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Original scientific paper

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Skill versus Inequality

Summary: This paper explores empirical evidence for a connection between income inequality and skill (advanced-level educated workers share) using panel data methods that take into account cross-section dependency and heterogeneity. To assess the income inequality associated with skill, we run a data set for 24 developed the Organisation for Economic Co-operation and Development (OECD) countries from 1995 to 2018. In order to determine the stationary characteristics of the variables, we employ the Cross-Sectionally Augmented Im, Pesaran and Shin (CIPS) test approach. Following this, we employ Westerlund (2007), and Gengenbach, Urbain, and Westerlund (2016) Panel Cointegration tests, and then the Panel Dynamic Ordinary Least Squares (PDOLS) estimator. Our empirical test results conclude that there is a relationship between inequality and skill in the long-run and the PDOLS estimator findings show that as the skill level in employment increases, inequality decreases. In addition, according to the findings, this negative relationship is more pronounced in the United States, whereas it is more moderate or not valid in European countries. The results obtained are primarily consistent with the framework presented by Acemoglu (2002, 2003). These findings constitute one of the main contributions of the study in terms of supporting Acemoglu's (2003) thesis that the skill premium is more pronounced in the United States.

Keywords: Income inequality, Skill, Skill-biased technical change, Panel data.

JEL: C23, D63, I24.

Increasing income and social inequalities have attracted enormous attention from economists, researchers, and policymakers (Angus Deaton 2013a; Thomas Piketty 2014; Philippe Aghion et al. 2015; Fatma E. Soylu 2022). According to Olivier Blanchard and Dani Rodrik (2021), inequality is "a defining issue" of our time. In fact, we live in an era of both increasing inequalities and rapid technological advances fueled by developments in information technology called the third industrial revolution. There is a commonly accepted view in the literature that today's skill-biased technological change tends to increase inequalities (Jan Tinbergen 1975; Alan B. Krueger 1993; Daron Acemoglu 1998, 2002, 2021; Claudia Goldin and Lawrence F. Katz 2007). The skill-biased technological change favors skilled workers because it increases the demand for skills and their wages. But at the same time, it replaces tasks performed by unskilled workers (Acemoglu 2002), and thus generates inequality by increasing the skill premium. Acemoglu (2002, 2003) introduces a framework that emphasizes that as the fraction of skilled workers in the labor force increases, the unskilled workers' wages increases, and the skill premium decreases. And this framework, which will be explained in detail in the second section, will guide this study.

In this paper, we aim to obtain empirical evidence for a connection between inequality and skill using panel data methods that consider cross-section dependency and heterogeneity. The analysis covers the period from 1995 to 2018 and includes 24 developed OECD countries. The contributions of this study to the existing literature are in three ways: (1) In our study, this relationship is evaluated within the framework presented by Acemoglu (2002, 2003). In other words, there are studies examining this relationship in the literature, but to our knowledge, there is no study that analyzes this relationship with the panel data technique by associating it with this framework. (2) The second contribution lies in the use of country-level panel data to investigate if there is a long-run relationship between the considered variables. In the literature, this relationship has been generally evaluated in a theoretical framework or over a single country. Having produced separate results for each of the 24 developed OECD countries make this study important. (3) In the findings, different estimation results were obtained for European countries and the United States. This result is also important in that it empirically supports Acemoglu's (2003) thesis that the skill premium is more dominant in the United States.

This paper is structured as follows: In the first section of the paper, we discuss cross-country inequality differences. In the second section of the paper, skill-biased technological change and its impact on inequalities and the rise of the skill premium in the theoretical framework are evaluated. Then, studies in the literature are evaluated in the third section. In the fourth section of the paper, finally, we analyze the association between income inequality and skill, and the final section includes conclusion.

1. Inequality and Cross-Country Differences

Income inequality is a combination of the apparent increase in the share of income accruing to a small group and stagnating average incomes at the bottom. The most controversial feature of this disproportioned income distribution is the apparent increase in the share of the top one percent (Daniel R. Feenberg and James M. Poterba 1992). Deaton (2013b) states that if few people get very rich without harming anyone, the rest of society would not complain about that. If the few get rich by harming others, inequality becomes a threat to social order. In many high-income countries, income going to the top 1% decile has risen rapidly to levels not seen for 100 years. At the same time, the rest of the people have seen little or no gain in their living standards (Deaton 2013b). This inequality has some inevitable consequences that affect society. These inequalities in income, i.e., differences in living standards, hinder people use their potential fully. Countries that have higher income inequality probably go with the following: (i) *higher poverty*, the number of people below the international poverty line (Branko Milanovic 1998; François Bourguignon 2004); (ii) *slower economic growth or financial instability*, which constrains the growth of mass demand (Alberto Alesina and Dani Rodrik 1994; Torsten Persson and Guido Tabellini 1994; Dierk Herzer and Sebastian Vollmer 2013); (iii) *higher crime*, some studies in the literature show that socioeconomic inequality between races and general inequality increase rates of criminal violence (Matthew R. Lee and William B. Bankston 1999; Piketty 2014); (iv) *health issues*, income inequality or social inequalities may be directly hazardous to individual health. According to a recent body of inequality literature, relatively equal societies supply social cohesion, solidarity, and less stress; they offer their citizens public goods, social support, and social capital, and they satisfy humans' evolved preference for fairness (David Cutler, Deaton, and Adriana Lleras-Muney 2006; Kate E. Pickett and Richard G. Wilkinson 2015; Boyka Bratanova et al. 2016); (v) *democracy* is incompatible with extreme inequality. The rich may write the rules in their favor, and they may work against the public provision (Kenneth A. Bollen and Robert W. Jackman 1985; William Easterly 2001; Deaton 2003, 2014; Acemoglu et al. 2013).

Since the 1980s, income concentration has in fact been increasing throughout the world. Moreover, it has dramatically risen in the United States. Top income inequality, as measured by the share of incomes accruing to individuals in the top percentiles of the distribution, has risen significantly (Fatih Guvenen and Greg Kaplan 2017). The top 1% has increased from 11% in 1970 to 19% in 2021 and at the same time, the top 10% has increased from around 33% in 1970 to almost 46% in 2021 (World Inequality Database - WID 2019)[1]. It is also important not to lose sight of the fact that the income shares of the bottom and middle percentiles in the Unites States have declined. This relates to the fact that there is a rising gap between rich and poor in the United States. Although it is not typical, many developed countries or developing countries have experienced these increases. Roughly the same has happened in India, China, Russia, and other English-speaking countries and inequality evolved along similar lines. Moreover, this trend is not restricted to top incomes; other measures of inequality, such as the Gini index, show similar trends. It has increased substantially in these countries (Elhanan Helpman 2016).

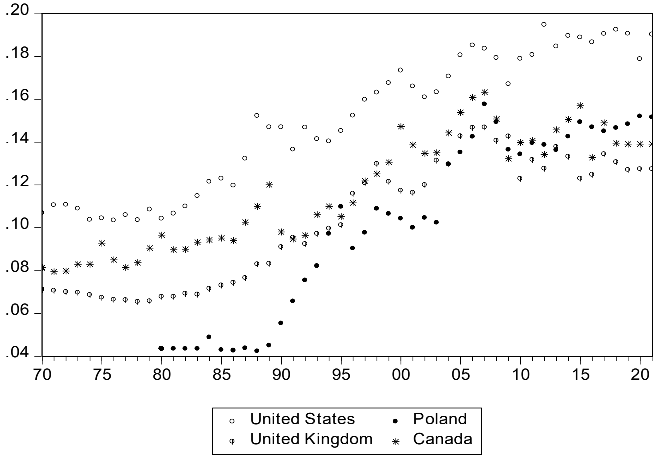
Many countries suffer from rising income inequality but there is also great cross-national variation. It has been stable or has declined in some countries. Income shares of the top 1 decile in the Netherlands have declined from around 9% in 1970 to around 7% in 2021. Some European or Nordic countries like France, Belgium, Switzerland, and Norway have a stable trend of inequality during the same period. And not surprisingly, the middle class hasn't lost its income share in these countries (WID 2019). In order to reveal these different inequality trends between countries, the trends of countries with high (United States, Poland, United Kingdom, and Canada) and low (Belgium, Netherlands, and Switzerland) inequality levels from the countries included in the analysis are shown in Figure 1 and Figure 2, respectively.

