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# Macroeconomic Conditions and Wage Inequality: Expanding and Analyzing the Worldwide Dataset*

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This paper introduces a comprehensive dataset examining wage inequality and returns to education across 40 countries, revisiting earlier studies on the effects of economic development, trade openness, and returns to skill on wage inequality. Our findings include: (i) the presence of Kuznets' "inverted U-curve" in wage inequality data, (ii) a positive relationship between trade openness and both wage inequality and returns to education, (iii) a positive relationship between levels of wage inequality and levels of return to education, and (iv) an intriguing phenomenon where accelerated skill-biased technological change leads to a deceleration of the wage gap widening process, as evidenced by the negative relationship between changes in wage inequality and changes in returns to education.

*Key Words*: Wage inequality; Kuznets curve; Trade openness; Skill-biased technological change.

*JEL Classification Numbers*: F66, I24, I26, J31, O33.

## 1. INTRODUCTION

Kuznets (1955) provided a hypothesis about the relationship between income inequality and the level of development that now bears his name: the Kuznets' inverted-U hypothesis. Specifically, the hypothesis is that inequality rises in the early stages of development and then gradually falls as

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the country moves forward in the development process. In the 30 years following its publication, his hypothesis was treated as an "inevitable and unavoidable socioeconomic 'law' that provided both scholars and policymakers with an articulated worldview of the nature of growth and inequalit" (Moran, 2005, p. 210).

Trade openness and skill-biased technological change (SBTC) have also been studied as potential causes of income and wage inequality changes. The openness approach refers to the effect of globalization on income inequality, and studies on the impact of trade openness on income distribution have had mixed and conflicting empirical results. Skill-biased technological change (SBTC) has become a standard alternative hypothesis about changes in wage inequality. There is now a consensus that both the trade openness and SBTC hypotheses are relevant to changes in wage inequality, particularly in the United States (Autor, Katz and Kearney, 2008).

Even though earnings are one of the principal sources of household income, there have not been many efforts to analyze wage inequality across the same range of countries as the literature on income inequality. This is surprising because wage rates, being a price, should be easier to analyze with standard price theory than a complex measurement like income. Indeed, the principal rationale for the trade openness and SBTC hypotheses involves changes in wage inequality caused by shifts in the demand and supply of labor. The problem is the data: there is no comprehensive dataset that permits the study of wage inequality for a worldwide range of countries at many levels of development over a substantial period. For this reason, previous studies have usually focused on a small number of wealthy countries, such as the US, the UK, and other OECD countries.

This paper presents a comprehensive dataset that permits the study of wage inequality and returns to education in forty countries. The dataset will then be used to test all three hypotheses — the Kuznets curve, the trade openness, and the SBTC — for both levels and changes in wage inequality.

## 2. LITERATURE REVIEW

### 2.1. Wage Inequality

Earnings are one of the three principal sources of household income: earnings, capital income, and government transfers. Because wage and earnings data have not been available in many countries, studies of wage inequality are not as numerous as studies of income inequality. Most previous studies of wage inequality are about a small number of countries over time. These countries include the US, UK, and some of the OECD countries such as Canada, Australia, Japan, Sweden, Denmark, France, Italy, Germany, South Korea, and the Netherlands (Katz and Autor, 1999; Berman, Bound and Machin, 1998; Freeman and Katz, 1994, 1995; Gottschalk and Smedding, 1997; OECD, 1993).

Changes in wage inequality over time are typically addressed with a supply-demand-institutions approach (Freeman and Katz, 1994; Katz and Autor, 1999). In this basic framework, the analysis of changes in wage inequality is carried out by distinguishing supply factors (education, training, skills, labor force participation, migration), demand factors (technological change and trade openness), and institutional factors (changes in unionization, minimum wages, and labor flexibility). Previous empirical studies have concluded that the key factor affecting wage inequality in advanced countries is the demand shift (Chusseau, Dumont and Hellier, 2008).

Skill-biased (or unskilled-labor-saving) technological change and increased exposure to international competition are the leading candidate explanations for the demand shift. Abundant literature has been devoted to measuring the respective influence of skill-biased technological change (SBTC) and north-south trade[1] (NST) on the cause of relative demand shift and wage inequality changes (Katz and Autor, 1999). Researchers have often emphasized the important role of SBTC in wage widening (Machin and Van Reenen, 1998; Autor, Katz and Krueger, 1998; Doms, Dunne and Troske, 1997; Acemoglu, 2002). When SBTC happens, the relative demand for more-skilled workers increases, and consequently, the wage gap widens. It is mostly driven by the computer revolution (Krueger, 1993) and changes in returns to skill (Juhn, Murphy and Pierce, 1993), often measured with returns to education and work experience (Machin and Van Reenen, 1998). Some critics argue that SBTC cannot be the reason for increased inequality because technical change is continuous, whereas the change in wage inequality is episodic. They argue that wage inequality is explained largely by non-market forces and the mechanical effects of labor force composition changes (Card and DiNardo, 2002; Lemieux, 2006b). There are some responses to these critics reaffirming that "skill demand shifts have played a central role in reshaping the wage structure, both during the monotone rise of inequality during the 1980s and the polarization of wage growth that followed" (Autor, Katz and Kearney, 2008, P. 320).

Others stress NST as the key explanation of the changes in wage inequality (Revenga, 1992; Borjas et al., 1997; Sachs et al., 1994; Wood, 1994, 1995). The original NST model is derived from the Heckscher-Ohlin

[1]The "north-south trade model (NST)" is derived from the Heckscher-Ohlin theory. 'The north' (developed countries) is characterized by a high endowment of skilled workers (skill abundant). In contrast, 'the south' (emerging countries) is characterized by a high endowment of low-paid unskilled workers (unskilled abundant). We use the words "north-south trade (NST)" for the international trade between skill-abundant countries and unskilled-abundant countries because this terminology has been used in previous literature.

theory, and researchers supporting NST have used the Heckscher-Ohlin framework to evaluate the impact of NST on wage inequality (Sachs et al., 1994; Sachs and Shatz, 1996; Wood, 1995). However, this explanation has been attacked by some empirical studies. Krugman and Lawrence (1993) claim that NST is not responsible for growing wage inequalities, but SBTC is. Lawrence et al. (1993) claim that NST cannot explain growing wage inequalities.

The consensus now is that both SBTC and NST are relevant to changes in wage inequalities, even if SBTC has stronger support than NST does, and that the impacts differ according to industries and countries (Katz and Autor, 1999). It is also agreed that outsourcing, rather than the pure Heckscher-Ohlin approach, is the main vector of impact from NST and that SBTC and NST interact (Chusseau, Dumont and Hellier, 2008; Machin and Van Reenen, 2016).

