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RESEARCH ARTICLE

Income inequality-labor productivity relationship: CS-ARDL approach*

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Abstract

With the acceleration of globalization, "Reducing Inequalities", which is the 10th of the sustainable development goals, has started to attract more attention in the world. Many factors lead to inequality. Therefore, inequality requires consensus and strength at the interdisciplinary, local, national, and international levels. The leading indicator of inequality is income inequality. Its measurability and widespread impact are sources of its importance and priority. Unfair income distribution might have unfavorable effects on employees such as being more reluctant to work and the well-being of workers. In addition, if workers believe they earn less than they deserve, this might negatively affect the labor productivity. Ultimately, this process may cause countries to reduce their production output.

This study aims to explore the link between income inequality and labor productivity among 31 countries in Europe with the period of 2005-2019. To do this, a cross-sectional auto-regressive distributed lag model (CS-ARDL) is employed. According to the results, wage inequality damages the productivity of labor. A 1% increase in the wage inequality reduces labor productivity by 0.16%. Moreover, the unequal income distribution has an explanatory power of approximately 33% on the decrease in productivity. This helps to determine the possible effects of the unequal income distribution leading towards two targets. These targets are to create an efficient wage structure and eliminate the destructive effects of inequality, respectively. In terms of the policy effectiveness, simultaneous application of tools may be more beneficial.

Keywords: Wage Inequality, Labor Productivity, Sustainable Development, CS-ARDL

JEL Codes: C23, D63, J24

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1. INTRODUCTION

In Brundtland Report (1987), the definition of sustainable development (SD) is "the needs of the present without compromising the ability of future generations to meet their own needs." The SD, led by the United Nations (UN), includes 17 objectives and many sub-objectives for achieving a sustainable future. The UN prioritized three SD goals from 2015 to 2030. One of the three main objectives is to "fight inequality & injustice." Its inclusion in this emergency plan demonstrates the importance of the subject (The Global Goals 2021).

The importance of inequality is related to its effects on various areas. In this respect, inequality negatively affects the well-being of individuals. It also affects the productivity level of the labor (hence, the economy). Moreover, inequality disrupts resource allocation. Therefore, it is a concern of sustainability because of the limited resources. One aspect of inequality is a waste of resources when the advantaged group has more resources than they need. On the other hand, disadvantaged groups have fewer resources, which they have to share.

Terminologically, not being equal in status, rights and opportunities is defined as inequality. This issue has different manifestations (Afonso et al. 2015: 1). Income or wage inequality is the most popular inequality measurement in social sciences. Uneven income distribution among the population is the definition of income inequality. Unequal wage distribution is a source of income inequality. On the opposite side, a fair wage allocation has the criteria of equal pay for equal work (Meidner and Rehn, 1957 cited in Policardo et al. 2018: 3). Income inequality sourced from wages occurs when work and wages are out of balance.

Usually, the formation mechanism of inequality is the focus of scientific research. However, if one would like to reduce income inequalities for a sustainable society, knowing about the consequences of inequalities can pave the way for determining for which, how much and how the necessary tools are applicable. In addition, income is one of the basic human needs for individuals and households. A sufficient and fair income level is a requirement to sustain the well-being. Moreover, equitable and effective wage level is also significant for the firms, industries, and economy. Unequal income distribution can cause employees to lose their enthusiasm and thus, to lower productivity and output per employee. Therefore, a sustainable economy might be exposed to unequal distribution negatively. On the productivity side, it is a rate between input and output. In addition, this ratio calculates the efficiency level of inputs such as capital and labor. Countries should measure and raise their productivity levels if they are enthusiastic about the high growth rates and competitiveness. Additionally, productivity data is beneficial to evaluate the performance of labor and product markets (Krugman 1994: 1). Labor productivity in the labor market has influences on the efficient wage level. More productive workers get higher wages than fewer ones. Ultimately, all workers get the wages they deserved.

Income inequality increases when income is distributed unjustly and disproportionately among workers. Rising inequality rates are mainly due to the financial liberalization and trade globalization (Stiglitz 2013: 59). Unequal income distribution is especially true for the manufacturing sector. Technological progress in this sector causes an increase in productivity and reduces the need for employment. At the same time, changes in the employment structure are favor more skilled workers and against unskilled workers. In addition, differences in skills generally lead to differences in wages (Stiglitz 2013: 61). Wages, which are especially optimal wages, differ based on industry, sector, and firm (Stiglitz 1982: 78).