Figure 1, which is based on data from the World Inequality Database (WID), presents a comparison of inequality in some countries with high levels of inequality, such as the United States, the United Kingdom, Canada, and Poland. These top 1 share trends are a typical illustration of the evidence that inequality has increased steadily in these countries from 1970 up to today.

The trend in Figure 1 is indisputable, but not all countries have a similar trajectory regarding inequality trend. Figure 2 shows a comparison of inequality in some countries with low or moderate levels of inequality, such as Belgium, Netherlands, and Switzerland. We can easily understand from Figure 2 that contrary to the United States,

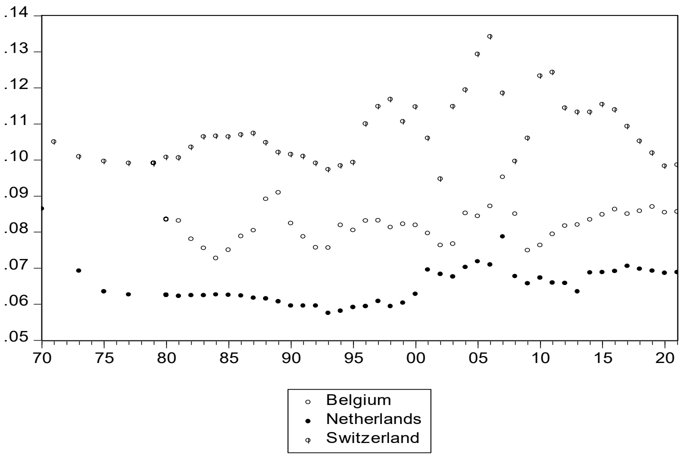
[1] **World Inequality Database.** 2019. Data. https://wid.world (accessed June 20, 2019).

United Kingdom, and Poland, which have a strong trend of inequality, these countries indicate an opposite trend. After the 1970s, the top 1 share has not risen markedly and even has been stable.



Source: Authors' calculations based on data from WID (2019).

Figure 1 Inequality Level (p99p100)



Source: Authors' calculations based on data from WID (2019).

Figure 2 Inequality Level (p99p100)

2. Skill-Biased Technological Change and Inequality: Background

Since the 1980s, there has been a huge widening of income differentials in many countries. The underlying factors behind the rising income concentration are hotly debated issues. This deepening income division is mainly attributed to skill-biased technological change (Tinbergen 1975; Krueger 1993; Acemoglu 1998, 2002, 2021; David H. Autor, Katz, and Krueger 1998; Goldin and Katz 2007; Acemoglu and Autor 2010; Milanovic 2016). Tinbergen (1975), in his pioneering work, argued that technological developments increase the demand for skills. Following Tinbergen's (1975) work, the relative demand for skills has been associated with technology or even directly with the skill bias of technological change. This point of view indicates that the return to skills (and to college) is determined by "a race between the increase in the supply of skills in the labor market and technological change which is assumed to be skill-biased". This technological change increases the demand for more "skilled" workers, especially for college graduates relative to non-college workers (Acemoglu and Autor 2010, p. 1044).

Several countries are experiencing this rising income inequality generated by skill-biased technological change which means rising demand for higher labor market skills (Timothy M. Smeeding 2002; Nancy L. Stokey 2016). The main factor of the increase in inequality appears to be a shift in the demand for more skilled workers. The demand has been increasing faster for high-educated and skilled workers than for low-educated and skilled workers.

Rapid growth in the demand for "more-educated workers" that is "more-skilled workers" appears to be the cornerstone of observed changes in the wage structure (Katz and Kevin M. Murphy 1992). Increase in the wages of skilled workers relative to unskilled workers is a direct consequence of the complementarity between skill and new technologies (Acemoglu 1998). The importance of skills on inequality was presented by Tinbergen (1975) with supply and demand agents. Tinbergen (1975) argued that "technological change is skill-biased in that it increases the demand for more skilled workers" and therefore increases their wage premium in the labor market (Acemoglu 2002). Changes in the wage structure have been linked to technical developments that are transforming the work structure. To capture this point, bear in mind that computers, computer-associated production techniques, and robotics appear to complement skilled workers and replace many labor-intensive tasks. And this is a direct outcome of technological change that affects inequality in recent years (Stijn Broecke, Glenda Quintini, and Marieke Vandeweyer 2016).

Acemoglu (2002) introduces a framework that links wages to the supply of skills and to the demand generated by technological possibilities. This framework would let us understand how skill-biased technological change generates the deterioration in wage structure. Skill-biased technological change means that the efficiency of skilled labor increased faster than the efficiency of unskilled labor. Some factors that transform work structure, such as skilled-biased technological change, affect skill demand and raise the relative demand for skills. Although its real impact on inequality is also determined by the supply of skills (Acemoglu 2002, 2003; Helpman 2016; Murphy and Robert H. Topel 2016). In this framework (Acemoglu 2002, 2003), we assume that there are two types of workers: (1) H(t) skilled/ high-educated and (2) L(t) unskilled/low-educated who are imperfect substitutes[2]. The production function for the aggregate economy at a given time (t):

[2] Unskilled workers have high school diploma and skilled workers have college degree, and in this section, terms of skill and education was used interchangeably.

$$Y(t) = [(A_l(t)L(t))^{\rho} + (A_h(t)H(t))^{\rho}]^{1/\rho}\,, \tag{1}$$

where $\rho \leq 1$ and $A_l(t)$ and $A_h(t)$ are factors augmenting technology terms. The elasticity of substitution between two types of workers is $\sigma = \frac{1}{1-\rho}$. As we noted above, labor markets are competitive, and so in this framework the unskilled worker wage is:

$$\omega_L = \frac{\partial Y}{\partial L} = A_l^{\rho}\left[A_l^{\rho} + A_h^{\rho}\left(\frac{H}{L}\right)^{\rho}\right]^{\frac{1-\rho}{\rho}}. \tag{2}$$

This equation implies $(\partial\omega_L / \partial(H/L) > 0)$ that as the fraction of skilled workers in the labor force increases, the unskilled worker wage increases. The skilled worker wage is:

$$\omega_H = \frac{\partial Y}{\partial H} = A_h^{\rho}\left[A_l^{\rho}\left(\frac{H}{L}\right)^{-\rho} + A_h^{\rho}\right]^{\frac{1-\rho}{\rho}}. \tag{3}$$

We can conclude that $(\partial\omega H / \partial(H/L) < 0)$ as the rate of skilled workers increases, their wages decreases. Starting from this point, if we combine these Equations (2 and 3), the skill premium[3] is:

$$\omega = \frac{\omega_H}{\omega_L} = \left(\frac{A_h}{A_l}\right)^{\rho}\left(\frac{H}{L}\right)^{-(1-\rho)} = \left(\frac{A_h}{A_l}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{H}{L}\right)^{-\frac{1}{\sigma}}. \tag{4}$$

In this framework, ω is referred to both as a measure of premium - skilled wage ω_H relative to unskilled wage ω_L - and as a measure of inequality. This equation can be re-interpreted with log forms:

$$\ln \omega = \frac{\sigma-1}{\sigma} \ln\left(\frac{A_h}{A_l}\right) - \frac{1}{\sigma} \ln\left(\frac{H}{L}\right). \tag{5}$$

As a natural consequence of this, we can conclude that the skill premium increases when skilled workers become scarcer, and the skill premium reduces when there is an increase in the supply of skill (Acemoglu 2002, 2003).