Institutional factors have been noticed as another main explanation for the changes in wage inequality. Researchers say that wage-setting institutions play a substantial role in the growth of inequality. Freeman and Katz emphasize the important role of institutional changes in wage inequality growth:

> "We turn to how institutional changes such as product market deregulation and changes in unionization alter the wage-setting calculus. In part, forces outside the labor market, such as political developments, will change labor institutions, but these institutions also respond to shifts in supply and demand. The important institutional changes in the 1980s were the decline in trade union power, which was exceptional in the United States, and the decentralization of collective bargaining that characterized diverse European countries. Both these developments are likely to produce greater earnings differentials (Freeman and Katz, 1995, p. 6)"

Lemieux (2008) argues that wage-setting institutions and social norms are the top executives of wage changes and that unions, minimum wages, and deregulation have played a big role in increasing wage inequality. DiNardo, Fortin and Lemieux (1996) use Current Population Survey data and claim that most of the growth in the 50-10 gap was due to the decline in the minimum wage in 1973-1992. Using the same data source, Lee (1999) reports the same results for 1979–1989. Fortin and Lemieux (1997) claim that government regulation of industry also indirectly affects wage inequality. They argue that the wave of economic deregulation of the late 1970s and 1980s is another significant institutional change that could account for some of the rises in wage inequality by comparing two different industries, which are regulated and deregulated, in the late 1970s.

Performance pay is another institutional factor affecting wage inequality. Using data from the Panel Study of Income Dynamics, Lemieux, MacLeod and Parent (2009) show that the fraction of US male workers on performance-pay jobs increased from about 30% in the late 1970s to over 40% in the late 1990s. They also show that wages are less equally distributed in performance-pay than non-performance-pay jobs, particularly because returns to education are higher in performance-pay jobs. They conclude that the growth of performance pay has contributed to about 25% of the increase in the variance of log wages between the late 1970s and the early 1990s.

Studies on wage inequality have focused on SBTC, NST, and institutional factors, and most researchers agree that all three explanations are relevant. However, there have not been many efforts to explain changes in wage inequality with the concepts that researchers have used to analyze the causes of income inequality: the Kuznets curve and openness.[2] While the part of the difference may simply be the parallel development of somewhat different terminology, some of the difference also lies in different econometrics based on different data designs.

### 2.2. Income Inequality

There is much longer and larger empirical literature about income inequality than wage inequality. One important distinction from studies of wage inequality is that studies of income inequality often include many countries at various stages of development because income data are more available than wage data. Most of these studies use cross-sectional or highly unbalanced panel designs, and sometimes they use income growth rate data instead of the level of income data. There have been two main approaches to explaining cross-national differences in income inequality: the Kuznets curve and openness.[3]

### 2.3. The Kuznets Curve Approach

The Kuznets hypothesis has dominated the literature on growth and inequality in the last half-century. This hypothesis states that income inequality increases until a critical income level is attained, after which inequality begins to decrease, drawing an "inverted-U" curve during the transition from an agricultural economy to an industrialized economy (Kuznets, 1955). Kuznets noted that inequality had declined in several nations across the mid-20th century and supposed that it probably had risen earlier. Kuznets supports his thesis, the "inverted-U" relationship between inequal-

[2]NST is similar to openness, but sometimes openness has been a broader concept than NST.

[3]Sometimes cohort size is mentioned as another main approach to explaining changes in income inequality. For instance, Higgins and Williamson (2002) provide strong empirical support for cohort size effects on inequality in the world using 30 years of the Gini coefficient drawn from Deininger and Squire (1996). However, this study focuses on the Kuznets curve and openness approaches rather than the cohort size approach.

ity and level of development, by describing the process of economic development:

"An invariable accompaniment of growth in developed countries is the shift away from agriculture, a process usually referred to as industrialization and urbanization. The income distribution of the total population, in the simplest model, may therefore be viewed as a combination of the income distributions of the rural and of the urban populations. What little we know of the structures of these two component income distributions reveals that: (a) the average per capita income of the rural population is usually lower than that of the urban; (b) inequality in the percentage shares within the distribution for the rural population is somewhat narrower than in that for the urban population — even when based on annual income; and this difference would probably be wider for distributions by secular income levels. Operating with this simpler model, what conclusions do we reach? First, all other conditions being equal, the increasing weight of urban populations means an increasing share for the more unequal of the two component distributions. Second, the relative difference in per capita income between the rural and urban populations does not necessarily drift downward in the process of economic growth: indeed, there is some evidence to suggest that it is stable at best, and tends to widen because per capita productivity in urban pursuits increases more rapidly than in agriculture. If this is so, inequality in the total income distribution should increase (Kuznets, 1955, p. 7-8)."

Because the income distribution of the total population is defined as a combination of the income distributions of the rural and the urban populations, during the transition from an agricultural society to an industrialized society, inequality rises in the early stages of development. It then gradually falls as the country moves forward in the development process. Kuznets provides some empirical evidence supporting his hypothesis by comparing the income distribution of developing and developed countries. Using family income data for India in 1949-1950, for Ceylon in 1950, and Puerto Rico in 1948, he claims that "the data show that income distribution in these underdeveloped countries is somewhat more unequal than in the developed countries during the period after the second world war" (Kuznets, 1955, p. 20). According to the data he provides, the shares of the lower three quintiles are 28% in India, 30% in Ceylon, and 24% in Puerto Rico, compared with 34% in the US and 36% in the UK. The shares of the top quintile are 55% in India, 50% in Ceylon and 56% in Puerto Rico, compared with 44% in the US and 45% in the UK. Due to a lack of data availability, he does not provide any test for his hypothesis with econometric methods, but many subsequent researchers have been actively testing his hypothesis.

The Kuznets hypothesis has been a huge academic battlefield with many supporting and refuting empirical works. Researchers have tested the Kuznets hypothesis using cross-sectional and highly unbalanced panel datasets, and many analyze income growth rates rather than income levels. All studies before Papanek and Kyn (1986) relied on cross-sectional regressions as a framework for their analysis (Jha, 1996). These studies reveal that the Kuznets curve was accepted through the 1970s as a strong empirical regularity (Barro, 2000). For example, Ahluwalia's two studies provide strong empirical support for Kuznets' hypothesis using cross-sectional income distribution data for 62 countries in the World Bank's Development Research Center (Ahluwalia, 1976b,a) .

Papanek and Kyn (1986) pool cross-sectional and time-series observations for 83 countries in their tests of the Kuznets hypothesis and find some support for it. Their data include 145 observations covering 1952-1978, with 44 single-observation countries, and they measure income inequality with Gini coefficients and the share of the poorest 40% of the population. Jha (1996) uses an unbalanced panel of income distribution drawn from the Social Indicators of Development (World Bank, 1994) and concludes that the Kuznets hypothesis holds. His dataset has 185 observations for 76 countries, with 61 countries having more than one observation, covering 1960-1992. He measures income distribution with the share of total income accruing to the poorest 20%, poorest 40%, and richest 20% of the population. He also used the ratio of the share of the poorest 20% to the share of the richest 40%. Using pooled and fixed effects estimates, Higgins and Williamson (2002) report strong evidence that inequality follows the "inverted-U" pattern originally described by Kuznets. They use two measures of income inequality: the Gini coefficient calculated by Deininger and Squire (1996)[4] and the ratio of income earned by the top income quartile to income earned by the bottom quartile, and they use real GDP per worker to measure the level of development. Recently, Baymul and Sen (2020) have reinterpreted Kuznets' curve as an observation pattern resulting from industry-driven structural transformation. This reinterpretation is based on their analysis of structural transformation data and income inequality data.

