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Addressing the Asymmetric Causality Between Technological Progress, Economic Globalization and Income Distribution: The Application of Hatemi-J Approach

Asst. Prof. Dr. Onur ÖZDEMİR *(https://orcid.org/ 0000-0002-3804-0062), İstanbul Gelişim University, Turkey;*
e-mail: onozdemir@gelisim.edu.tr

Abstract

The existing literature on distributional concerns has been substantially pointed out the crucial importance of two major factors in the last four decades: (i) technological progress and (ii) economic globalization. However, instead of their negative side-effects on income distribution, most of the current studies have put forward the arguments that each indicator should be spread in the economic relations. Starting from that point of view, this paper investigates the causal relationship from technological progress and economic growth to income distribution (proxied by labor share of income) by implementing the Hatemi-J asymmetric causality test, which divides positive and negative shocks on the benchmark variables, across the G-7 economies over the 1970-2018 period. The empirical findings show that there are large negative effects of technological progress and economic globalization on labor's share in the presence of shocks, which also contradicts with the mainstream wisdom.

Keywords: Income Distribution, Labor Share of Income, Technological Progress, Economic Globalization, Hatemi-J Asymmetric Causality Test

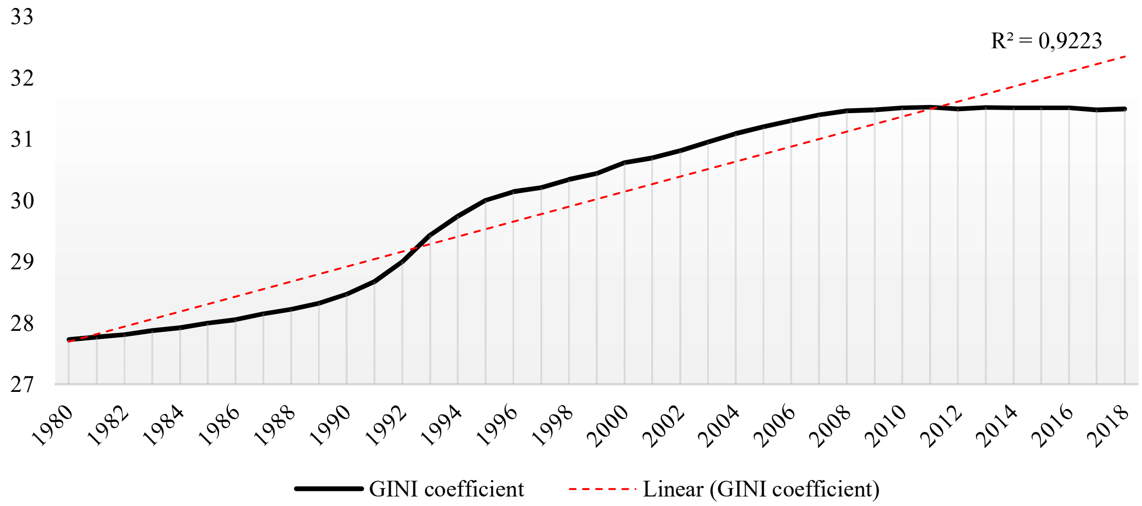
JEL Codes: D33, F6, O33,

1. Introduction

There have been a vast of changes in the concept of income distribution in terms of its causes, reasons, and structural significance across different nations and regions over the years. However, some of the topics have still much debate for their importance of historical impacts on income distribution. In that vein, this paper concentrates upon a critical analysis of widely recognized factors for the notable changes in distributional practices that have emerged in a couple of countries during the last four decades. In particular, the subject did not only limit to the economic discipline but also interested by the other disciplines. Even though a bulk of studies has been listed several reasons that might change the inter- and intra-dynamics of income distribution over time, this paper will consider and will heavily emphasize the role of two major factors: (i) the total factor productivity and (ii) the economic globalization. While the total factor productivity is considered as a proxy to assess the impact of technological progress on income distribution, the series for economic globalization are used to figure out the effects of both trade and financial liberalization over the post-1980 period on distributional conflicts among the productive units. One of the common arguments in the heterodox approach is that technological development and the liberalization of trade and financial accounts can be accepted as the primary influences on income distribution over the last four decades, especially in the industrial economies. On the one hand, technological development leads to an increase in a debate of its negative impact on labor markets through the emergence of "technological unemployment". On the other hand, the liberalization policies through the trade and financial accounts provide a way for the capital to freely out from the host countries which then results in the deterioration of investments and production. This paper investigates the significance of these arguments and provides further insights into the heterodox approach. It also considers whether technological development and/or economic globalization are still effective on income distribution in G-7 economies.