3. Literature Review

As we learn from the previous section, technological change is skill-biased, and consequently, demand for more skilled workers and their wage premium increased. The recent changes in the wage structure and the returns to college, especially in the U.S. labor market, have mobilized a large literature focusing on the relationship between technological change and inequality (Acemoglu and Autor 2010, p. 1044). The most important and influential study has been done by Krueger. Krueger's (1991) paper on computers and inequality examined the effect of the computer revolution on wage structure for the period from 1984 to 1989. Krueger analyzed the wage differentials of two types of workers (a type of worker who uses a computer and earns a higher wage, and a type of worker who doesn't use the computer) and indicated that workers are rewarded more highly if they use computers at work. Katz and Murphy (1992) used a supply and demand framework to analyze changes in the U. S. wage structure for the period from 1963 to 1987. They pointed out that the rapid growth in the demand for

[3] The wage of skilled workers relative to the wage of unskilled workers.

educated, skilled, and female workers appears to be the driving power behind the changes in the U.S. wage structure. Acemoglu (1998) suggested that a high fraction of skills in the labor force refers to a large size of the market for skill complementary technologies and encourages faster upgrading of the productivity of a skilled worker. As a consequence of this, an increase in the supply of skilled workers reduces the skill premium in the short-run, but then it increases the skill premium. This theory implies that the rapid increase in the fraction of college graduates in the U.S. labor force in the 1970s may have been a causal factor in both the decline in college premiums during the 1970s and the large increase during the 1980s. Autor, Katz, and Krueger (1998) examined the effect of skill-biased technological change on U.S. educational wage differentials. They showed that there was a strong and persistent growth in relative demand favoring college graduates and their analyses also showed that the rate of skill upgrading has been greater in more computer-intensive industries. Autor, Katz, and Melissa S. Kearney (2006) offered evidence in their analysis that shifts in demand are likely to be a key component as a persuasive explanation for the changing U.S. wage structure. Ariel Burstein, Javier Cravino, and Jonathan Vogel (2011) employed a tractable quantitative model of international trade in capital goods to analyze the extent to which international trade raises the relative demand for skill, hence increases the skill premium. Their study shows that international trade can have an important impact on the skill premium, especially in countries that import large fractions of capital equipment. Aghion et al. (2015) used panel data analysis to indicate a correlation between innovation and top income inequality in the United States. Their findings promote the Schumpeterian judgment that the rise in top income is partially related to innovation-led growth and innovation fosters social mobility at the top through creative destruction. Jong-Wha Lee and Dainn Wie (2015) explore the empirical evidence of the impact that technological progress has on wage inequality in Indonesia. Their analysis shows that both the between and within industry shifts of labor demand that favored skilled workers contributed to the widening wage inequality since the early 2000s. Broecke, Quintini, and Vandeweyer (2016) used the Survey of Adult Skills (PIAAC) to explain international differences in wage inequality *via* the importance of skill. Results show that demand and supply analysis indicates that the relative net supply of skills could explain 29% of the higher top-end wage inequality in the United States. And their analysis also shows that skills could explain an essential part of the racial wage gap. Imran Aziz and Guido Matias Cortes (2021) show that educational expansions will lead to changes in wage inequality, that is, an increase in the supply of skills will reduce inequality as it puts downward pressure on the skill premium.

Compared to the existing literature, our study broadens this discussion mainly in the following aspects. Firstly, our study evaluates this discussion between skill and inequality in the context of the framework presented by Acemoglu (2002, 2003) and analyzes this discussion with a current econometric method. We believe that the selected countries (24 developed OECD countries) and the period (1995-2018) for the analysis contribute to this discussion in terms of being a period and sample in which both the significant effects of the skill-biased technological change and top-income shares can be observed. The use of panel data analysis as an econometric method and thus obtaining country-level results is another feature that distinguishes this study from the existing literature. Because in the literature, this relationship has generally been evaluated in a theoretical framework or over a single country.

4. Data, Methodological Background, and Analysis

In this section, we briefly describe the data that we use, the steps of our estimation methodology, and finally our estimation findings.

4.1 Data and Model Specification

In the analysis, we explore the empirical evidence of skill effect on income inequality. To explore this relationship, we employ a data set for 24 developed OECD countries (including Norway, Sweden, Finland, Denmark, Switzerland, Ireland, Lithuania, Germany, Greece, Hungary, Italy, Austria, Spain, Netherlands, Luxembourg, Slovenia, Portugal, France, Belgium, Poland, United States, United Kingdom, Canada, and Korea) and for the period from 1995 to 2018.

As we know, technological change increases the demand for more "skilled" workers, especially for college graduates relative to non-college workers (Acemoglu and Autor 2010). Acemoglu (2002) states that there are two types of workers: (1) unskilled/low-educated workers and (2) skilled/high-educated workers, and "the unskilled workers as those with a high school diploma" and "the skilled workers as those with a college degree". Based on his classification, this study uses the share of advanced-level education in employment as the effect of the skill. In line with this information, we use the employment distribution by advanced level education data (%) to consider skilled workers, and this data is taken from the International Labour Organization (ILO 2019)[4]. The inequality data (top income shares) is taken from the World Inequality Database (WID 2019). Statistics on employment by level of education are based on the categories of the ISCED (International Standard Classification of Education). Accordingly, the ILO considers the following classification of employment by advanced-level education statistics: (1) short-cycle tertiary education; (2) bachelor's or equivalent level; (3) master's or equivalent level; (4) doctoral or equivalent level (ILO 2019). Data series of employment by level of education from ILO mostly starts after the 1990s for many countries and the balanced time series data - there are many gaps in the time series dimension - are not available for many countries. And to obtain a balanced panel data set, we tried not to include the countries with gaps for this period. Thus, the advanced level of educated worker employment data availability is a decisive factor in the choice of the country and the period. Because this data series covers a number of countries and periods compared to the inequality data. In this direction, we paid attention to the fact that countries have both employment and inequality data for the period from1995 to 2018 in the country selection. The countries that we used in the analysis were preferred according to their availability in ILO and WID.

The WID started to constitute the historical top income share series just for France, the United States, and the United Kingdom and then extended to a growing

[4] **International Labor Organization.** 2019. Data and Statistics. https://www.ilo.org/global/statistics-and-databases/lang--en/index.htm (accessed June 20, 2019).

number of countries (Facundo Alvaredo et al. 2017). Top income shares refer to the share of total pre-tax national income going to the top decile. Although the most commonly used measure of overall inequality is the Gini index, in this article, we employ an alternative source of data set on inequality called top income shares from WID to explore the empirical evidence of skill effect on income inequality. The Gini index is the most commonly accepted measure of income inequality, but it also has some limitations (Anthony B. Atkinson, Piketty, and Emmanuel Saez 2009; Alvaredo 2011; Atkinson 2015; Alvaredo et al. 2018). According to Alvaredo et al. (2018), the strength of the Gini index is also its main weakness. Because it combines a distribution in a single index, a given value for the Gini index may result from different distributions. A country may have both a Gini-reducing decrease in poverty and a rise in the share of top income, which increases the Gini index. But in such a case, the middle class is squeezed while Gini index remains stable (Alvaredo et al. 2018, p. 27). In addition, Gini index is adequate at capturing the income distribution for the bottom 99%, but it is poor at measuring (to tax record data) the top 1% of the population. The Gini index also gives equal weight to inequality at the top, middle, and bottom of the distribution, which makes it more sensitive to transfers at the center of the distribution than at the tails compared to alternative inequality measures (Atkinson, Piketty, and Saez 2009, p. 7; Richard V. Burkhauser, Jan-Emmanuel De Neve, and Nattavudh Powdthavee 2015, p. 6). C.Y. Cyrus Chu and Yi-Ting Wang (2021) explored why the top income share index is a better measure than the Gini index to capture the recent deterioration of inequality. They compared the elasticities of the Gini index and the top income share with respect to an increase in the income of the rich group, reflecting the recent trend. Their research findings show that when there is an increase in income for the rich group, the elasticity difference between these two indexes can be as large as seven times. This means that the Gini index is less sensitive to the increase in the income of the rich group and the top income share is more sensitive to the increase in the income of the rich group. However, it is known that there has been a dramatic increase in the top income inequality particularly in developed countries for the last 40 years or so (Aghion et al. 2015). So, in this study rather than use the Gini index, we decided it is preferable to use top income shares as an alternative measure of inequality.