Other researchers are more skeptical about the Kuznets curve. Using a dynamic transition model, Aghion and Commander (1999) simulate the

[4]Deininger and Squire (1996)'s article, "A New Data Set Measuring Income Inequality," provides a highly unbalanced panel of Gini coefficients. They assembled and processed the Gini coefficients and other income distribution measures from different sources. This dataset has 682 observations (for 108 countries), of which about 65% are based on primary sources such as national statistical agencies (50%) or compilations of such results by reputable international agencies (15%). The remaining 35% of the data are based on primary sources that a reliable secondary source has quoted.

changes in inequality measures over 50 periods and find that the Kuznets curve held in Central Europe but not in Russia and the Former Soviet Union. Deininger and Squire (1998) also claim that the Kuznets curve disappears when a Latin American dummy is introduced, and this result is consistent with Ahluwalia (1976b). Latin countries tend to have higher inequality, and in the 1960s, before the Asian miracle, they were closer to the middle of the income per capita ranking (Higgins and Williamson (2002). Using a three least squares (3SLS) estimator with Deininger and Squireâs panel dataset, Barro (2000) argues that the Kuznets curve explains relatively little of the variation in inequality across countries over time. Forbes (2000) ïnds a positive relationship between inequality and growth using a generalized method of moments technique developed by Arellano and Bond (1991) with a worldwide panel dataset. Li and Zou (1998) also ïnd a positive relationship between income inequality and growth using Deininger and Squireâs data.

### 2.4. Openness Approach

The openness approach to income inequality is based on the Heckscher-Ohlin theory.[5] Adrian Wood has a good explanation of the linkage between Heckscher-Ohlin theory and inequality:

"Heckscher-Ohlin theory asserts that countries export goods that use intensively those factors of production that are relatively abundant at home and import goods that use intensively factors that are relatively scarce. Trade thus increases the demand for abundant factors, because of the expansion of export sectors, and reduces the demand for scarce factors, because of the contraction of import-competing sectors, with corresponding effects on factor prices. In developing countries, where unskilled labor is abundant and skilled labor is scarce, trade tends to raise unskilled wages and to lower skilled wages and hence to narrow the gap between them (Wood, 1997, P. 34)."

[5]One question may arise: how is openness being measured? There are three broad categories of measures of trade openness: outcome measures, policy indicators, and deviation measures. An outcome measure is the most common way to measure trade openness. It describes the volume of trade or its components, and this measurement has been used by Barro (2000), Dollar and Kraay (2002), Li, Squire and Zou (1998), and Epifani and Gancia (2008). Policy indicators describe the institutional features of a countryâs stance toward the rest of the world with respect to trade and factor flows. The Sachs-Warner indicator is one example, and it represents each countryâs liberalization status by taking a value of 1 for liberalized countries and 0 for closed countries (Sachs et al., 1995). Deviation measures, deviations of observed trade volume from the predicted free-trade volume, are also used to measure how restrictive the trade regime is. For example, factor endowment and gravity models of trade generate predictions about a country's propensity to trade internationally (Leamer, 1988; Wacziarg, 2001).

The effect of globalization on income inequality has been in the spotlight for decades. Most of the early studies concentrated on the effects of wage and income inequality in the US, Western Europe, and other rich countries Milanovic, 2005; Burda and Dluhosch, 1998; Schott, 2003), and the other studies have focused on how globalization affects world income distribution through differences in mean per capita growth rates (Milanovic, 2005, 2011; Milanovic and Yitzhaki, 2002; Schultz, 1998; Sala-i Martin, 2002). In the last decade, there have been several studies of the impact of openness on income distribution in both poor and rich countries, but they have had conflicting empirical results.

Using the Sachs-Warner indicator to measure openness, Lundberg and Squire (2003) find that openness has either no or a mildly negative effect on inequality. Barro (2000) and Ravallion (2001) measure openness with the ratio of exports plus imports to GDP, adjusted for the estimated effects of this ratio from the logs of population and land area. Both use an unbalanced panel, and they find that trade volumes are significantly positively associated with the Gini coefficient in a sample of 64 countries and that the disequalizing effect of openness is greater in poor countries. Using an unbalanced panel, Dollar and Kraay (2002) find that openness, defined as exports plus imports as a share of GDP, is positively associated with per capita income. However, it has no systematic impact on inequality. Also, Li, Squire and Zou (1998) find no statistically significant effect of openness on the Gini coefficient, using the ratio of exports to GDP as an explanatory variable for the Gini coefficient. Their Gini coefficient panel is drawn from Deininger and Squire (1996). It has 573 observations covering 49 developed and developing countries for 1947-1994, and openness data are calculated with export and GDP data from the World Tables (World Bank). Using data taken from World Bankâs World Development Indicators 2006 covering the period 1985-2004 of 83 countries, Qureshi and Wan (2008) find that globalization, defined as a ratio of total trade volume to GDP, does not emerge as a significant factor in driving cross-country inequality. Epifani and Gancia (2008) show that returns to education, skill premia, and income inequality all increase with openness using data from Banerjee and Duflo (2005), Psacharopoulos and Patrinos (2004), UN –â? General Industrial Statistics database, Dollar and Kraay (2002), Penn World Table, and Barro and Lee (2001).

## 3. DATA

In shifting focus from income to wage inequality, a new dataset with relevant analysis variables is needed. This paper employs four inequality measures –â? Theil wage inequality, annual change of Theil wage inequality, Mincerian returns to education, and annual change of Mincerian returns to education –â? and fifteen regressors –â? population, real GDP per capita, growth of real GDP per capita, openness, democracy index, East Asia dummy, Latin America dummy, OECD dummy, life expectancy at birth, fertility rate, inflation, government consumption share, two geography variables (LCR100km, KGATRSTR), and linguistic fractionalization. We concentrate on Theil wage inequality and Mincerian returns to education as measures of wage inequality, detailing how these inequality measures and regressors are compiled.