The problem is that the investigation towards the tripartite linkage between income distribution, economic globalization, and technological progress might also lead to an emergence of further policy questions and controversy in theoretical propositions. It is evident that several arguments have their theoretical facts and visions to grasp the technological changes and globalization of world economies which are produced evidence in the presence of particular hypotheses. Therefore, it is not possible to argue that there is common knowledge on those two issues whether they have positive or negative impacts on income distribution in G-7 economies. For instance, a quick glance over some stylized facts of the four decades in terms of income distribution provides an obvious result that income inequality has been raised in industrial countries. This practical expression is valid for both household-based and production-based income categories of allocation. On the one hand, the household-based allocation of income, which is proxied by the GINI coefficient, has an upward tendency over the 1980-2018 period in industrial countries at all. Provided by Solt (2020) in SWIID, Figure 1 depicts the trends in income inequality, proxied by the GINI coefficient in which it represents inequality in disposable (post-tax, post-transfer) income, over the 1980-2019 period for selected industrial economies.

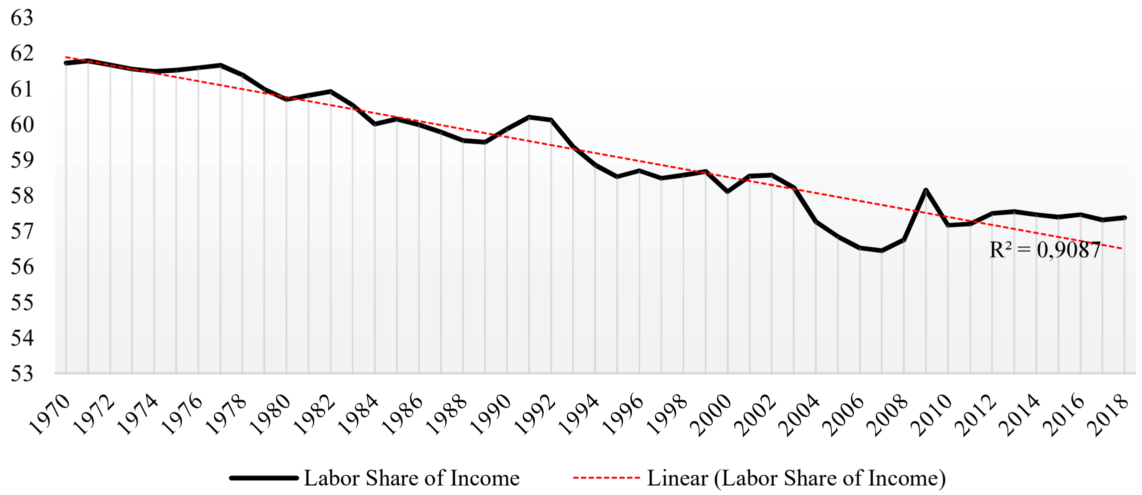
Figure 1. The Trend of Income Inequality



Source: Solt (2020)

On the other hand, the distributional problems can also be investigated in the context of production-based allocation of income. For example, the labor share of income can be selected as an indicator to understand the theoretical basis on which the data can be obtained from Penn World Tables version 10 produced by Feenstra et al. (2015). Figure 2 shows the trends in labor's share over the 1970-2019 period for industrial economies. As the results imply that labor's share decreased in that period which indirectly means that the capital's share then raised if the rest of the labor's share is accepted as a share of capital.

Figure 2. The Trend of Labor Share of Income



Source: Penn World Tables

It is the purpose of this study to provide a way for an understanding of the potential asymmetric causality among three leading indicators – namely technological progress, economic globalization, and income distribution – by implementing the Hatemi-J test. The sample of the analytical structure is based on the countries from the G-7 economies. The major reason to choose those countries depends on the fact that those economies have a relatively high level of technological progress and the degree of economic globalization along with a moderate level of income inequality. Therefore, the critical assumption of the empirical part is grounded on the idea that two factors have relatively high potential to affect the distributional conflicts in G-7 economies, instead of the rest of the other countries. In this sense, our main objective is also to refocus the principal issues and key elements in the ongoing debate over the given subject, to evaluate the heterodox thoughts in the presence of using Hatemi-J asymmetric causality test, to investigate how significant the current literature based on the empirical findings, and to extend the heterodox assumptions on these questions.

As mentioned above that the study concentrates on G-7 economies. Similar to the method of Singh and Dhumale (2000), the main reason for this sample selection is not only that greater and more reliable knowledge is available for those countries but also extensive literature exists for this group of countries.

The paper is organized as follows. Section 2 reviews the literature and thereby classifies the major factors that may have an ample effect on the income distribution. Section 3 describes the empirical methodology, which is based on the Hatemi-J asymmetric causality test. Section 4 summarizes the empirical findings along with the implementation of the empirical strategy. Section 5 concludes.