It will be useful to give more information about top-income shares. Although top income shares represent a very small amount of the population, they have a very significant share of total income and total taxes paid (Atkinson, Piketty, and Saez 2009). Top income shares, such as the top 1% and the top 10% have become more available in many countries for a long period. But are these useful measures of overall inequality? To answer this question, Andrew Leigh (2007) analyzed the relationship between top income shares and other measures of inequality. Leigh (2007) concludes that there is a “strong and significant relationship between top income shares and broader inequality measures, such as the Gini index”. This suggests that theoretically, top income series are a useful proxy for inequality because these shares can affect overall inequality. From this perspective, in this paper, we take into consideration top income shares as an inequality measure and in our analysis, we employ two main top income shares such as TOP1 and TOP10 share series. We used two main top income shares data because we did not want to choose between two main income shares.

Therefore, in order to use two different top income shares as an inequality measure, we created two different models.

Table 1 shows the details of the datasets. A general summary of the data is presented in the upper part of Table 1 and at the bottom of the table, there are descriptive statistics. The maximum and minimum values of the skill variable are 0.668 and 0.088, respectively, and the mean value is 0.307. The standard deviation of the skill is 0.1076, which suggests that skill does not differ significantly across the countries included in the sample. Descriptive statistics of two inequality variables show similarity with the skill variable.

Table 1 Data Set

Title	Variables	Sources	Period
Inequality	Top1 income share (%)	WID	1995-2018
	Top10 income share (%)		
Skill	Employment distribution by education: Advanced-level educated workers share (%)	ILO	

Summary statistics

Variable	Mean	Std. dev.	Min	Max	
Skill	0.3071372	0.1076486	0.088	0.668	obs=576 n=24 t=24
Inequality (TOP1)	0.1107993	0.0255464	0.059	0.1933	
Inequality (TOP10)	0.3437759	0.0411234	0.2586	0.4671	

Source: Authors' calculations.

The study aims to investigate the empirical evidence of skill effect on income inequality, using panel data estimators. The models we used in the analysis are as follows:

$$TOP1_{it} = \beta_0 + \beta_1 Skill_{it} + \varepsilon_{it}, \tag{6}$$

$$TOP10_{it} = \beta_0 + \beta_1 Skill_{it} + \varepsilon_{it}, \tag{7}$$

where Top1 and Top10 represent the inequality variable (top income share); skill represents the skill ratio in employment measured as employment distribution by advanced level education. (i) and (t) represent time and cross section dimensions, and (ε_{it}) is the error term. According to this information, this paper explores empirical evidence of skill effect on income inequality employing panel data analysis. In the analysis, firstly, cross-sectional dependence (CSD) and homogeneity were investigated before the panel data analysis. After determining the CSD and heterogeneity, the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) unit root test was employed as a second-generation approach that takes CSD into account to determine the stationary characteristics of the variables. Following the unit root test, we employed Christian Gengenbach, Jean-Pierre Urbain, and Joakim Westerlund (2016), and Westerlund ECM panel cointegration tests that consider CSD. And then we adopted the Panel Dynamic Ordinary Least Squares (PDOLS) panel data estimator which is robust to heterogeneity and CSD.

4.2 Testing Cross-Sectional Dependence and Homogeneity

Cross-sectional dependency and homogeneity are the most important diagnostic tests that should be investigated before performing panel data analysis. The macroeconomic series of different units could be influenced by the same event due to globalization. Thus, for the panel data with large cross section dimensions (N), the residuals are not exhibited to be cross-sectional independent. Therefore, in the first step, to analyze CSD, we use four different tests. The Breusch and Pagan (1980) LM test (Trevor S. Breusch and Adrian Pagan 1980), Pesaran (2004) scaled LM test (M. Hashem Pesaran 2004), Pesaran (2004) CD test, and Badi H. Baltagi, Qu Feng, and Chihwa Kao's (2012) bias-corrected scaled LM test were utilized. The LM test is more generally applicable and does not require a particular ordering of the cross-sectional units. However, it is unable to account for a large cross-section. The efficiency of the LM statistic decreases when N increases. Pesaran (2004) extends the LM test to address this matter. Pesaran (2004) suggested two different tests, namely Pesaran (2004) scaled LM test and Pesaran (2004) CD test. The last test is the bias-corrected scaled LM test by Baltagi, Feng, and Kao (2012). CSD test results are given in Table 2. The null hypothesis claims that the absence of CSD is rejected for all variables and models.

Another important step before starting the panel data analysis is to test whether or not the slope coefficients are homogenous. The familiar method to test the homogeneity of the slope coefficients is to apply the standard F test. However, the F test is valid where the number of cross sections (N) is relatively small and the panel's time dimension (T) is large; the explanatory variables are strictly exogenous, or the error variances are homoscedastic. Paravastu A. V. B. Swamy (1970) proposed the slope homogeneity test to minimize the homoscedasticity assumption in the F test. Similarly, this test requires a panel sample where N is small relative to Pesaran and Takashi Yamagata (2008) suggested a standardized version of Swamy's test, the so-called $\widetilde{\Delta}$ test to test slope homogeneity in larger panels. In this analysis, the $\tilde{\Delta}$ test was used to determine homogeneity. Table 2 also includes homogeneity test results. The results of the slope homogeneity indicate that the null hypothesis which claims that the model is homogeneous is rejected. Therefore, looking at Table 2, we can easily say that there is a CSD for both variables and models, and the countries that we used have a heterogeneous structure.

Table 2 Results of Cross-Section Dependency and Homogeneity

	Top1	Top10	Skill	Model I (Top1 and skill)	Model II (Top10 and skill)
CD_{LM1}	359.727 (0.000)***	343.226 (0.004)***	532.553 (0.000)***	1020.313 (0.000)***	1072.427 (0.000)***
CD_{LM2}	3.564 (0.000)***	2.861 (0.002)***	10.920 (0.000)***	31.680 (0.000)***	33.898 (0.000)***
CD_{LM}	-2.870 (0.002)***	-2.790 (0.003)***	0.527 (0.299)	19.272 (0.000)***	20.949 (0.000)***
$CD_{adj.}$	1.470 (0.071)*	1.352 (0.088)*	3.725 (0.000)***	159.724 (0.000)***	198.250 (0.000)***

Test of homogeneity		
Model I (Top1 and Skill)		
$\tilde{\Delta}$	Statistic: 17.591	p-value: 0.0000***
$\tilde{\Delta}_{adj}$	Statistic: 18.752	p-value: 0.0000***
ModelII (Top10 and Skill)		
$\tilde{\Delta}$	Statistic: 25.245	p-value: 0.0000***
$\tilde{\Delta}_{adj}$	Statistic: 26.912	p-value: 0.0000***

Notes: ***, ** , * indicate the significance at 1%, 5% and %1 level, respectively.

Source: Authors' calculations.