The Theil measure of inequality is the only index that satisfies all of the following three desirable characteristics of an inequality measure: (1) scale-invariance, (2) the principle of transfers, and (3) decomposability into between-group inequality and within-group inequality. When individual data are available, the Theil measure of wage inequality is given by the following formula:

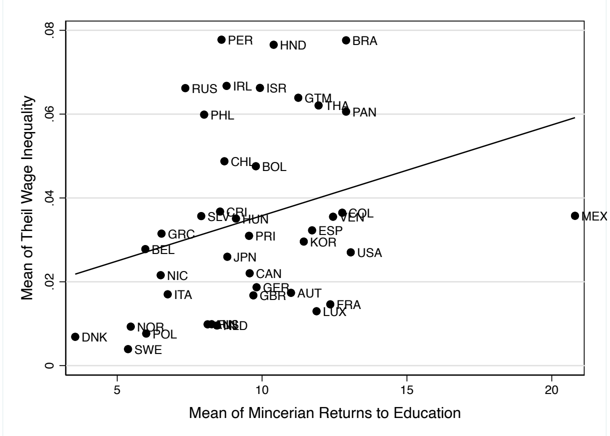
$$T = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{Y_i}{\overline{Y}}\right)\ln\left(\frac{Y_i}{\overline{Y}}\right) = \underbrace{\sum_{g}\left(\frac{n_g\overline{Y}_g}{n\overline{Y}}\right)\cdot T_g}_{\text{(a)}} + \underbrace{\frac{1}{n}\sum_{g}\left(\frac{n_g\overline{Y}_g}{\overline{Y}}\right)\ln\left(\frac{\overline{Y}_g}{\overline{Y}}\right)}_{\text{(b)}} \quad (1)$$

where $n$ is the number of all earners in the country, $Y_i$ is the wage of individual $i$, is the mean wage of the population in the country, $g$ is the number of groups, $n_g$ is the number of earners in group $g$, $\overline{Y}_g$ is the mean wage for group $g$, and $T_g$ is the Theil index of group $g$ (Wolff, 1997; Cowell, 2000). If every earner has exactly the same wage, $T$ will be zero; this represents perfect equality and is the minimum value of Theil measure of wage inequality. On the other hand, if one individual has all of the wages, $T$ will equal $\ln g$; this represents maximum inequality and is the maximum value of Theil measure of wage inequality (Milanovic, 2011). The key distinction of the Theil measure of wage inequality is its decomposability. The first term (a) is a weighted sum of the Theil indices of each group (that is, a weighted sum of *within-group inequality*), where the weight for each group $g$ is the group $g$'s share of total income. The second term (b) represents the *between-group inequality*, calculated by the Theil formula as if each group was treated as an individual (Wolff, 1997).

The Theil wage inequality data for this paper originates from two versions of the UTIP-UNIDO datasets, created by the University of Texas Inequality Project (UTIP). UTIP-UNIDO is a global dataset that computes industrial pay-inequality measures for numerous countries over comprehensive periods. The first version, a non-public dataset, covers 156 countries from 1963-2003.[6] The second version, publicly available on their website,

[6]I am grateful to Prof. James Galbraith at the University of Texas at Austin for providing the first version of the UTIP-UNIDO dataset. Additionally, I thank Prof. Dennis Sullivan at Miami University for facilitating the connection for this research project.

**FIG. 1.** Theil Wage Inequality vs Mincerian Returns to Education




covers 151 countries from 1963-2015 (Galbraith et al., 2015).[7] We combined these versions for extensive analysis.[8] Figure 1 illustrates the distribution of the mean Theil wage inequality across countries. The annual change of Theil wage inequality ($dtheil$) is defined as:

$$dtheil_t = \frac{theil_{t+n} - theil_t}{n} \tag{2}$$

where $theil$ is the Theil wage inequality and $n$ is the year difference. If there are no missing years in the data, the annual change in Theil wage inequality is simply the difference between Theil wage inequality each year. However, if missing years exist, the difference between Theil wage inequality of two discontinuous years should be divided by the year difference ($n$).

Mincerâs landmark book *Schooling, Experience, and Earnings* (Mincer, 1974) has had a profound and lasting influence on empirical work in the field of labor economics. He models the natural logarithm of earnings as a function of years of education and years of potential labor market experience. In the most widely used version of the Mincerian returns to education formula, log earnings are modeled as the sum of a linear function of years of education and a quadratic function of years of potential experience:

$$\log \gamma = \log \gamma_0 + rS + \beta_1 X + \beta_2 X^2 \tag{3}$$

where $\gamma$ is earnings ($\gamma_0$ is the level of earnings of an individual with no education and no experience), $S$ is years of schooling, and $X$ is years of

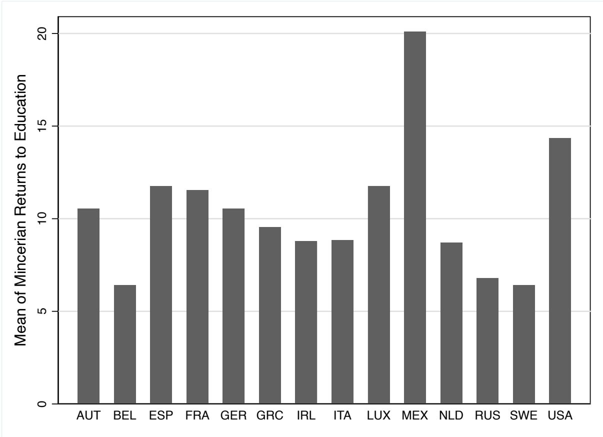
[7]https://utip.gov.utexas.edu/

[8]Sim and Lee (2020) is an example of multi-country analysis in a dynamic setting.

potential labor market experience (age minus years of schooling minus six). The schooling coefficient, $r$, provides an estimate of the rate of return to education which is assumed to be constant in this specification. The concavity of the observed earnings profile is captured by the quadratic experience terms, $X$ and $X^2$, whose coefficients, $\beta_1$ and $\beta_2$, are respectively positive and negative. Though this equation is a good approximation in many cases, it may overstate or understate the effect of experience and schooling on earnings for some groups due to possible self-selection problem (Mincer, 1974; Lemieux, 2006a; Psacharopoulos, 1994; Psacharopoulos and Patrinos, 2004; Willis, 1986).

Mincerian returns to education data for this paper is drawn from many different sources and pooled together. Figure 1 shows the spread of the mean of Mincerian returns to education across countries.[9] First, they have been collected from Psacharopoulos and Patrinos (2004), Banerjee and Duflo (2005), Blom, Holm-Nielsen and Verner (2001), and Funkhouser (1996). Psacharopoulos and Patrinos (2004) collect available returns to education data from many countries, and Banerjee and Duflo (2005) update Psacharopoulos and Patrinosâ? dataset with recent returns to education data for more countries. We added more data on their work from Blom, Holm-Nielsen and Verner (2001) and Funkhouser (1996).