2. Literature Review

According to the mainstream approach, technological change and the globalization of economic structure is one of the major facts as "the engine of growth". Besides the concentration of technology in economic systems, there are also two major outcomes that the current period is faced: (I-i) the stagnation in production and (ii) the explosive hoarding of financial capital (Andersson and Stone, 2017; Zygmunt, 2017). In this sense, the investigation of the technology-income distribution nexus provides significant outcomes for understanding much-debated topics or issues since they have already been widely discussed in the literature.

The overall outlook on the technological change throughout the historical process leads us to grasp some major pros and cons in terms of its effect on societal formation. Some of those pros and cons can be listed as follows: (i) a higher level of automation in production, (ii) the transformation and diversification of the production methods, (iii) much lower transportation costs, (iv) a higher level of efficiency in information and communication services. According to the mainstream approach, the overall result of the technological progress upon the labor market is an increase in labor productivity, also providing of new employment opportunities and a higher range of product groups to consume. However, the alternative arguments heavily concentrate on the effect of technological change on labor markets in terms of its role of leading to an increase in "technological unemployment". Therefore, the ongoing debate in the theoretical context for the effect of technological change on income distribution is still controversial and mixed. In particular, the mainstream approach mostly states that increased productivity and intensified labor mobility across the borders widens the opportunities of economic actors for their productive skills and behavioral development. For instance, Vveinhardt and Kuklytė (2016) put forward an argument that people may become more successful and educated along with a higher level of income if they involve in the globalization movement of economic relations. In addition, contrary to the alternative arguments, technological innovations and enhanced automation in production does not increasingly lead to an emergence of "technological unemployment" but provoke a rise in the rate of labor productivity conjunction with an increase in workers' skill. Therefore, the technological change ultimately stimulates a change of distribution of an aggregate income on behalf of both workers and capital. Since the workers earn income in return for their marginal contribution to the production, their returns from the production will increase along with technological improvements. Moreover, the returns of capital also increase since each unit of product is now produced in a shorter time. Therefore, the total amount of products will be much higher relative to the periods in which less-developed technologies were used in production.

However, the practical implications provide a different story about the effects of technological progress on income distribution. For instance, the technology-led changes in production have led to dramatic stratification in the societal dynamics where automation tends to widen the income gap between skilled and unskilled workers (Simionescu et al., 2017). As Zarotiadis and Gkagka (2013) state that all previously earned gains of labor vanished in the European Union countries along with the continuum process of internationalization. Pernica (2017) also points out the case that the last ten years have been witnessed a high level of inequality which prevents economic growth. Furthermore, Ostry et al. (2014) and Sanusi et al. (2017) discuss the role of government policies in terms of income redistribution and find that those policies have a significant impact on economic growth. In particular, fiscal policies may lead to negative pressure on income inequality due to the following such factors: (i) social security benefits, (ii) income transfers, (iii) subsidies to firms, and (iv) progressive taxes. On the other hand, Rajan (2015) implies the preventive measure such as educational reforms to show that policy interventions may temper an increase in income inequality since Rajan (2015) argues that a high portion of the middle-income population become distanced from the quality education and thus most of those people in that income group will be hurt in case of their standards of living. However, Dabla-Norris et al. (2015) state that each country has its own dynamics; and therefore, the income allocation only becomes to be positively affected by redistributive policies when they are cautiously chosen by the policy authorities.

Mnif (2016) focuses on the analysis of the bilateral relationship between technological change and income inequality. The empirical findings show that technological changes (i.e., increased innovation) have positive effects on inequality but a negative effect of inequality on technological changes also seems to be statistically approved. Following the empirical propositions provided by Acemoglu (1998; 2003), Zhang et al. (2017) argue that one of the major drivers of rising inequality in China is a technical change. Aghion et al. (2019) also remark that there is a positive correlation between innovation and top income inequality and then state that given correlation at least partly reflects a causality from innovation to top income shares in the presence of its positive effect on social mobility. Briguglio and Vella (2016) find that technological progress is negatively correlated with the labor share of income in the member states of the European Union which is derived from the CES production function. Therefore, the authors indicate the importance of some form of policy intervention in reducing of income inequality. Neto and Ribeiro (2019) use the Neo-Kaleckian model to grasp the linkage between skill-biased technological change and income distribution. Their model highlights two contending effects of technological change at play: (i) technological change leads to the emergence of positive structural transformation and thus boosts net exports and output growth and (ii) technological change disproportionately affects unskilled workers and hence negatively intensifies the intra-working-class income distribution along with causing the reduction of economic growth. The empirical outputs imply that one of the major precautions to alleviate the unwanted effects of a contractionary wave of technological change on income distribution may be an increase in incentives of the income transfer and public investments in higher education. In consideration of those different arguments and empirical findings, the next sub-section explains the data set and the methodological background. The following sub-section also provides the major hypotheses in which they will be tested through the implementation of the Hatemi-J asymmetric causality approach.