Moreover, productivity and wage level have a bidirectional relationship. Productive workers may receive higher wages, or higher wage levels increase their productivity by leading workers to exert more effort. The structure is also significant for perceived fairness in wages. If workers believe that the wage structure is not equitable, belief in inequality is on hand. Akerlof (1984) and Akerlof & Yellen (1986) argue that employees put in less effort if they believe they are underpaid (cited in Liu 2002: 454). If workers believe that the wage structure is unjust, their belief would reinforce the reality of income inequality.

There is a wealth of literature related to inequality and productivity measurement focusing on the effect of productivity on wage or vice versa. There are only a few papers directly mentioning the link between wage inequality and productivity level. Moreover, inequality indicators generally use the Gini coefficient and firm or sector data but not country-level. Related studies do not examine the variables for the long-run relationship. In the light of this information, our contribution to the literature is in three aspects. The first contribution is using the income quintile share ratio as an inequality indicator. The latter is to use the country-level panel data and the last contribution is the estimation of long-run coefficients by employing the cross-sectional panel cointegration technique.

In this regard, the second section covers a literature review. The third section gives information about the data and the methodology. The last section reveals the empirical results.

2. LITERATURE

Factor productivity has been a topic of much thought and discussion within the field, especially for economics. There is a large and diverse literature on productivity. Some of them examine the determinants of productivity such as Isaksson (2007), Choudhry (2009), Islam (2008), Isaksson and Ng (2006), Khan et al. (2011), Loko and Diouf (2009), Kose et al. (2009), Aghion et al. (2009). Some papers also investigate regional or spatial differences in productivity or unequal productivity distribution (i.e. He et al. 2017; Ezcurra et al. 2007).

Another group argues the historical process of macroeconomic variables with inequality and productivity. Paul (2020) focuses on the historical process of inequality and productivity. He finds that rising inequality and low productivity are predictors of crises for 17 countries' different crisis dates. Meager and Speckesser (2011) also find that the growth of productivity and wages depicts simultaneous movement for 25 countries during 1995-2009.

Additionally, the related literature investigates the connection between productivity and income inequality. However, the direction of the effect is from productivity to inequality as in technical changes based on skill biases. The skill-biased shifts suggest that innovations in production technology are against the low-skilled labor but not the skilled ones. As a result, there might be a wage gap between more and low-skilled laborers. More skilled laborers benefit from a rise in total factor productivity, but inequality worsens. Some of the other studies in the literature could be listed as Gries and Naudé (2018), Hornbeck and Moretti (2018), Maoz and Sarid (2021), Fuentes et al. (2014), Kampelmann and Rycx (2012), Caroli and Van Reenen (2001) and Leung (2001).

Some papers investigate the wage effects on productivity level or wage efficiency theory arguing that an increase in (real) wages stimulates productivity in labor. Furthermore, we account literature such as Basril et al. (2018), Stansbury and Summers (2018), Trpeski, et al. (2016), Cohn et al. (2015), Feldstein (2008), Zhang and Liu (2013), Herman (2020), Levine (1992), Akerlof and Yellen (1990), Spitz (1989), Levine (1989), Rebitzer (1987), Katz (1986).

The last group of literature and the focus of this study are related to the income inequality effects on labor productivity. However, scholars rarely investigate the unequal determination of the wages's effects on productivity level (Policardo et al. 2018: 2-3; Espoir and Ngepah 2020: 2612). Thus, papers studying on the connection between inequality and productivity are limited. Here, some examples of the most relevant studies and their findings are provided.

Freeman and Medoff (1984) are pioneering works analyzing the connection between inequality and productivity. They focus on union and nonunion workers for selected sectors in the United States. They reveal that wages are more homogeneous in unionized firms. Hence, inequality is low in these firms and this reduction might exist because of union workers' preferences and ideas about fairness. They also state that workers in the unionized companies are more productive. Productivity growth might be due to "industrial relations climate" and "more rational, professional management" (cited in Liu 2002: 455).

Liu (2002) examines the manufacturing industries following wage inequality and industrial productivity. Liu investigates the effects of wage inequality in the context of relative deprivation and efficient wage. Sen's index is a measurement for determining the relative deprivation and efficient wage levels. Sample countries are Taiwan (1979-1996) and South Korea (1993-1996). In the regression analysis of this study, the hourly output of labor is a dependent variable, and the Sen index for aggregated relative deprivation is one of the explanatory variables. The Gini index is inside the Sen's index, which is a tool for measuring the extent of economic deprivation in society as aggregate or relative deprivation. Regression results revealed that workers are reluctant when payments are less than they deserve. The coefficients of relative deprivation are highly negative for the two countries. However, this result is not consistent with the literature in which efficient wage affects industrial productivity. He also found that relative deprivation and efficient wages are more important than wage inequality.