**FIG. 2.** Mean of Mincerian Returns to Education (Lee-LIS dataset)




Second, we generate our own returns to education dataset named "Lee-LIS" using the Luxembourg Income Study database (LIS). [10] To be consistent with the other data sources, we follow the standard Mincerian returns

[9]This pooling method is also used in previous studies such as Psacharopoulos and Patrinos (2004) and Banerjee and Duflo (2005).
[10]http://www.lisdatacenter.org/

to education formula. Accordingly, each country's returns to education is estimated with the equation below:

$$\ln(wage_i) = \beta_0 + \beta_1 \cdot exp_i + \beta_2 \cdot (exp_i)^2 + \beta_3 \cdot femail_i + \beta_4 \cdot years_i + \epsilon_i \quad (4)$$

where $wage_i$ indicates person $i$'s gross or net wage, $exp_i$ indicates person $i$'s years of potential work experience, $female_i$ is a dummy variable which equals to 1 if person $i$ is female, and $years_i$ indicates person $i$'s years of education. We run this regression with datasets for Austria (1994, 1997, 2000), Belgium (1985, 1988, 1992, 1995, 1997, 2000), France (1994, 2000), Germany (1984, 1989, 1994, 2000), Greece (1995, 2000), Ireland (1994, 1995, 1996, 2000), Italy (1987, 1989, 1991, 1993, 1995, 1998, 2000), Luxembourg (1997, 2000, 2004), Mexico (1984, 1989, 1992, 1994, 1996, 1998, 2000, 2002, 2004), Netherlands (1991, 1994, 1999), Russia (2000), Spain (1995, 2000), Sweden (1992, 1995) and United States (1986, 1991, 1994, 1996, 1997, 2000, 2004). Figure 2 describes the variation of the mean of Mincerian returns to education, generated by the above regression for each country. We then combine returns to education data drawn from previous articles with the Lee-LIS dataset. The annual change of Mincerian returns to education ($dmincer$) is defined as:

$$dmincer_t = \frac{mincer_{t+n} - mincer_t}{n} \quad (5)$$

where $mincer$ is the Mincerian returns to education and $n$ is the year difference. If there are no missing years in the data, the annual change in Mincerian returns to education is simply the difference between Mincerian returns to education each year. However, if missing years exist, the difference between Mincerian returns to education of two discontinuous years should be divided by the year difference ($n$).

Control variables encompass demography (population, life expectancy at birth, fertility rate), macroeconomic policy (real GDP per capita, real GDP per capita growth, openness, government consumption share, inflation), regional heterogeneity (East Asia, Latin America, other regions), geography (LCR100km, KGATRSTR), fractionalization (linguistic fractionalization), and institutions (democracy index, OECD). Data for population, real GDP per capita, real GDP per capita growth, openness, and government consumption share are sourced from Penn World Table version 10.01 (Feenstra, Inklaar and Timmer, 2015).[11] Life expectancy at birth is drawn from the United Nations Population Division's World Population Prospects (2022 Revision), while fertility rate comes from OECD Labour Force Statistics

[11] https://www.rug.nl/ggdc/productivity/pwt/

**TABLE 1.**

Descriptive Statistics

| Variable | Obervations | Mean | Median | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Theil Wage Inequality | 154 | 0.0309 | 0.0256 | 0.0237 | 0.00288 | 0.132 |
| Annual Change of Theil Wage Inequality | 119 | 0.00104 | $-4.20 \times 10^{-5}$ | 0.00740 | −0.0283 | 0.0493 |
| Mincerian Returns to Education (%) | 154 | 9.505 | 8.984 | 3.680 | 2.600 | 22.85 |
| Annual Change of Mincerian Returns to Education (%) | 119 | 0.0311 | −0.0333 | 0.853 | −2.750 | 5.216 |
| Population (in thousands) | 154 | 42,736 | 14,952 | 61,073 | 417.2 | 284,154 |
| Real GDP per Capita (dollar in 2000 constant prices) | 154 | 14,809 | 16,868 | 8,589 | 2,297 | 48,217 |
| Annual Growth of Real GDP per Capita (% in 2000 constant prices) | 154 | 2.043 | 2.297 | 3.283 | −8.823 | 9.677 |
| Openness (% in current prices) | 154 | 63.83 | 53.74 | 38.88 | 13.97 | 282.9 |
| Democracy Index (Range: $1 \sim 7$, 1: Free, 7: Not Free) | 147 | 1.789 | 1 | 1.371 | 1 | 7 |
| East Asia Dummy | 154 | 0.0455 | 0 | 0.209 | 0 | 1 |
| Latin America Dummy | 154 | 0.279 | 0 | 0.450 | 0 | 1 |
| OECD Dummy | 154 | 0.740 | 1 | 0.440 | 0 | 1 |
| Life Expectancy at Birth | 150 | 72.39 | 75.05 | 6.259 | 51.62 | 79.78 |
| Fertility Rate | 128 | 2.076 | 1.810 | 0.804 | 1.170 | 6.330 |
| Inïation (Consumer Prices, Annual %) | 147 | 72.54 | 6.966 | 344.9 | 0.0833 | 2,948 |
| Government Consumption Share | 150 | 0.176 | 0.168 | 0.0540 | 0.0782 | 0.334 |
| LCR100km | 118 | 0.600 | 0.595 | 0.355 | 0.0247 | 1 |
| KGATRSTR | 118 | 0.269 | 0 | 0.376 | 0 | 1 |
| Linguistic Fractionalization | 117 | 0.230 | 0.151 | 0.208 | 0.00280 | 0.836 |

Note: The sample includes 40 countries. Population, Real GDP per Capita, Openness, and Government Consumption Share are sourced from PWT 10.01. Real GDP per Capita is a chain index, Openness is calculated as (Exports + Imports) / GDP, and Government Consumption Share is the share of government consumption at current PPPs (PWT 10.0, Appendix). Democracy Index refers to the Gastil Index of Political Rights, obtained from various editions of the Freedom in the World survey (1972-2012). Life Expectancy at Birth is from the UN Population Division's World Population Prospects: 2022 Revision. Fertility Rate is from OECD Labour Force Statistics. Inflation is from IMF's International Financial Statistics database. LCR100km and KGATRSTR are from CID at Harvard University. LCR100km represents the percentage of a country's land area within 100km of an ice-free coast, and KGATRSTR is the percentage of land area classified as tropical and subtropical using the Koeppen-Geiger system. Linguistic Fractionalisation is constructed by Alesina et al. (2003), measuring linguistic fractionalization based on shares of mother tongue languages.

(2003).[12] Inflation data are from IMF's International Financial Statistics database.[13] LCR100km represents the percentage of a country's land area within 100km of an ice-free coast, and KGATRSTR indicates the pro-

[12] The total fertility rate in a given year represents the total number of children that would be born to each woman if she lived through her child-bearing years and gave birth to children conforming to the current age-specific fertility rates. This rate is computed by summing the age-specific fertility rates, which are defined in five-year intervals. The data can be accessed at https://data.oecd.org/pop/fertility-rates.htm.

[13] Inflation, measured by the consumer price index, represents the annual percentage change in the cost for the average consumer to acquire a basket of goods and services, which may be fixed or updated regularly.

portion of land area classified as tropical or subtropical according to the KÃ¶ppen-Geiger climate classification system. Linguistic fractionalization is based on shares of languages spoken as mother tongues, with these three variables taken from Durlauf, Kourtellos and Tan (2012).[14] Democracy Index refers to the Gastil Index of Political Rights, sourced from various editions of the *Freedom in the World* survey (1972-2012).[15] Regional and OECD dummies are also included as control variables.[16]

In the original unprocessed dataset, numerous observations were excluded due to missing values for Theil wage inequality or Mincerian returns to education. Our refined dataset comprises 154 observations across 40 countries, representing both affluent and less affluent nations in America, Asia, Europe, and Oceania. The included countries are Australia, Austria, Belgium, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Denmark, Spain, Finland, France, United Kingdom, Germany, Greece, Guatemala, Honduras, Hungary, Ireland, Israel, Italy, Japan, South Korea, Luxembourg, Mexico, Nicaragua, Netherlands, Norway, Panama, Peru, Philippines, Poland, Puerto Rico, Russian Federation, El Salvador, Sweden, Thailand, United States, and Venezuela. Table 1 presents the descriptive statistics for this dataset.