3. Data Analysis and Methodological Framework

In this study, the main concentration is based on the model in which the causal tripartite relationship between technological progress, economic globalization, and income distribution is analyzed using Hatemi-J asymmetric causality test (Hatemi-J, 2012) for the G-7 countries over the 1970-2018 period. In that vein, the major aim of this paper is to illustrate from which directions that income distribution can be affected. Therefore, the empirical findings most probably shed light on the theoretical validity of both mainstream and alternative assumptions. The next two sub-sections focus on the explanations of data set and the methodological structure, respectively.

3.1. Data Analysis

The empirical analysis will be based on using three variables which are listed as follows: (i) technological progress, (ii) economic globalization, and (iii) income distribution. First, the technological progress is measured by the total factor productivity index obtained from Penn World Tables version 10. This proxy variable is calculated by dividing aggregate output by the weighted geometric average of labor and capital input. The major fact of using this variable is to measure the effect of productive efficiency in that it measures how much aggregate output can be produced from a certain number of inputs. Moreover, it accounts for part of the variations in cross-country per-capita income. Second, economic globalization is measured by the weighted average of two sub-indices: (i) trade globalization and (ii) financial globalization. The method for calculating those individual variables depends on principal components analysis on a 10-year rolling window of data to determine time-varying weights. The data is normalized to produce an index with a scale from one to one hundred, where 100 is assigned to the maximum value of a specific variable over the whole sample of countries and the entire period. The data comes from the KOF Globalization Index produced by Gygli et al. (2019), which is constructed on a yearly basis. Finally, the labor share of income is used as a proxy to measure the income distribution. The labor's share is obtained from Penn World Tables version 10. It is calculated as the compensation of employees over aggregate output. The important feedback of the labor's share is to assume that the capital share can also be calculated as the residual. Therefore, the rest of the labor's share can be considered as a capital share. In consideration of these explanations, Table 1 presents the descriptive statistics for technological progress, economic globalization, and the labor share of income.

Table 1. Descriptive Statistics

		Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Canada	*TFP*	0.971	0.969	1.011	0.928	0.022	0.124	1.997	2.178
	EC	57.84	58.37	71.07	42.58	10.53	-0.110	1.308	5.942
	LS	68.38	67.35	77.09	62.94	3.951	0.750	2.593	4.937
France	*TFP*	0.908	0.927	1.028	0.704	0.096	-0.553	1.959	4.708
	EC	66.14	66.63	79.21	42.34	10.54	-0.587	2.173	4.217
	LS	63.73	62.17	69.12	60.73	2.788	0.919	2.243	8.071
Germany	*TFP*	0.825	0.878	1.000	0.598	0.127	-0.305	1.534	5.145
	EC	69.00	66.60	81.02	52.41	9.405	-0.142	1.580	4.278
	LS	64.97	66.18	67.79	59.01	2.312	-0.813	2.520	5.874
Italy	*TFP*	1.084	1.099	1.148	0.995	0.048	-0.623	2.084	4.887
	EC	58.36	61.47	72.78	42.22	10.28	-0.205	1.423	5.419
	LS	54.95	54.32	59.89	49.88	3.645	0.107	1.357	5.602
Japan	*TFP*	0.898	0.922	1.000	0.778	0.068	-0.409	1.726	4.676
	EC	46.16	43.25	67.71	30.09	10.75	0.408	2.147	2.846
	LS	58.98	58.91	62.60	55.03	2.456	0.039	1.569	4.189
United Kingdom	*TFP*	0.903	0.902	1.027	0.753	0.086	-0.213	1.653	4.075
	EC	73.32	72.78	82.01	51.26	7.442	-0.915	3.464	7.285
	LS	56.99	55.72	60.35	53.39	2.101	0.209	1.390	5.646
United States	*TFP*	0.877	0.863	1.008	0.763	0.078	0.223	1.542	4.748
	EC	55.42	56.40	68.41	38.82	10.59	-0.319	1.518	5.318
	LS	61.39	61.42	64.89	58.79	1.543	0.312	2.325	1.728