Kim and Sakamoto (2008) examine the American manufacturing industry ranging from 1979 to 1996. They use productivity data for 72 manufacturing industries and the Gini index. Other variables are real capital stock, material cost spent, and the number of workers. Their results are not proof of the skill-biased technological-change argument and they find that wage inequality negatively affects productivity. The Gini coefficient is – 0.15 and statistically valid for the second model. 1% increase in inequality causes 0.15 % decrease in productivity on average. The general interpretation of the coefficients is that the relationship between inequality and productivity is significantly negative if the model has fixed effects for industry and year.

Mahy et al. (2009) evaluate the effect of inequality on productivity level with wage dispersion for Belgium. Wage dispersion is a measure for wage differentials between similar workers. They calculate conditional wage inequality using Winter-Ebmer and Zweimüller (1999) methodology. They also use age, education, sex, gross income, working hours, and occupation and sector employers, number of employees, wage bargaining. The results of ordinary least squares demonstrate that there is a relationship between wage dispersion and productivity. Namely, a small wage dispersion might be detrimental to productivity. Moderate wage increases are beneficial to firm performance. Hibbs and Locking (2000) also analyze wage dispersion for Sweden from 1960 through 1980. Model's variables are hourly wage distribution and value-added per worker. They reveal that a reduction in interindustry wage differences might lead to a productivity improvement.

DiPietro (2014) uses productivity growth as a dependent variable, an average annual Gini coefficient from 2000 to 2010. Six control variables are included in the model such as the level of economic development, the amount of human capital, the size of the private sector, wage flexibility, and government waste. He employs regression analysis to examine the cross-country data. Unfortunately, he does not mention which countries are included in his work. He reports that the coefficient of Gini is approximately -0.78 if there is only one explanatory variable. If control variables are included to the models one by one, this value becomes – 0.99.

Policardo et al. (2018) investigate that wage inequality and labor productivity for 34 Organisation for Economic Co-operation and Development (OECD) countries. They use generalized methods of moments for the period of 1995-2007. Labor productivity per hour worked is used as the dependent variable; the Gini index is employed as the independent variable. Control variables are Gross Domestic Product per capita, fertility, life expectancy, annual hours per worker, and total employed population rate. They find that wage inequality harms labor productivity. The coefficient of this effect is about -0.06 in which a one-dollar increase in the inequality index causes 6 cent decrease in labor productivity.

Britton and Propper (2016) investigate the impact of teacher pay on school productivity in England. They collect cross-sectional data from more than 3000 schools and around 200.000 teachers . Variables used in the analysis are school performance and the wage gap. Moreover, the school efficiency is the added value of the school measures by national tests. They depict that the teachers respond to the low payments. An unforeseen 10% change in the wage gap worsens school performance by 2%. A larger wage gap between formal payments and non-labor market wage levels reduces the school productivity.

Espoir and Ngepah (2020) examine the effects of income inequality on total factor productivity based on location and distance for South Africa. For this purpose, they apply the spatial econometric technique and use municipal panel data from 1995 to 2015. Their findings conclude that there are positive spatial interactions in the effects of income inequality on total factor productivity. It means that there is a neighboring effect among the municipalities. They further reveal that the impact of income inequality on productivity is negative for the direct effect and it is positive for the indirect effect. Municipalities (with high inequality) transfer jobs, investments, and skilled labor to municipalities (with medium income inequality and high-income opportunities).

Da Silveira and Lima (2021) investigate the endogenous macroeconomic fluctuations with the effects of wage inequality. They employ the frequency distribution at the micro-dynamic base. Their results demonstrate that the labor productivity is changeable across workers depending on different levels of wages. They also provide empirical evidence for the endogeneity of labor productivity and the persistency of wage inequality.

3. DATA AND METHODOLOGY

This chapter gives information about the the data and the methodology

3.1. Data

Finding sufficient and powerful data is usually difficult if one would like to examine unequal income distribution. This is because some indicators could be available for restricted periods and countries. Missing observations might be notable. Collecting two variables (labor productivity and income inequality) from the same source contributes to the availability and robustness of the data. In this vein, Statistics of the European Commission (Eurostat) has various and qualified data related to income inequality and labor productivity. Inequality of income is the measurement of the S80/S20 income quintile share ratio. This ratio is the household income ratio obtained by dividing the top 20% by the bottom 20%. The second variable is labor productivity calculated per person employed and hour worked (EU27_2020=100). The logarithmic transformations of variables as *log_inc* and *log_pro* representing income inequality and labor productivity are employed for the analysis, respectively.