## 4. RESULTS

This section of the paper employs cross-country regression analysis to analyze levels and changes in wage inequality, using the concepts that previous researchers have used to analyze income inequality: the Kuznets curve and openness. It also tests the influence of returns to skill on wage inequality, treating the Mincerian returns to education as a measure of returns to skill and changes in such returns as a measure of skill-biased technological change.[17]

[14]LCR100km and KGATRSTR data are originally sourced from the Center for International Development (CID) at Harvard University, while linguistic fractionalization data can be attributed to Alesina et al. (2003).

[15]The Gastil Index, compiled by Gastil and subsequent researchers, has been employed in various growth econometric studies, including those by Barro (1996, 1997) and Barro and Lee (1994).

[16]Regional dummy variables include East Asia and Latin America, with other regions serving as the base category. The Sub-Saharan Africa dummy is not utilized, as the data does not encompass any African countries.

[17]Skill bias and skill-biased technological change (SBTC) are often measured by returns to human capital (education and work experience) and changes in returns to human capital, respectively. This measure is widely accepted for the OECD countries, including the US and the UK (Machin and Van Reenen, 2016).

Table 2. Wage Inequality Regressions I (Part A)

| Inequality Measure: | Theil Wage Inequality | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) PLR | (12) PLR |
| Population | 1.656*** | | | | 1.655*** | 1.756*** | 1.590*** | 1.370*** | 1.652*** | 1.411*** | 1.336*** | 0.994** |
| | (0.301) | | | | (0.300) | (0.310) | (0.303) | (0.290) | (0.307) | (0.300) | (0.453) | (0.412) |
| Real GDP per Capita | −0.196*** | −0.151*** | −0.151*** | | −0.196*** | −0.228*** | −0.163*** | −0.116*** | −0.181*** | −0.128*** | | |
| | (0.0206) | (0.0207) | (0.0205) | | (0.0205) | (0.0272) | (0.0293) | (0.0265) | (0.0322) | (0.0335) | | |
| Annual Growth of Real | −0.00471 | 0.00724 | | −0.0339 | | | | | | | | |
| GDP per Capita | (0.0492) | (0.0537) | | (0.0620) | | | | | | | | |
| Openness | 0.246*** | 0.0969** | 0.0987** | −0.00684 | 0.244*** | 0.278*** | 0.231*** | 0.200*** | 0.265*** | 0.230*** | 0.214*** | 0.202*** |
| | (0.0510) | (0.0473) | (0.0454) | (0.0523) | (0.0492) | (0.0525) | (0.0490) | (0.0475) | (0.0512) | (0.0502) | (0.0670) | (0.0617) |
| Democracy Index | | | | | | −0.0223 | | | −0.0216 | −0.00920 | −0.0199 | 0.00279 |
| | | | | | | (0.0149) | | | (0.0152) | (0.0142) | (0.0195) | (0.0189) |
| East Asia Dummy | | | | | | | −0.110 | | −0.0748 | | −0.132 | |
| | | | | | | | (0.0779) | | (0.0821) | | (0.0945) | |
| Latin America Dummy | | | | | | | 0.0993** | | 0.131** | | 0.116 | |
| | | | | | | | (0.0491) | | (0.0522) | | (0.0802) | |
| OECD Dummy | | | | | | | | −0.200*** | | −0.221*** | | −0.309*** |
| | | | | | | | | (0.0454) | | (0.0481) | | (0.0683) |
| Constant | 0.373*** | 0.469*** | 0.469*** | 0.320*** | 0.373*** | 0.440*** | 0.311*** | 0.443*** | 0.350*** | 0.478*** | | |
| | (0.0389) | (0.0380) | (0.0378) | (0.0371) | (0.0388) | (0.0589) | (0.0534) | (0.0399) | (0.0657) | (0.0557) | | |
| Observations | 154 | 154 | 154 | 154 | 154 | 147 | 154 | 154 | 147 | 147 | 146 | 146 |
| Year FE | N | N | N | N | N | N | N | N | N | N | N | N |
| Adjusted $R^2$ | 0.372 | 0.249 | 0.254 | −0.011 | 0.376 | 0.393 | 0.406 | 0.444 | 0.429 | 0.469 | 0.120 | 0.231 |

Note: The sample comprises 40 countries. Real GDP per Capita is used as the nonlinear component in the partially linear regression models (PLRs). Smoothing parameters are set at 0.8 for the PLRs, with results remaining highly robust across various smoothing parameter values. Standard errors are indicated in parentheses.
Rescaling: Theil Wage Inequality is multiplied by 10; Micerian Returns to Education is divided by 100; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

### 4.1. The Effect of Income on Wage Inequality: The Kuznets Curve

Recall that earlier in this paper, the Kuznets curve was interpreted as a relationship between inequality and the level of development. The hypotheses are that the coefficients on the level of real GDP per capita or the squared real GDP per capita should be negative, while the coefficient on the annual growth of real GDP per capita should be positive. The first hypothesis evaluate the existence of a typical Kuznets curve with inequality and income measured in levels. The second hypothesis examines whether rapid income growth is associated with inequality or increases in inequality.[18]

Theil wage inequality is the measure used to test the Kuznets hypothesis in the data. The basic ordinary least square estimation method (OLS) is used, and population and trade openness are added as control variables. The model takes the form:

$$theil_i = \beta_0 + \beta_1 pop_i + \beta_2 rgdpch_i + \beta_3 rgdpch_i^2 + \beta_4 grgdpch_i + \beta_5 openc_i \quad (6)$$

where, for each observation $i$, $theil_i$ is the Theil wage inequality, $pop_i$ is population, $rgdpch_i$ is the real GDP per capita, $grgdpch_i$ is the annual growth of real GDP per capita, and $openc_i$ is the outcome level of trade openness. In line with the basic model presented in equation (6), we initially conducted four estimations using our dataset, both with and without control variables. The results of these estimations can be found in columns (1) to (4) of Table 2 (Part A). Additionally, we tested the inclusion of regional dummies and democracy index, which are displayed in columns (5) to (10) of the table. These variables are employed to account for regional and political heterogeneity among countries. As Durlauf, Kourtellos and Tan (2008) highlight, regional heterogeneity and characteristics play a crucial role in accounting for cross-country variation in growth econometrics. Regression results indicate that although coefficients on the democracy index are generally insignificant, coefficients on regional dummies are highly significant across all specifications. Columns (11) and (12) present the results of the semiparametric partially linear regression (PLR) formulation, where real GDP per capita is treated as a nuisance variable. The semiparametric PLR model can be expressed as follows:

$$Y_i = X_i^T \beta + g(Z_i) + u_i, i = 1, ..., n \quad (7)$$

where $X_i$ is a vector of random variables, $\beta$ is a vector of unknown parameters, $Z_i$ is a random variable, and $g(\cdot)$ is an *unknown* function. The function

[18] Some researchers have also used growth rates of development instead of the level of development to test if the rapid growth of income is associated with increases in inequality.