3.2. Methodological Framework

Following the descriptive statistics, the first stage of the empirical analysis is to test whether there is a cross-sectional dependence across the G-7 economies. According to Pesaran (2006), if the cross-sectional dependence is ignored in the analysis, it may lead to substantial bias and size distortions in estimating the linkage among the selected variables. Therefore, to check whether those countries are cross-sectionally dependent, the parametric testing procedure is used as a way for understanding the problem (Pesaran, 2004). Depending on the test statistic of cross-sectional dependence analysis, the second issue is to determine whether the panel data has slope homogeneity. To detect the slope homogeneity of estimated coefficients for each panel unit, the testing procedure developed by Pesaran and Yamagata (2008) will be followed. Finding the absence of cross-sectional dependence and slope homogeneity in the panel series, the third step is to control whether the panel series are stationary in order to produce unbiased estimation results. Therefore, there will be used three different panel unit root tests provided by Maddala and Wu (1999), Im et al. (2003), and Pesaran (2007). On the one hand, the major aim to use the testing procedure of Im et al. (2003) depends on the reason that it enables to control of the serial correlation and heterogeneity of error variance across the units. On the other hand, Maddala and Wu (1999) provide an approach which is based on the combination of p-values for a unit root in each cross-sectional unit. In the final step, the causal linkages between technological progress, economic globalization, and labor's share are tested through the implementation of the asymmetric causality test, which is proposed by Hatemi-J (2012). Instead of the Granger causality test, the major reason to handle the Hatemi-J test depends on the fact that the former strategy is grounded on the framework that both positive and negative shocks have the same absolute magnitude of causal effects; and therefore, it neglects the potential presence of asymmetric causal effects (Hatemi-J, 2012). Since the markets may confront with asymmetric information as Akerlof (1970), Spence (1973), and Stiglitz (1974) argued, one of the major actions for testing the causality nexus among the variables is to consider the presence of having asymmetries in the series (Granger and Yoon, 2002; Hatemi-J et al., 2014).

According to Hatemi-J (2012), the positive and negative cumulative sums are exercised to obtain the results for the asymmetric causality test. The assumption towards the use of two variables such as y_1 and y_2 is based on their integration at the first stage in conjunction with the implementation of a recursive method as follows:

$$y_{1,t} = y_{1,t-1} + \varepsilon_{1,t} = y_{1,0} + \sum_{j=1}^{t} \varepsilon_{1,j} \tag{1}$$

$$y_{2,t} = y_{2,t-1} + \varepsilon_{2,t} = y_{2,0} + \sum_{j=1}^{t} \varepsilon_{2,j} \tag{2}$$

where $y_{1,0}$ and $y_{2,0}$ denote the initial values, n represents the number of cross-sections in the panel structure, and ε is the white noise error term.

The positive ($\varepsilon_{1,j}^{+}$ and $\varepsilon_{2,j}^{+}$) and negative shocks ($\varepsilon_{1,j}^{-}$ and $\varepsilon_{2,j}^{-}$) can be expressed as follows, respectively: $\varepsilon_{1,j}^{+} = max\ (\varepsilon_{1,j}, 0)$, $\varepsilon_{2,j}^{+} = max\ (\varepsilon_{2,j}, 0)$, $\varepsilon_{1,j}^{-} = min\ (\varepsilon_{1,j}, 0)$, and $\varepsilon_{2,j}^{-} = min\ (\varepsilon_{2,j}, 0)$. In consideration of positive and negative shocks, Hatemi-J (2012) measures the cumulative sums of shocks, which are represented as $y_{1,t}^{+}$, $y_{2,t}^{+}$, $y_{1,t}^{-}$ and $y_{2,t}^{-}$:

$$Positive\ shocks: y_{1,t}^{+} = y_{1,0}^{+} + \varepsilon_{1,j}^{+} = y_{1,0} + \sum_{j=1}^{t} \varepsilon_{1,j}^{+}\ and\ y_{2,t}^{+} = y_{2,0}^{+} + \varepsilon_{2,j}^{+} = y_{2,0} + \sum_{j=1}^{t} \varepsilon_{2,j}^{+} \quad (3)$$

$$Negative\ shocks: y_{1,t}^{-} = y_{1,0}^{-} + \varepsilon_{1,j}^{-} = y_{1,0} + \sum_{j=1}^{t} \varepsilon_{1,j}^{-}\ and\ y_{2,t}^{-} = y_{2,0}^{-} + \varepsilon_{2,j}^{-} = y_{2,0} + \sum_{j=1}^{t} \varepsilon_{2,j}^{-} \quad (4)$$

Moreover, a vector autoregressive type with a seemingly unrelated regression model of order k is implemented to test the causality as follows (Hatemi-J, 2012):

$$\begin{bmatrix} y_{1,t}^{+} \\ y_{2,t}^{+} \end{bmatrix} = \begin{bmatrix} \beta_{1,0} \\ \gamma_{1,0} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{k} \beta_{1,r} & \sum_{r=1}^{k} \beta_{2,r} \\ \sum_{r=1}^{k} \gamma_{1,r} & \sum_{r=1}^{k} \gamma_{2,r} \end{bmatrix} * \begin{bmatrix} y_{1,t-r}^{+} \\ y_{2,t-r}^{+} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,j}^{+} \\ \varepsilon_{2,j}^{+} \end{bmatrix} \quad (5)$$

Finally, the null hypothesis of this test is constructed as follows: $H_0: \beta_{2,r} = 0, \forall$ where r=1,…,k. By using the Wald test, the null hypothesis suggests that $y_{2,t}^{+}$ does not cause $y_{1,t}^{+}$ for the cross-sectional unit j in the panel. Similar to that theoretical structure, the other combinations (i.e., $[y_{1,t}^{-}, y_{2,t}^{+}]$, $[y_{1,t}^{+}, y_{2,t}^{-}]$ and/or $[y_{1,t}^{-}, y_{2,t}^{-}]$) can be grounded on the same pattern. In the next section, those tests are implemented by using the technological progress, economic globalization, and labor share of income.