The sample period ranges from 2005 to 2019 for 31 countries in Europe. These countries are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom.

3.2. Methodology

This section provides information concerning the co-integration approach used to estimate the long-run coefficients in the study. The cross-sectional dependence and the stationary tests are necessary before the estimation of the long-run coefficients. The methodology of Frees (1995) to test the existence of the cross-sectional dependence is explained below:

$$R_{AVE} = \binom{n}{2}^{-1} \sum_{i<j} r_{ij} \tag{1}$$

where represents the Spearman rank correlation coefficient between the ith and jth units. The cross-section dependence tests of Pesaran (2004), Frees (1995), and Friedman (1937) are initially used in this study. However, test statistics come up with some contradictory results. Pesaran and Friedman tests confirm the null hypothesis suggesting that there exists no cross sectional dependence across units in the panel but Frees test does not. Therefore, we conclude that there is cross-sectional dependence across units according to DeHoyos and Sarafidis (2006: 494).

Having found that there is a cross-sectional dependence among units, we should use the unit root test allowing cross-sectional dependence Because of the unbalanced panel data, we can apply Pesaran's (2007) methodology. Pesaran developed the cross-sectionally augmented Dickey-Fuller (CADF) statistics. In the process, he calculated a general panel unit root statistics by using unit root statistics of each cross-section in a panel data (Koçbulut and Altıntaş 2016: 16). CIPS is a general test statistic for unit root (Pesaran 2007: 276):

$$CIPS(N,T) = N^{-1} \sum_{i=1}^{N} t_i(N,T) \tag{2}$$

where $t_i(N,T)$is the CADF statistic for the i. cross-section unit based on CADF regression ($\Delta y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{i,t}$) (Pesaran 2007: 269). The null hypothesis has the statement of non-stationary series ($H_0: b_i = 0$ for all i) (Pesaran 2007: 268-69).

Because of the connected units, the existence of a small sample (micro panel), and having different integration levels for series, the panel auto-regressive distributed lag (ARDL) model is the most suitable for the long-run coefficient estimation. Deviations from long-run equilibrium are significant than short-run equilibrium. Therefore, the long-run relationship between variables and unbiasedness are favorable in the estimation process (Granger 1986: 213). We run the ARDL approach under the integration level of I(1) for dependent variable and I(0) for explanatory variable (Pesaran et al. 2001: 315). The fundamental model of ARDL (p_x, p_y) with respect of dependent and independent variables (Ditzen 2018: 6):

$$y_{i,t} = \sum_{I=1}^{p_y} \lambda_{I,i}\, y_{i,t-I} + \sum_{I=0}^{p_x} \beta_{I,i}\, x_{i,t-I} + e_{i,t} \tag{3}$$

where the lag length of y and x are p_x,p_y, respectively. If we calculate the coefficients of long-run β and average group (Ditzen 2018: 6):

$$\theta_i = \frac{\sum_{I=0}^{p_x} \beta_{I,i}}{1-\sum_{I=1}^{p_y} \lambda_{I,i}}, \qquad \bar{\theta}_{MG} = \sum_{i=1}^{N} \theta_i \tag{4}$$

In calculating θ_i and $\bar{\theta}_{MG}$ values, Chudik et al. (2016) suggest the cross-sectionally augmented ARDL (CS-ARDL) and the cross-sectionally augmented distributed lag (CS-DL) estimators. CS-ARDL technique calculates the long-run coefficients from short-run coefficients and includes cross-sectional average. Extended version of equation 3 is explained below (Ditzen 2018: 9):

$$y_{i,t} = \sum_{I=1}^{p_y} \lambda_{I,i}\, y_{i,t-I} + \sum_{I=0}^{p_x} \beta_{I,i}\, x_{i,t-I} + \sum_{I=0}^{p_T} \gamma'_{I,i}\, \bar{z}_{i,t-I} + e_{i,t} \tag{5}$$

where $\bar{z}_{t-I}$ consists of $\bar{y}_{i,t-I}$ and $\bar{x}_{i,t-I}$. $e_{i,t}$. is serially uncorrelated process across for all i. Adding the cross-sectional mean to the formula can remove cross-sectional dependence in the errors. Thus, the estimation fulfills the validity criteria (Erülgen et al. 2020: 9).