Table 2 continued. Wage Inequality Regressions I (Part B)

| Inequality Measure : | Theil Wage Inequality | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) |
| Population | 1.294*** | 0.909*** | 0.889** | 0.886** | 0.872*** | 0.829** | 0.840** | 0.910*** | 0.852** | 0.858** |
| | (0.331) | (0.342) | (0.343) | (0.348) | (0.322) | (0.343) | (0.349) | (0.326) | (0.354) | (0.339) |
| Real GDP per Capita | −0.250*** | 0.221** | 0.168* | 0.243** | 0.300*** | 0.287*** | 0.269** | 0.241** | 0.254* | 0.242* |
| | (0.0517) | (0.0975) | (0.0983) | (0.118) | (0.0944) | (0.108) | (0.123) | (0.104) | (0.134) | (0.124) |
| (Real GDP per Capita)$^2$ | 0.00487 | −0.0786*** | −0.0635*** | −0.0812*** | −0.0928*** | −0.0895*** | −0.0861*** | −0.0834*** | −0.0764*** | −0.0783*** |
| | (0.0161) | (0.0215) | (0.0211) | (0.0239) | (0.0206) | (0.0225) | (0.0242) | (0.0214) | (0.0251) | (0.0238) |
| Annual Growth of Real | 0.0491 | 0.0549 | 0.104* | 0.0647 | 0.105* | 0.0789 | 0.0932 | 0.133** | 0.113* | 0.140** |
| GDP per Capita | (0.0567) | (0.0591) | (0.0585) | (0.0622) | (0.0574) | (0.0600) | (0.0635) | (0.0592) | (0.0623) | (0.0593) |
| Openness | 0.190*** | 0.214*** | 0.186*** | 0.213*** | 0.222*** | 0.188** | 0.182** | 0.193*** | 0.169** | 0.182** |
| | (0.0604) | (0.0633) | (0.0608) | (0.0640) | (0.0595) | (0.0746) | (0.0755) | (0.0708) | (0.0732) | (0.0705) |
| 1 / Life Expectancy at Birth | | 141.1*** | 121.0*** | 148.6*** | 122.3*** | 155.9*** | 160.8*** | 104.5** | 134.5*** | 87.00* |
| | | (38.53) | (40.84) | (39.27) | (36.62) | (41.82) | (43.06) | (42.62) | (46.69) | (46.83) |
| Log of Fertility Rate | | 0.271*** | 0.290*** | 0.227** | 0.234*** | 0.211*** | 0.206** | 0.270*** | 0.228** | 0.285*** |
| | | (0.0745) | (0.0703) | (0.0909) | (0.0708) | (0.0790) | (0.0911) | (0.0770) | (0.0906) | (0.0786) |
| Government Consumption Share | | | 0.768** | | | | | | 0.935** | 0.492 |
| | | | (0.333) | | | | | | (0.383) | (0.385) |
| Inïation (Consumer Prices, Annual %) | | | 0.132*** | | | | | | 0.0990* | 0.109** |
| | | | (0.0481) | | | | | | (0.0576) | (0.0545) |
| Democracy Index | | | −0.0233 | | | | | | −0.0183 | 0.00612 |
| | | | (0.0196) | | | | | | (0.0285) | (0.0250) |
| East Asia Dummy | | | | −0.0526 | | | −0.0885 | | 0.0603 | |
| | | | | (0.107) | | | (0.110) | | (0.128) | |
| Latin America Dummy | | | | 0.0560 | | | −0.0149 | | 0.0644 | |
| | | | | (0.0928) | | | (0.102) | | (0.111) | |
| OECD Dummy | | | | | −0.217*** | | | −0.342*** | | −0.287** |
| | | | | | (0.0610) | | | (0.104) | | (0.119) |
| LCR100km | | | | | | 0.0197 | 0.0269 | 0.0296 | 0.0187 | 0.0256 |
| | | | | | | (0.0658) | (0.0677) | (0.0625) | (0.0656) | (0.0620) |
| KGATRSTR | | | | | | 0.168* | 0.174* | −0.187 | 0.0963 | −0.163 |
| | | | | | | (0.0847) | (0.0922) | (0.135) | (0.130) | (0.165) |
| Linguistic Fractionalization | | | | | | 0.131 | 0.122 | 0.0827 | 0.0837 | 0.0428 |
| | | | | | | (0.105) | (0.106) | (0.101) | (0.105) | (0.102) |
| Constant | 0.480*** | −2.109*** | −1.903*** | −2.218*** | −1.741*** | −2.390*** | −2.431*** | −1.351* | −2.225*** | −1.270* |
| | (0.0614) | (0.593) | (0.597) | (0.611) | (0.567) | (0.659) | (0.682) | (0.701) | (0.717) | (0.756) |
| Observations | 148 | 121 | 119 | 121 | 121 | 121 | 121 | 121 | 119 | 119 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Adjusted $R^2$ | 0.453 | 0.506 | 0.570 | 0.502 | 0.563 | 0.516 | 0.509 | 0.565 | 0.555 | 0.588 |

Note: The sample comprises 40 countries. Standard errors are indicated in parentheses.
Rescaling: Theil Wage Inequality is multiplied by 10; Micerian Returns to Education is divided by 100; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100; Inflation is divided by 1,000.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

$g(\cdot)$ is a smooth, single-valued function with a bounded first derivative, and the parametric $(X_i^T\beta)$ and nonparametric $[g(Z_i)]$ parts are additively separable (Liu and Stengos, 1999). We use semiparametric PLR to conceal the influence of $Z_i$ (real GDP per capita) in the regression function and focus on estimating parameter vector $\beta$. The results show that coefficients on population, openness, and regional dummies are still significant, but the fit of the PLR models does not improve.[19]

Kuznets' hypothesis suggests that during the initial stages of development, inequality increases and then gradually decreases as a country advances, creating an "inverted U-curve" represented by a quadratic form. According to this hypothesis, coefficients on real GDP per capita squared should be negative, as stated in our second hypothesis. Upon testing, we found that coefficients on the quadratic terms were consistently positive and often statistically insignificant without accounting for additional country characteristics. Table 2 (Part B) presents regression results with more control variables, including life expectancy at birth, fertility rate, government consumption share, inflation, LCR100km, KGATRSTR, and linguistic fractionalization. The coefficient on squared real GDP per capita is positive and insignificant in column (13), but becomes significantly negative in all other specifications when life expectancy at birth and fertility rate are controlled for, as demonstrated in columns (14) through (22). We confirm the presence of the "inverted U-curve" in our wage inequality data. The estimation results in this table support the second hypothesis, as the coefficients on the annual growth of real GDP per capita are consistently positive and occasionally significant. Furthermore, in line with Durlauf, Kourtellos and Tan (2008), we reiterate that regional heterogeneity and country characteristics play a vital role in accounting for cross-country variation in this type of analysis.