4. Empirical Findings

This paper considers the asymmetric causality test provided by Hatemi-J (2012) across the G-7 economies over the 1970-2018 period. In this sense, the first issue is to check whether there is a cross-sectional dependence among the panel units. To control this issue, the following testing procedure provided by Pesaran (2004) is implemented for the units. Table 2 reports the test statistics along with their corresponding p-values. As Table 2 shows, the CD test does not reject the null hypothesis of no cross-sectional dependence. In other words, the test statistics of Pesaran (2004)'s method imply that the presence of the cross-sectional independence in the panel series is prevailing.

Table 2. Result for Cross-Sectional Dependence

	Test Statistic	p-value
CD test	-0.148	0.8825
Average absolute value of the off-diagonal elements = 0.376		

The next issue is to test the slope homogeneity in panels. In order to understand whether the panels are faced with slope homogeneity, the method provided by Pesaran and Yamagata (2008) is implemented. The major importance to test for slope homogeneity is to determine an appropriate econometric method. The results are illustrated in Table 3. For each model that Table 3 represents, the null hypothesis is rejected, assuming that the homogeneity tests reject the equality hypothesis, which means that the slope coefficients are heterogeneous. Therefore, it should be noted that the homogeneity restriction for each selected variable cannot be implemented to analyze the panel unit-root tests and causality method, which will then provide misleading inferences.

Table 3. Result for Slope Homogeneity

	Delta test statistics	***p*-value**	**Delta-adj. test statistics**	***p*-value (adj.)**
Model A: $LS_{it} = \vartheta_0 + \vartheta_1 EC_{it} + \vartheta_2 TFP_{it} + \varepsilon_{it}$	28.599***	0.000	29.843***	0.000
	Delta test statistics	***p*-value**	**Delta-adj. test statistics**	***p*-value (adj.)**
Model B: $EC_{it} = \vartheta_0 + \vartheta_1 LS_{it} + \vartheta_2 TFP_{it} + \varepsilon_{it}$	28.023***	0.000	29.242***	0.000
	Delta test statistics	***p*-value**	**Delta-adj. test statistics**	***p*-value (adj.)**
Model C: $TFP_{it} = \vartheta_0 + \vartheta_1 EC_{it} + \vartheta_2 LS_{it} + \varepsilon_{it}$	37.145***	0.000	38.761***	0.000

Note: *** represents the significance level at 1%.

The third issue is to check whether the panel series are stationary. In theoretical structure, the cumulative sums for each unit require to be nonstationary to employ the Hatemi-J asymmetric causality approach. In this sense, three major unit-root tests – Maddala and Wu (1999), Im et al. (2003), and Pesaran (2007) – are implemented to assess the asymmetric causality nexus among the variables. The unit-root test results are illustrated in Table 4. Based on the unit-root tests statistics, both series are stationary at their first differences.

Table 4. Result for Panel Unit-Root Tests

	Maddala-Wu (1999)		Im et al. (2003)		Pesaran (2007)	
	Statistic	***p*-value**	**Statistic**	***p*-value**	**Statistic**	***p*-value**
TFP	5.998	0.967	1.064	0.856	0.061	0.524
EC	8.861	0.841	0.008	0.503	0.020	0.508
LS	18.619	0.180	0.409	0.659	-0.279	0.390
ΔTFP	72.774***	0.000	-12.043***	0.000	-3.958***	0.000
ΔEC	55.704***	0.000	-13.167***	0.000	-3.416***	0.000
ΔLS	43.409***	0.000	-11.302***	0.000	-2.047**	0.020

Note: *** denotes the rejection of the null hypothesis at 1% significance level. Δ represents the first difference operator. The maximum lag lengths are selected through the Akaike Information Criteria (AIC). Time trend is included in all testing procedures.

In consideration of those issues, the results for the asymmetric causality test are summarized in Tables 5-11 for each country. So, following the procedure of Hatemi-J (2012), the bootstrap simulations are implemented by using the GAUSS code – namely ACtest. First, the asymmetric causality test results for Canada show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share can be rejected at 10% significance level, respectively. In addition, the negative shocks in economic globalization cause positive effects on labor's share. In a similar vein, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 1% and 10% significance levels, respectively.