4.3 Panel Unit Root Test

Our variables have CSD, so we cannot use first-generation unit root tests. We need to use a second-generation procedure that considers CSD to implement these tests. One of the second-generation unit root tests is the CIPS test. Pesaran (2007) developed a method for dealing with the difficulty of CSD. For this purpose, he augmented the standard Dickey Fuller (DF) or augmented Dickey Fuller (ADF) regressions with the cross section averages of lagged levels and first differences of the individual series, and he proposed to use cross section averages to perform a similar task in dealing with CSD. These test results are referred to as the cross-sectionally augmented IPS (CIPS) test. The cross-sectionally augmented Dickey Fuller (CADF) regression (Pesaran 2007):

$$\Delta Y_{it} = \alpha_i + b_i Y_{i,t-1} + c_i \bar{Y}_{t-1} + d_i \Delta \bar{Y}_t + \varepsilon_{it}, \tag{8}$$

where ε_{it} is the regression error; $\bar{Y}_t$ is the mean of all *n* observations with respect to time *t*. The unit root hypothesis can be written as:

$$H_0: \beta_i = 0 \; for \; all \; i$$
$$H_0: \beta_i < 0, I = 1,2, \ldots . N_1 \quad \beta_i = 0, \; i = N_1 + 1, \; N_1 + 2, \ldots, N.$$

Cross-sectionally augmented version of the IPS (CIPS) test can be shown as:

$$CIPS\,(N,T) = N^{-1} \sum_{i=1}^{N} t_i\,(N,T). \tag{9}$$

$t_i(N, T)$ is the augmented Dickey Fuller statistic across the cross section for the i^{th} cross section unit.

Table 3 shows CIPS unit root test results. According to the unit root test results for inequality variables, at the 90% (cv10), 95% (cv5), and 99% (cv1) significance levels, CIPS statistic (t-bar) is less than all critical values (-1.984 and -1.827). Therefore, according to the CIPS test, unit root hypothesis cannot be rejected (*p*-values of 0.121 and 0.349). According to unit root test results for skill, at the 90% (cv10), 95% (cv5), 99% (cv1) significance levels, CIPS statistic (t-bar) is -2.016 and less than all critical values. Therefore, according to the CIPS test, unit root hypothesis cannot be rejected (*p*-value of 0.101). The unit root test is employed for the level values of the variables, and after this, we show that all variables become stationary when the first difference is taken, which is also presented in Table 3.

Table 3 CIPS (Unit Root) Test

Top1(Inequality)					
Level					
t-bar	**cv10**	**cv5**	**cv1**	**Z[t-bar]**	**p-value**
-1.984***	-2.070	-2.150	-2.300	-1.170	0.121
First differences					
-3.627	-2.070	-2.150	-2.300	-9.382	0.000
Top10(inequality)					
Level					
-1.827***	-2.070	-2.150	-2.300	-0.387	0.349
First differences					
-3.683	-2.070	-2.150	-2.300	-9.661	0.000
Skill					
Level					
t-bar	**cv10**	**cv5**	**cv1**	**Z[t-bar]**	**p-value**
-2.016***	-2.070	-2.150	-2.300	-1.332	0.101
First differences					
-3.403	-2.070	-2.150	-2.300	-8.265	0.000

Notes: ***, stands for significance at 1% levels.

Source: Authors' calculations.

4.4 Panel Cointegration Tests

After applying the unit root test, long-run relationship of the model is analyzed. In the existence of the CSD problem, first generation cointegration tests are also insufficient, similar to the unit root tests. To test for a long-run relationship between the two variables, we employed Westerlund (2007) and Gengenbach, Urbain, and Westerlund (2016) panel cointegration test techniques. Each of these second generation panel cointegration tests are robust to CSD.

Westerlund (2007) suggested four cointegration tests based on the error correction model to test the existence of cointegration. The basic logic of the tests is to test the existence of cointegration by deciding whether each unit has its own error correction. In the Westerlund test, the autoregressive parameter is allowed to be evaluated in two ways, for each unit or for the entire panel. The following equations are used to compute the group mean statistics G_a and G_t:

$$G_a \ statistics : G_a = \frac{1}{N} \sum_{i=1}^{N} \frac{T\widehat{a_i}}{\widehat{a_i}(1)}, \tag{10}$$

$$G_t \ statistics : G_t = \frac{1}{N} \sum_{i=1}^{N} \frac{\widehat{a_i}}{SE\ (\widehat{a_i})}, \tag{11}$$

where $SE\ (\widehat{a_i})$ represents the usual standard error of $\widehat{a_i}$. When G_a and G_t statistics reject the null hypothesis, it can be concluded that cointegration exists.

Pa and *Pt* statistics are calculated by using the information of the whole panel. If the null hypothesis is rejected, it can be concluded that cointegration exists for the whole panel. The panel statistics are as follows:

$$P_a \ statistics : P_a = T\hat{a}, \tag{12}$$

$$P_t \ statistics: P_t = \frac{\widehat{a_i}}{SE\ (\widehat{a})}. \tag{13}$$

Although Westerlund (2007) is defined in the first generation panel cointegration tests, in the existence of CSD, robust critical values can be obtained at the end of the bootstrap process (Ferda Y. Tatoğlu 2017, p. 204).

Table 4 denotes Westerlund panel cointegration test results. The results before applying bootstrap show that our two variables (inequality and skill) are co-integrated for all the tests. Therefore, there is a long-run relationship between the variables, but because of having CSD, only the results of robust *p*-value should be considered. The robust *p*-values of *Gt*, *Pt*, and *Pa* statistics for Model I and the robust *p*-values of *Gt*, *Pt* and *Pa* statistics for Model II indicate the rejection of the null hypothesis of no cointegration between the variables. Thus, we can conclude that there is a cointegration between inequality and skill and these variables are cointegrated in the long-run.

Table 4 Westerlund ECM Panel Cointegration Tests

Stat.	Value	Z-value	*p*-value	Robust *p*-value
Model I: (Top 1 and skill)				
Gt	-2.793	-5.512	0.000***	0.000***
Ga	-9.302	-1.899	0.029**	0.280
Pt	-12.076	-4.790	0.000***	0.050*
Pa	-8.380	-4.296	0.000***	0.060*
Model II: (Top 10 and skill)				
Gt	-2.851	-5.831	0.000***	0.000***
Ga	-10.282	-2.785	0.003***	0.140
Pt	-13.211	-5.910	0.000***	0.050*
Pa	-9.020	-4.980	0.000***	0.030**

Notes: Using the bootstrap approach of Westerlund to account for CSD, the number of replications is 100. *, **, *** indicate that statistics are significant at the 10%, 5% and 1% level of significance, respectively.

Source: Authors' calculations.

Another second generation panel cointegration that we used is the Gengenbach, Urbain, and Westerlund (2016) panel cointegration test. An error-correction-based cointegration test for panel data that considers heterogeneity and CSD, developed by Gengenbach, Urbain, and Westerlund (2016). Gengenbach, Urbain, and Westerlund (2016) panel cointegration equation is (Tatoğlu 2017):

$$\Delta yi = d\delta y.xi + ayiyi{-}1 + \omega i{-}1\gamma i + ui\pi i + \varepsilon_{y.x_i} = ayiyi{-}1 + gid + \lambda i + \varepsilon_{y.x_i}. \tag{14}$$

Null and alternative hypotheses for panel cointegration are as follows:

$$H0: ay1 \ = \ \ldots\ldots. =: \ ayN \ = \ 0$$

$$H_1: a_{y1} < 0$$

Gengenbach, Urbain, and Westerlund (2016) panel cointegration test is based on the earlier work of Westerlund (2007) and this cointegration test augments the model with cross-sectional averages. The pooled test statistic, which takes CSD according to the units into account and uses the cross-sectional averages, is as follows:

$$\bar{t}_c = \frac{1}{N} \sum_{i=1}^{N} t_{c_i}. \tag{15}$$

The results of the error-correction-based cointegration test suggested by Gengenbach, Urbain, and Westerlund (2016) are presented in Table 5. According to the cointegration test results for the two models, we can conclude that there is cointegration between inequality and skill, and these variables are cointegrated in the long-run.

Table 5 Gengenbach, Urbain, and Westerlund (2016) Panel Cointegration

Model I: (Top 1 and skill)			
Test Stat.	Coef	t-bar	*p*-val*
y(t-1)	-0.694	-3.030	<=0.01
Model II: (Top 10 and skill)			
y(t-1)	-0.810	-3.425	<=0.01

Source: Authors' calculations.