4. ANALYSIS

At the beginning of the analysis, a related cross-sectional dependence test is necessary to check the possible correlations among units. The null hypothesis consists of a cross-sectional independence argument (DeHoyos and Sarafidis 2006: 492). The test statistics of Frees is 5.589 and critical values are 0.2828 (0.10), 0.3826 (0.05), and 0.5811 (0.01). Because Frees' statistics are bigger than critical values, we reject the null hypothesis suggesting the cross-sectional independence. After that, we implement cross-sectional augmented Dickey Fuller method. The results are reported in Table 1.

Table 1. Stationary Test Results

cons.	cons. & trend	lag	cons.	cons. & trend	lag
	log_pro			**log_inc**	
0.873	0.837	0	-2.828 **	-2.135 **	0
- 0.300	- 0.449	1	-1.690 **	1.394	1
	Δlog_pro			**Δlog_inc**	
-7.310 ***	-4.674***	0	-12.002 ***	-10.302 ***	0
-4.243 ***	-1.067	1	-3.510 ***	-0.594	1

Note: ***, **, and * represent % 1, % 5 and % 10 respectively.

When we examine the stationary levels of the variables, log_pro and log_inc are integrated I(1) and I(0), respectively. Furthermore, cross-sectional dependent variables necessitate the CS-ARDL approach. Table 2 reports the analysis results with different lag lengths.

Table 2. Long-Run Coefficients

Coef.	z stat.	Lag(s)	F stat.	R-sqr.	CD-stat. (p)
-0.1302 (0.0616)	-2.12**	0	1.53***	0.21	0.32 (0.750)
-0.1609 (0.0764)	-2.11**	1	1.58***	0.33	-0.63 (0.532)
-0.1475 (0.052)	-1.73 *	2	1.68***	0.46	-0.67 (0.503)
-0.1258 (0.0895)	1.40	3	1.55***	0.57	-0.15 (0.884)

Note: ***, **, and * represent % 1, % 5 and % 10 respectively. Standard errors in parentheses.

All models are statistically valid according to the F statistics. The most suitable model is ARDL (1,1). One lagged values of variables have a long-run relationship. There is a negative relationship between wage inequality and labor productivity. 1 % increase in wage inequality results in a 0.16 % decrease in labor productivity. Wage inequality explains 33% of productivity declines. This percentage is high if we consider only one explanatory variable. Moreover, the CD test is a post-estimation test for validity and shows that errors are cross-sectionally independent.

In the analysis, the income quintile share ratio is used as an inequality indicator while other studies employ the Gini index. Furthermore, this study estimates the long-run coefficients, other studies make general estimations without any differentiation. Considering the results, the coefficient is close to the 0.15 value of Kim and Sakamoto (2008), smaller than 0.78 and 0.99 of DiPietro (2014). In addition, it is bigger than the 0.06 and 0.02 of Policardo et al. (2018) in absolute values. Our findings are consistent with the theory and the empirical studies except for DiPietro. Briefly, we should pay attention to the dynamics between wage and productivity for a stable improvement in labor productivity in the long run. In addition, control variables can clarify the impact of wage inequality on the productivity level.

5. CONCLUSION

Improving productivity and diminishing inequal income/wage distribution require long-term policy and strategies. Therefore, this paper investigates the long-term parameters. An inequal income ratio negatively affects labor productivity. Unfair wage determination is one of the sources of income inequality. Various factors such as gender discrimination, subjective assessment, and regional differences might be other sources. Therefore, penetrating or reducing the inequalities probably depict long-run rather than short-run solutions.

In this respect, sustainable development goals determine reductions in inequalities as one of the three urgent goals. Three goals are “fight inequality & injustice,” “end extreme poverty,” and “fix climate change” from 2015 to 2030. Alternative policies at local, regional, territorial, and global levels might be more beneficial and powerful for this purpose. Furthermore, policy recommendations may include some measures on how to reduce inequality. Remuneration determination criteria based on skills, abilities, education, and the perception of the right wage level can help to prevent wage inequality. In addition, the government can detect and control whether the companies determine fair wages.

Cross-sectional dependency and data size restrict possible analysis techniques. A larger and more comprehensive data set will allow for more appropriate analysis. Further research can analyze time series data with different methods considering structural breaks and nonlinear dynamics. Researchers might extent and develop cross-sectional or panel models with spatial effects.

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