Table 5. Results for Asymmetric Causality Test – Canada

Null Hypothesis	Wald Statistics	Bootstrap Critical Values		
		1%	5%	10%
$EC^+ \nRightarrow LS^+$	6.09*	15.02	8.77	5.99
$EC^- \nRightarrow LS^-$	6.32*	18.19	8.44	6.01
$EC^+ \nRightarrow LS^-$	3.10	13.93	7.44	5.24
$EC^- \nRightarrow LS^+$	5.59*	10.65	6.35	4.62
$TFP^+ \nRightarrow LS^+$	19.04***	13.48	7.46	5.32
$TFP^- \nRightarrow LS^-$	7.46*	13.98	8.45	5.90
$TFP^+ \nRightarrow LS^-$	7.97	17.71	11.16	8.74
$TFP^- \nRightarrow LS^+$	2.17	13.53	7.64	5.59

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. ⇏ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

Second, the asymmetric causality test results for France show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share cannot be rejected. However, similar to the case of Canada, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 1% significance level, respectively. Moreover, the negative technological shocks result in a positive effect on labor's share at 1% significance level.

Table 6. Results for Asymmetric Causality Test – France

Null Hypothesis	Wald Statistics	Bootstrap Critical Values		
		1%	5%	10%
$EC^+ \nRightarrow LS^+$	5.05	14.73	7.91	5.48
$EC^- \nRightarrow LS^-$	5.37	14.85	7.98	5.54
$EC^+ \nRightarrow LS^-$	3.86	13.47	8.40	5.92
$EC^- \nRightarrow LS^+$	4.44	16.42	8.69	6.34
$TFP^+ \nRightarrow LS^+$	6.41*	12.65	7.09	5.11
$TFP^- \nRightarrow LS^-$	5.39*	11.64	7.15	5.16
$TFP^+ \nRightarrow LS^-$	5.09	21.79	13.84	9.65
$TFP^- \nRightarrow LS^+$	18.62***	11.75	6.98	5.04

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. ⇏ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

Third, the asymmetric causality test results for Germany show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share can be rejected. In addition, the positive (negative) shocks in economic globalization cause a negative (positive) effect on labor's share. Furthermore, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 5% significance level, respectively.

Table 7. Results for Asymmetric Causality Test – Germany

Null Hypothesis	Wald Statistics	Bootstrap Critical Values		
		1%	5%	10%
$EC^+ \nRightarrow LS^+$	6.82**	7.60	4.18	2.94
$EC^- \nRightarrow LS^-$	6.52**	8.32	4.31	2.96
$EC^+ \nRightarrow LS^-$	4.90**	7.87	4.17	2.89
$EC^- \nRightarrow LS^+$	10.49**	12.15	5.57	4.07
$TFP^+ \nRightarrow LS^+$	8.40**	8.68	4.37	3.05
$TFP^- \nRightarrow LS^-$	8.17**	8.27	4.42	2.97
$TFP^+ \nRightarrow LS^-$	0.90	10.53	5.69	3.81
$TFP^- \nRightarrow LS^+$	0.12	11.21	5.52	3.87

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. $\nRightarrow$ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

Fourth, the asymmetric causality test results for Italy show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share can be rejected at the 1% significance level. Moreover, the negative shocks in economic globalization cause positive effects on labor's share. In case of the effects of technological progress on income distribution, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 10% significance level, respectively.

Table 8. Results for Asymmetric Causality Test – Italy

Null Hypothesis	Wald Statistics	Bootstrap Critical Values		
		1%	5%	10%
$EC^+ \nRightarrow LS^+$	12.02***	8.74	4.56	3.06
$EC^- \nRightarrow LS^-$	12.95***	8.25	4.45	2.99
$EC^+ \nRightarrow LS^-$	2.58	8.14	4.38	2.98
$EC^- \nRightarrow LS^+$	23.65***	9.12	4.79	3.27
$TFP^+ \nRightarrow LS^+$	4.71*	9.38	4.95	3.39
$TFP^- \nRightarrow LS^-$	4.53*	8.67	4.76	3.25
$TFP^+ \nRightarrow LS^-$	1.84	9.49	5.17	3.59
$TFP^- \nRightarrow LS^+$	2.01	8.53	4.58	3.18

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. ⇏ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

Fifth, the asymmetric causality test results for Japan show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share can be rejected at the 1% significance level. In addition, the positive (negative) shocks in economic globalization cause a negative (positive) effect on labor's share. Furthermore, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 10% and 1% significance levels, respectively.