4.5 DOLS Regression

If there is a CSD problem in the residuals of the cointegration model, the first generation estimators would be biased, and the second generation estimators should be used. In addition, the homogeneity/heterogeneity of the panel should be considered in the selection of the estimator. In line with both the existence of the CSD problem and the heterogeneity information, to estimate the relationship between the variables for each of the two models, we adopt the PDOLS regression introduced by Peter Pedroni (2001). Pedroni's (2001) PDOLS is robust to the CSD as it considers the correlation across panel members. Other than the CSD, this estimator allows for heterogeneous slope coefficients, which provide individual country results. The PDOLS estimator is based on the following DOLS equation for each cross section (Pedroni 2001);

$$Y_{i,t} = a_i + \beta_i X_{i,t} + \sum_{j=-p}^{p} c_{i,j} \, \Delta X_{i,t-j} + u_{i,t}, \tag{16}$$

i = 1, 2,…, N is the number of unit in the panel, t = 1, 2,…, T is the number of time periods, p is the number of lags and leads of the DOLS regression, and β_i is the slope coefficient. $Y_{i,t}$ refers to inequality, and $X_{i,t}$ refers to skill as explanatory variable.

The estimates of PDOLS regression for Model I (Top1 income share) are presented in Table 6. All the estimated parameters for the group are statistically significant when Top1 is taken as the dependent variable. The estimated coefficients of the explanatory variable (i.e., skill for the full sample) is negative, this implies that a 1% increase in skill will decrease inequality by 0.24 in the long-term. The impact of skill on inequality, which is based on Top1, is consistent with the framework presented by Acemoglu (2002) as pointed out in the previous section. Briefly, income inequality decreases as the share of skilled workers in employment increases. When we evaluate the model separately for each of the 24 countries, it is seen that the estimated parameters of units vary across countries. As the skill level in employment increases, the top income share decreases in Denmark (-0.3856), Switzerland (-0.4586), Ireland (-0.3874), Germany (-0.5512), Luxembourg (-0.4351), Slovenia (-0.2219), Spain (-0.4172), United States (-0.8895), United Kingdom (-0.4078), and Korea (-0.9265); increases in Belgium (0.4263) and Poland (0.6289).

The estimates of PDOLS regression for Model II (Top10 income share) are presented in Table 6 as well. All the estimated parameters for the group are statistically significant when the Top10 income share is taken as the dependent variable. The estimated coefficients of the explanatory variable (i.e., skill for the full sample) are negative, this implies that a 1% increase in skill will decrease inequality by 0.04 in the long-term. For many countries, this mechanism is working as well. The impact of skill on inequality which is based on the Top10 is consistent with the framework presented by Acemoglu (2002) as pointed out in the previous section. When we evaluate the model separately for each of the 24 countries, it is seen that the estimated parameters of units vary across countries. As the skill level in employment increases, the top income share decreases in Denmark (-0.2516), Switzerland (-0.3912), Ireland (-0.2425), Germany (-0.2448),) Luxembourg (-0.3475), Slovenia (-0.08524), United States (-0.5912), and Korea (-0.5444); increases in Belgium (0.4263) and Poland (0.4565).

Table 6 PDOLS Estimator

	Model I	Model II
	Beta (t-stat)	**Beta (t-stat)**
Pedroni's PDOLS (group mean average)		
Panel (skill explanatory variable)	-0.2385 (4.602)***	-0.04147 (-1.751)*
PDOLS regression for countries		
Norway	-0.284 (-1.532)	-0.0752 (-0.298)
Sweeden	0.3302 (1.553)	0.2611 (1.462)
Finland	0.1773 (1.444)	0.3534 (1.508)
Denmark	-0.3856 (-3.859)***	-0.2516 (-3.368)***
Switzerland	-0.4586 (-3.076)***	-0.3912 (-3.427)***
Ireland	-0.3874 (-4.55)***	-0.2425 (-4.614)***
Litwania	-0.127 (-1.39)	-0.07622 (-1.096)
Germany	-0.5512 (-6.431)***	-0.2448 (-3.766)***
Greece	-2.305 (-1.573)	-0.3438 (-0.4152)
Hungary	0.2278 (0.7718)	-0.23 (-1.419)
Italy	-0.09119 (-0.7464)	0.03261 (0.3546)
Austria	-0.03016 (-0.2951)	-0.0545 (-0.54)
Spain	-0.4172 (-2.634)***	-0.05812 (-0.2825)
Netherland	0.01284 (0.2404)	0.03948 (0.9013)
Luxembourg	-0.4351 (-3.813)***	-0.3475 (-3.137)***
Slowenia	-0.2219 (-5.229)***	-0.08524 (-2.139)***
Portugal	-0.1536 (-0.9258)	0.1488 (1.429)
France	-0.5323 (-1.435)	-0.2226 (-0.8757)
Belgium	0.4263 (1.71)*	0.08002 (0.8322)
Poland	0.6289 (5.488)***	0.4565 (6.835)***
USA	-0.8895 (-8.909)***	-0.5912 (-5.895)***
UK	-0.4078 (-2.652)***	0.02399 (0.1491)
Canada	-0.1894 (-1.085)	0.07894 (0.2977)
Korea	-0.9265 (-10.36)***	-0.5444 (-8.927)***

Notes: Values in parentheses indicate the t-statistic value. *, **, *** indicate that statistics are significant at the 10%, 5% and 1% level of significance, respectively.

Source: Authors' calculations.

As a result of these analyses, income inequality based on two main top income shares decreases when the rate of skilled workers increases. For the entire panel in both models, this relationship is valid. When we evaluate the model separately, it is seen that the estimated parameters vary across countries. Countries, where the relationship between skills and inequality is statistically significant and negative in both models, are almost the same (Denmark, Switzerland, Ireland, Germany, Luxembourg, Slovenia, USA, and Korea). Except for Belgium and Poland, there is a negative relationship between the variables in countries where the relationship is statistically significant.

The most striking detail in the findings of both models is that the United States (for Top1, -0.8895; for Top10, -0.5912) is one of the countries (besides Korea) where the coefficient of the relationship is higher. On the other hand, although this coefficient is relatively low in some developed European countries in the analysis such as Denmark, Switzerland, Germany or Ireland, this relationship is not valid in other European developed countries such as Norway, Sweden, Finland, or Austria. In summary, this relationship is more pronounced in the United States, whereas it is more moderate or not valid in European countries.

5. Conclusion

Over the past 40 years or more, the world economy has witnessed a significant increase in income inequality. Following Tinbergen's (1975) work, the relative demand for skills has become associated with technology and in particular, the skill-bias of technical change. This view implies that the return to skills is determined by a race between "the increase in the supply of skills in the labor market and technical change assumed to be skill biased". From this point of view, improvements in technology increase the demand for more "skilled" workers - college graduates relative to non-college degree workers - and their earnings from the labor market have been rising as well (Acemoglu and Autor 2010).

The technical change favors skilled workers, replaces tasks previously performed by the unskilled, and it exacerbates inequalities (Acemoglu 2002). Increases in the wages of skilled workers relative to unskilled are a direct consequence of the complementarity between skill and new technologies (Acemoglu 1998). According to this approach, demand has been increasing for high-educated and skilled workers much faster than for low-educated and skilled workers. Acemoglu (2002, 2003) introduces a framework that emphasizes that as the fraction of skilled workers in the labor force increases, the unskilled workers' wages increase, and the skill premium decrease. In conclusion, skill-biased technical change will thus generate inequality by increasing the skill premium.

In our analysis, the starting point of which is this framework, we aim to obtain the income inequality associated with skill using panel data methods that consider cross-section dependency and heterogeneity. The empirical results firstly indicate that the findings are consistent with the framework presented by Acemoglu (2002, 2003). PDOLS estimator findings show that as the skill level in employment increases, inequality (for two top income share variables) decreases for 24 developed OECD countries during the 1995-2018 period. This result is also consistent with the study of Aziz and Cortes (2021). For the entire panel in both models, this relationship is valid.

