, 1, 1)

Conclusion

The study aimed to sort out the impact of sectoral per capita output versus overall per capita output on income inequality. Income inequality is regressed on the per capita output of the agriculture sector, industrial sector, service sector, overall per capita output, and inflation rate for G7 countries. The empirical results show that the sectoral share of per capita output impacts income inequality differently as compared to overall per capita output. The agriculture and service sector negatively impact income inequality. It showed that the movement of workers in the service sector has a negative impact on income inequality at a later stage of structural transformation. However, the impact in the agriculture sector is relatively minimum (Baymul & Sen, 2020). The phenomenon is expected to happen in technically advanced economies like G7 countries.

Any rise in the industrial sector and per capita output raises income inequality. The positive impact of the industrial sector on income inequality outweighs the negative impact of agriculture and the service sector. It means that G7 countries are highly industrialized moving towards a more skewed capitalist society (Li et al., 2016). The study confirms that both positive and negative relationships between sectoral growth and income inequality can exist within the sectors of different economies (Shin, 2012). The study suggests the significant short-run as well as the long-run relationship among variables of interest. The study contributes the literature in the following ways: Firstly, it is generalized that the impact of sectoral per capita output is different as compared to overall per capita output. Secondly, it is better to use disaggregate data for unbiased prediction of output impact on income inequality even for highly developed economies like G7 countries. Because due to structural transformation either in underdeveloped, developing and developed countries, the dis-aggregate data gives better results. Thirdly, it is verified that the industrial sector is a major contributor in industrialized economies causing income inequality to rise with the rising level of income. So, the Kuznets hypothesis is irrelevant at a very higher level of income.

The study suggests that the agriculture sector and service sector are friendlier for equitable distribution of factors income as compared to the industrial sector. Any government policy favoring the agriculture and service sector causes income inequality to fall in the long run. Subsidies for the promotion of agriculture sub-sectors, mechanization of the agriculture sector, linkages with the industrial sector, provision of on-farm training to directly access the market, provision of technical skills to labor and industrial workers, and implantation of minimum wage law's may be very helpful for equitable income redistribution.

The industrial sector causing the shift of resources from the poor and middle class to the wealthier entrepreneurs in case rich countries. For workers in the industrial sector, more emphasis is needed by the G7 countries to protect their rights, perks, and other social security protections. The regulatory role of the government and progressive taxes, reduction in the wage differential gap may be suggested for the industrial sector. The findings of the study are limited to the supply side factor; sectoral per capita output only and the effects of financial markets, globalization, and some aggregate demand-side components are ignored. Future studies could be helpful in understanding the relationship of financial markets and income inequality.

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