Table 9. Results for Asymmetric Causality Test – Japan

Null Hypothesis	Wald Statistics	Bootstrap Critical Values		
		1%	5%	10%
$EC^+ \nRightarrow LS^+$	30.98***	19.12	9.10	6.21
$EC^- \nRightarrow LS^-$	99.08***	16.67	8.56	6.12
$EC^+ \nRightarrow LS^-$	9.29*	20.85	9.86	6.62
$EC^- \nRightarrow LS^+$	170.4***	18.28	9.42	6.71
$TFP^+ \nRightarrow LS^+$	4.49*	8.94	4.52	3.02
$TFP^- \nRightarrow LS^-$	23.34***	8.12	4.30	2.96
$TFP^+ \nRightarrow LS^-$	0.01	18.77	12.23	9.48
$TFP^- \nRightarrow LS^+$	0.00	9.47	4.89	3.29

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. ⇏ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

Sixth, the asymmetric causality test results for the United Kingdom show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share can be rejected at the 5% significance level. Moreover, the positive (negative) shocks in economic globalization cause a negative (positive) effect on labor's share. In addition, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 1% significance level, respectively. And also the positive shocks in technological progress cause a negative shock on labor's share in the United Kingdom.

Table 10. Results for Asymmetric Causality Test – United Kingdom

Null Hypothesis	Wald Statistics	Bootstrap Critical Values 1%	5%	10%
$EC^{+} \nRightarrow LS^{+}$	6.82**	7.60	4.17	2.94
$EC^{-} \nRightarrow LS^{-}$	6.83**	8.32	4.30	2.96
$EC^{+} \nRightarrow LS^{-}$	4.90**	7.87	4.16	2.89
$EC^{-} \nRightarrow LS^{+}$	30.75***	10.10	5.44	3.78
$TFP^{+} \nRightarrow LS^{+}$	11.25***	8.92	4.39	3.02
$TFP^{-} \nRightarrow LS^{-}$	13.28***	8.08	4.33	2.94
$TFP^{+} \nRightarrow LS^{-}$	11.51***	10.50	5.75	3.83
$TFP^{-} \nRightarrow LS^{+}$	0.01	9.72	5.10	3.51

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. $\nRightarrow$ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

Finally, the asymmetric causality test results for the United States show that the null hypothesis of cumulative positive and negative shocks of economic globalization shows not causing positive and negative effects on labor's share can be rejected at the 1% significance level. Moreover, the cumulative positive and negative shocks of technological progress cause positive and negative effects on labor's share at 1% significance level, respectively.

Table 11. Results for Asymmetric Causality Test – United States

Null Hypothesis	Wald Statistics	Bootstrap Critical Values 1%	5%	10%
$EC^{+} \nRightarrow LS^{+}$	30.05***	17.36	8.57	5.97
$EC^{-} \nRightarrow LS^{-}$	30.39***	16.32	8.49	6.06
$EC^{+} \nRightarrow LS^{-}$	0.11	15.52	8.57	6.27
$EC^{-} \nRightarrow LS^{+}$	29.45	16.51	9.27	6.71
$TFP^{+} \nRightarrow LS^{+}$	70.91***	8.89	4.67	3.25
$TFP^{-} \nRightarrow LS^{-}$	74.95***	8.57	4.52	3.07
$TFP^{+} \nRightarrow LS^{-}$	0.42	15.54	9.86	7.51
$TFP^{-} \nRightarrow LS^{+}$	0.00	10.64	5.65	3.98

Note: +, + denotes the cumulative positive shocks, -, - denotes the cumulative negative shocks, +, - represents the positive to negative shocks, and -, + shows the negative to positive shocks. ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. AIC is used as the information criterion. The maximum lags are determined according to the AIC. $\nRightarrow$ denotes the null hypothesis that there is no causality among the series. The bootstrap simulations are selected as 10.000 for computing the bootstrapped critical values.

5. Concluding Remarks

The last four decades have been confronted with an increase in income inequality across different countries and regions as a leading issue for the economic structure. A quick glance to the underlying factors of this issue leads us to focus on two major reasons. The first one depends on the liberalization trends of both trade and financial accounts, in which these are commonly reflected by the cumulative framework – namely the economic globalization. The second reason is captured by the outstanding rise in technological development all over the world but relatively more in advanced economies. In consideration of these two reasons, the relevant literature has provided mixed and controversial outcomes. While the mainstream approach supports a more liberalized economic structure, the alternative assumptions highlight the significance of the unfettered power of capital.

In this regard, this paper investigated the tripartite relationship between technological progress, economic globalization, and labor share of income across the G-7 economies over the 1970-2018 period. However, instead of looking at all the causal linkages, the main concentration inclined to examine the direction of effects/shocks from technological progress and economic globalization to labor's share. In order to carry out this direction, the study benefited from the asymmetric causality test proposed by Hatemi-J (2012). The empirical findings showed that the null hypothesis of both positive and negative shocks in technology and economic globalization not causing any positive or negative effect on labor's share was substantially rejected for G-7 economies. Therefore, the results imply that the alternative assumptions are more coherent with the current findings. In other words, both technological progress and economic globalization have ample effect on the dynamics of income distribution, which contradicts with the theoretical wisdom of mainstream approach.

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Research and Publication Ethics:

In this study, the rules of research and publication ethics were fully followed by author.