Although this relationship is valid for the entire panel in the models used, the results differ by country. The countries where the relationship is negative and significant are Denmark, Switzerland, Ireland, Germany, Luxembourg, Slovenia, Spain, United States, United Kingdom, and Korea. As seen, the first important finding obtained in the analysis is that as the rate of skilled workers in employment increases, income inequality decreases. Thus, how can the skill rate in employment be increased? Employee familiarity with technology, which is one of the important determinants of income inequality, is largely through education (Tinbergen 1974; Goldin and Katz 2007). In general, if the adaptation of workers to technology in the employment structure is below the expectations of the market, the cost of education and wages of skilled workers increases, and inequality increases. However, if the technological adaptation of these workers is of a quality that meets the expectations of the market, the skill supply increases, and the skill premium and inequality decrease (Deaton 2013a). Therefore, in such a period when the value of education is increasing, making "quality" education "accessible" for everyone can be an important step in controlling inequalities. Moreover, it can enable more people to benefit from the increase in material wealth and welfare created by technology in the last 30-40 years. In summary, policy makers have an important toolkit like "education" (Tinbergen 1974; Goldin and Katz 2007) in avoiding dramatic inequalities and its negative consequences.

In the sample created according to the availability of data, it is seen that the countries are developed OECD countries as well as European countries, excluding the United States and Korea. In this respect, it can be said that the second important finding of the analysis is that "the inverse relationship between employment skill ratio and inequality is more pronounced in the United States and is relatively low or not valid in European countries". The fact that this relationship is relatively lower in other countries compared to the United States or that this relationship is not valid in others may be related to the reasons presented by Acemoglu (2003). Acemoglu (2003) states that many countries have similar technological developments but not all of them have inequality generated by skill premia. There are three points which have been useful tool in understanding the United States wage inequality or the lack of increase in inequality in Europe (Acemoglu 2003):

- The relative supply of skills increased faster in Europe;
- European wage-setting institutions prevented wage inequality from increasing;
- For exogenous or endogenous reasons, technical change has been less skill biased in Europe.

These factors, such as the faster growth of skills supply in Europe or the wage-setting institutions, may shed light on the differences between countries and explain why the United States is more dominant in this regard, as shown in the analysis.

If we reiterate, the main finding of our study is that there is a long-term relationship between skill and inequality, and income inequality decreases as the rate of skilled workers increases. This result requires mentioning the study of Goldin and Katz (2007). According to their work, technology has been skill biased and it's creating an increasing demand for greater human capital, and there is a race between skill-biased technological change and education. If this race is won by technology, the premium for skills increases and then inequality increases; if it is won by education, the premium decreases and then inequality decreases. Therefore, based on both arguments put forward by Goldin and Katz (2007) and the findings we obtained in our study (assuming that a skilled worker is a person with an advanced level of education), the spread of educational opportunities can offer a starting point for reducing inequalities. That is, when more people have access to educational opportunities, more people will acquire skills and the skills premium will decrease, which will allow inequalities to decrease. Ultimately, it should be noted that education plays a key role in reducing inequalities. Therefore, policy makers should take this into account in order to reduce inequalities that have many negative social and economic effects.

References

Acemoglu, Daron. 1998. "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *The Quarterly Journal of Economics*, 113(4): 1055-1089.

Acemoglu, Daron. 2002. "Technical Change, Inequality, and the Labor Market." *Journal of Economic Literature*, 40(1): 7-72. http://dx.doi.org/10.1257/0022051026976

Acemoglu, Daron. 2003. "Cross-Country Inequality Trends." *The Economic Journal*, 113(485): 121-149. http://dx.doi.org/10.1111/1468-0297.00100

Acemoglu, Daron, and David H. Autor. 2010. "Skills, Tasks and Technologies: Implications for Employment and Earnings." National Bureau of Economic Research Working Paper 16082. http://dx.doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, Daron, Suresh Naidu, Pascual Restrepo, and James A. Robinson. 2013. "Democracy, Redistribution and Inequality." National Bureau of Economic Research Working Paper 19746. http://dx.doi.org/10.1016/B978-0-444-59429-7.00022-4

Acemoglu, Daron. 2021. "Could We and Should We Reverse (Excessive) Automation." In *Combating Inequality: Rethinking Government's Role*, ed. Oliver Blanchart and Dani Rodrik. Cambridge, M. A.: The MIT Press.

Aghion, Philippe, Ufuk Akcigit, Antonin Bergeaud, Richard Blundell, and David Hemous. 2015. "Innovation and Top Income Inequality." National Bureau of Economic Research Working Paper 21247. http://dx.doi.org/10.1093/restud/rdy027

Alesina, Alberto, and Dani Rodrik. 1994. "Distributive Politics and Economic Growth." *The Quarterly Journal of Economics*, 109(2): 465-490. http://dx.doi.org/10.2307/2118470

Alvaredo, Facundo. 2011. "A Note on the Relationship between Top Income Shares and the Gini Coefficient." *Economics Letters*, 110(3): 274-277. http://dx.doi.org/10.1016/j.econlet.2010.10.008

Alvaredo, Facundo, Lucas Chancel, Thomas Piketty, Emmanuel Saez, and Gabriel Zucman. 2017. "Global Inequality Dynamics: New Findings from Wid.World." National Bureau of Economic Research Working Paper 23119. http://dx.doi.org/10.1257/aer.p20171095

Alvaredo, Facundo, Thomas Piketty, Emmanuel Saez, Lucas Chancel, and Gabriel Zucman, ed. 2018. *World Inequality Report*. Cambridge, M. A.: Belknap Press of Harvard University Press.

Atkinson, Anthony B., Thomas Piketty, and Emmanuel Saez. 2009. "Top Incomes in the Long Run of History." National Bureau of Economic Research Working Paper 15408. http://dx.doi.org/10.1257/jel.49.1.3

Atkinson, Anthony B. 2015. "Can We Reduce Income Inequality in OECD Countries?" *Empirica*, 42(2): 211-223. http://dx.doi.org/10.1007/s10663-015-9288-0

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics*, 113(4): 1169-1213. http://dx.doi.org/10.1162/003355398555874

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review Papers and Proceedings*, 96(2): 189-194. http://dx.doi.org/10.1257/000282806777212620

Aziz, Imran, and Guido Matias Cortes. 2021. "Between-Group Inequality May Decline despite a Rising Skill Premium." *Labour Economics*, 72(C). http://dx.doi.org/10.1016/j.labeco.2021.102063

Baltagi, Badi H., Qu Feng, and Chihwa Kao. 2012. "A Lagrange Multiplier Test for Cross-Sectional Dependence in a Fixed Effects Panel Data Model." *Journal of Econometrics*, 170(1): 164-177. http://dx.doi.org/10.1016/j.jeconom.2012.04.004

Blanchard, Olivier, and Dani Rodrik. 2021. *Combating Inequality: Rethinking Government's Role*. Cambridge, M. A.: The MIT Press.

Bollen, Kenneth A., and Robert W. Jackman. 1985. "Political Democracy and the Size Distribution of Income." *American Sociological Review*, 50(4): 438-457. http://dx.doi.org/10.2307/2095432

Bourguignon, François. 2004. "The Poverty-Growth-Inequality Triangle." Indian Council for Research on International Economic Relations Working Paper 125.

Bratanova, Boyka, Steve Loughnan, Olivier Klein, Almudena Claassen, and Robert Wood. 2016. "Poverty, Inequality, and Increased Consumption of High Calorie Food: Experimental Evidence for a Causal Link." *Appetite*, 1(100): 162-171.

Breusch, Trevor S., and Adrian Pagan. 1980. "The Lagrange Multiplier Test and Its Applications to Model Specification in Econometrics." *The Review of Economic Studies*, 47(1): 239-253. http://dx.doi.org/10.2307/2297111

Broecke, Stijn, Glenda Quintini, and Marieke Vandeweyer. 2016. "Wage Inequality and Cognitive Skills: Re-opening the Debate." National Bureau of Economic Research Working Paper 21965. http://dx.doi.org/10.3386/w21965

Burkhauser, Richard V., Jan-Emmanuel De Neve, and Nattavudh Powdthavee. 2017. "Top Incomes and Human Well-Being around the World." *Journal of Economic Psychology*, 62: 246-257. http://dx.doi.org/10.2139/ssrn.2714405

Burstein, Ariel, Javier Cravino, and Jonathan Vogel. 2011. "Importing Skill-Biased Technology." National Bureau of Economic Research Working Paper 17460. http://dx.doi.org/10.1257/mac.5.2.32

Chu, C. Y. Cyrus, and Yi-Ting Wang. 2021. "Gini Coefficient versus Top Income Shares - Pattern Change Differences." *Economics Letters*, 201. http://dx.doi.org/10.1016/j.econlet.2021.109769

Cutler, David, Angus Deaton, and Adriana Lleras-Muney. 2006. "The Determinants of Mortality." *Journal of Economic Perspectives*, 20(3): 97-120. http://dx.doi.org/10.1257/jep.20.3.97

Deaton, Angus. 2003. "Health, Inequality and Economic Development." *Journal of Economic Literature*, 41(1): 113-158. http://dx.doi.org/10.1257/002205103321544710

Deaton, Angus. 2013a. *The Great Escape: Health, Wealth, and the Origins of Inequality*. Princeton, N. J.: Princeton University Press.

Deaton, Angus. 2013b. "What Is Wrong with Inequality?" *Lancet*, 381(9864): 363. http://dx.doi.org/10.1016/S0140-6736(13)60154-3

Deaton, Angus. 2014. "Inevitable Inequality?" *Science*, 344(6186): 783. http://dx.doi.org/10.1126/science.1255661

Easterly, William. 2001. "The Middle Class Consensus and Economic Development." *Journal of Economic Growth*, 6(4): 317-335.

Feenberg, Daniel R., and James M. Poterba. 1992. "Income Inequality and the Incomes of Very High Income Taxpayers: Evidence from Tax Returns." National Bureau of Economic Research Working Paper 4229. http://dx.doi.org/10.3386/w4229

Gengenbach, Christian, Jean-Pierre Urbain, and Joakim Westerlund. 2016. "Error Correction Testing in Panels with Common Stochastic Trends." *Journal of Applied Econometrics*, 311(6): 982-1004. http://dx.doi.org/10.1002/jae.2475

Goldin, Claudia, and Lawrence F. Katz. 2007. “The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005.” National Bureau of Economic Research Working Paper 12984. http://dx.doi.org/10.3386/w12984

Guvenen, Fatih, and Greg Kaplan. 2017. “Top Income Inequality in the 21st Century: Some Cautionary Notes.” National Bureau of Economic Research Working Paper 23321. http://dx.doi.org/10.21034/qr.3811

Helpman, Elhanan. 2016. “Globalization and Wage Inequality.” National Bureau of Economic Research Working Paper 22944.

Herzer, Dierk, and Sebastian Vollmer. 2013. “Rising Top Incomes Do Not Raise the Tide.” *Journal of Policy Modeling*, 35(4): 504-519. http://dx.doi.org/10.1016/j.jpolmod.2013.02.011

Katz, Lawrence F., and Kevin M. Murphy. 1992. “Changes in Relative Wages, 1963-1987: Supply and Demand Factors.” *The Quarterly Journal of Economics*, 107(1): 35-78. http://dx.doi.org/10.2307/2118323

Krueger, Alan B. 1993. “How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989.” *Quarterly Journal of Economics*, 108(1): 33-60. http://dx.doi.org/10.2307/2118494

Lee, Jong-Wha, and Dainn Wie. 2015. “Technological Change, Skill Demand, and Wage Inequality: Evidence from Indonesia.” *World Development*, 67(C): 238-250. http://dx.doi.org/10.1016/j.worlddev.2014.10.020

Lee, Matthew R., and William B. Bankston. 1999. “Political Structure, Economic Inequality and Homicide: A Cross-National Analysis.” *Deviant Behavior*, 20(1): 27-55. http://dx.doi.org/10.1080/016396299266588

Leigh, Andrew. 2007. “How Closely Do Top Income Shares Track Other Measures of Inequality?” *The Economic Journal*, 117(524): 619-633. http://dx.doi.org/10.1111/j.1468-0297.2007.02099.x

Milanovic, Branko. 1998. *Income, Inequality, and Poverty during the Transition from Planned to Market Economy*. Washington, D. C.: World Bank Regional and Sectoral Studies.

Milanovic, Branko. 2016. *Global Inequality: A New Approach for the Age of Globalization*. Cambridge, M. A.: Belknap Press of Harvard University Press. http://dx.doi.org/10.2307/j.ctvjghwk4

Murphy, Kevin M., and Robert H. Topel. 2016. “Human Capital Investment, Inequality and Economic Growth.” National Bureau of Economic Research Working Paper 21841. http://dx.doi.org/10.3386/w21841

Pedroni, Peter. 2001. “Purchasing Power Parity Tests in Cointegrated Panels.” *The Review of Economics and Statistics*, 83(4): 727-731. http://dx.doi.org/10.1162/003465301753237803

Persson, Torsten, and Guido Tabellini. 1994. “Is Inequality Harmful for Growth?” *The American Economic Review*, 84(3): 600-621.

Pesaran, M. Hashem. 2004. “General Diagnostic Tests for Cross Section Dependence in Panels.” *Journal of Econometrics*, 69(7). http://dx.doi.org/10.2139/ssrn.572504

Pesaran, M. Hashem. 2007. “A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence.” *Journal of Applied Econometrics*, 22(2): 265-312. http://dx.doi.org/10.1002/jae.951

Pesaran, M. Hashem, and Takashi Yamagata. 2008. "Testing Slope Homogeneity in Large Panels." *Journal of Econometrics*, 142(1): 50-93. http://dx.doi.org/10.1016/j.jeconom.2007.05.010

Pickett, Kate E., and Richard G. Wilkinson. 2015. "Income Inequality and Health: A Causal Review." *Social Science and Medicine*, 128(C): 316-326. http://dx.doi.org/10.1016/j.socscimed.2014.12.031

Piketty, Thomas. 2014. *Capital in the Twenty-First Century*. Cambridge, M. A.: The Belknap Press of Harvard University Press.

Smeeding, Timothy M. 2002. "Globalization, Inequality and the Rich Countries of the G-20: Evidence from the Luxembourg Income Study (LIS)." Luxembourg Income Study Working Paper 320.

Soylu, Fatma E. 2022. "Eşitsizliğin Kaynağı Olarak Sınıflar: Bir Geri Dönüş Hikayesi." In *Refah Ekonomisi ve Eşitsizlik*, ed. Ömer Faruk Çolak and Leyla F. Arda Özalp. Ankara: Eflatun Yayın.

Stokey, Nancy L. 2016. "Technology, Skill and the Wage Structure." National Bureau of Economic Research Working Paper 22176. http://dx.doi.org/10.3386/w22176

Swamy, Paravastu A. V. B. 1970. "Efficient Inference in a Random Coefficient Regression Model." *Econometrica*, 38(2): 311-323. http://dx.doi.org/10.2307/1913012

Tatoğlu, Ferda Y. 2017. *Panel Zaman Serileri Analizi*. İstanbul: Beta Yayınları.

Tinbergen, Jan. 1974. "Substitution of Graduate by Other Labor." *Kyklos*, 27(2): 217-226. http://dx.doi.org/10.1111/j.1467-6435.1974.tb01903.x

Tinbergen, Jan. 1975. *Income Difference: Recent Research*. Amsterdam: North-Holland Publishing Company.

Westerlund, Joakim. 2007. "Testing for Error Correction in Panel Data." *Oxford Bulletin of Economics and Statistics*, 69(6): 709-748. http://dx.doi.org/10.1111/j.1468-0084.2007.00477.x

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