Table 3 shows results when the Mincerian returns to education is used as a measure of wage inequality. The baseline model takes the form:

$$mincer_i = \beta_0 + \beta_1 pop_i + \beta_2 rgdpch_i + \beta_3 rgdpch_i^2 + \beta_4 grgdpch_i + \beta_5 openc_i \tag{8}$$

where, for each observation $i$, $mincer_i$ is the Mincerian returns to education, $pop_i$ is population, $rgdpch_i$ is the real GDP per capita, $grgdpch_i$ is the annual growth of real GDP per capita, and $openc_i$ is the outcome level of trade openness. Examining the results in columns (1) through (4) of Table 3 (Part A), we observe that coefficients on real GDP per capita are significant and negative in all estimations, while coefficients on annual growth of real GDP per capita are consistently insignificant.

[19]The fit of the PLR models decreases because real GDP per capita, whose coefficient is very significant in OLS models, is no longer in the parametric part.

Table 3. Wage Inequality Regressions II (Part A)

| Inequality Measure : | Mincerian Returns to Education | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11)PLR | (12)PLR |
| Population | 0.330$^{***}$ | | | | 0.333$^{***}$ | 0.321$^{***}$ | 0.275$^{***}$ | 0.345$^{***}$ | 0.275$^{***}$ | 0.331$^{***}$ | 0.169$^{**}$ | 0.132$^{*}$ |
| | (0.0515) | | | | (0.0516) | (0.0528) | (0.0496) | (0.0529) | (0.0498) | (0.0547) | (0.0695) | (0.0692) |
| Real GDP per Capita | −0.0162$^{***}$ | −0.00722$^{**}$ | −0.00666$^{*}$ | | −0.0158$^{***}$ | −0.0103$^{**}$ | 0.00175 | −0.0190$^{***}$ | 0.00510 | −0.0132$^{**}$ | | |
| | (0.00353) | (0.00365) | (0.00365) | | (0.00353) | (0.00463) | (0.00481) | (0.00484) | (0.00523) | (0.00610) | | |
| Annual Growth of Real | 0.0114 | 0.0138 | | 0.0118 | | | | | | | | |
| GDP per Capita | (0.00842) | (0.00947) | | (0.00951) | | | | | | | | |
| Openness | 0.0199$^{**}$ | −0.00972 | −0.00642 | −0.0147$^{*}$ | 0.0229$^{***}$ | 0.0214$^{**}$ | 0.0151$^{*}$ | 0.0247$^{***}$ | 0.0169$^{**}$ | 0.0229$^{**}$ | 0.00966 | 0.00190 |
| | (0.00873) | (0.00834) | (0.00805) | (0.00803) | (0.00847) | (0.00894) | (0.00803) | (0.00867) | (0.00831) | (0.00916) | (0.0103) | (0.0104) |
| Democracy Index | | | | | | 0.00456$^{*}$ | | | 0.00253 | 0.00417 | −0.000512 | −0.00153 |
| | | | | | | (0.00254) | | | (0.00247) | (0.00260) | (0.00300) | (0.00317) |
| East Asia Dummy | | | | | | | 0.0222$^{*}$ | | 0.0207 | | 0.0310$^{**}$ | |
| | | | | | | | (0.0128) | | (0.0133) | | (0.0145) | |
| Latin America Dummy | | | | | | | 0.0411$^{***}$ | | 0.0432$^{***}$ | | 0.0434$^{***}$ | |
| | | | | | | | (0.00805) | | (0.00847) | | (0.0123) | |
| OECD Dummy | | | | | | | | 0.00804 | | 0.00653 | | 0.0314$^{***}$ |
| | | | | | | | | (0.00829) | | (0.00877) | | (0.0115) |
| Constant | 0.0898$^{***}$ | 0.109$^{***}$ | 0.109$^{***}$ | 0.102$^{***}$ | 0.0896$^{***}$ | 0.0741$^{***}$ | 0.0586$^{***}$ | 0.0867$^{***}$ | 0.0470$^{***}$ | 0.0730$^{***}$ | | |
| | (0.00666) | (0.00669) | (0.00671) | (0.00569) | (0.00668) | (0.0100) | (0.00875) | (0.00728) | (0.0107) | (0.0102) | | |
| Observations | 154 | 154 | 154 | 154 | 154 | 147 | 154 | 154 | 147 | 147 | 146 | 146 |
| Year FE | N | N | N | N | N | N | N | N | N | N | N | N |
| Adjusted $R^2$ | 0.235 | 0.031 | 0.023 | 0.012 | 0.231 | 0.251 | 0.337 | 0.230 | 0.361 | 0.248 | 0.124 | 0.081 |

Note: The sample comprises 40 countries. Real GDP per Capita is used as the nonlinear component in the partially linear regression models (PLRs). Smoothing parameters are set at 0.8 for the PLRs, with results remaining highly robust across various smoothing parameter values. Standard errors are indicated in parentheses.
Rescaling: Theil Wage Inequality is multiplied by 10; Micerian Returns to Education is divided by 100; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100.
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

Adjusted R-squared values are low, except when population is included. These results align with the first hypothesis but not the second. Columns (5) through (10) in the table present regression results with regional dummies and democracy index. Although coefficients on the democracy index are generally insignificant, coefficients on regional dummies are highly significant across specifications.[20] Coefficients on real GDP per capita are typically negative and significant, but become insignificant when Latin America dummies are added.[21] Columns (11) and (12) present the results of the semiparametric partially linear regression (PLR) formulation, where real GDP per capita is treated as a nuisance variable. The findings indicate that coefficients on population and regional dummies remain significant, but the fit of the PLR model does not improve.

Table 3 (Part B) presents regression results with additional control variables, including life expectancy at birth, fertility rate, government consumption share, inflation, LCR100km, KGATRSTR, and linguistic fractionalization. The coefficients on real GDP per capita are predominantly negative and occasionally significant, supporting our first hypothesis. However, the coefficients on squared real GDP per capita are consistently positive, contradicting our hypothesis. We can conclude that Mincerian returns to education as an inequality measure partially support the presence of the "inverted U-curve." The estimation results in this table support the second hypothesis, as the coefficients on the annual growth of real GDP per capita are consistently positive. In a couple of specifications, the coefficients are negative but insignificant. Additionally, we again observe that regional heterogeneity and country characteristics are crucial in accounting for cross-country variation, as emphasized by Durlauf, Koutellos and Tan (2008).

Table 4 shows results from testing whether real GDP per capita or annual growth of real GDP per capita explains the growth of wage inequality. The models take the form:

$$dtheil_i = \beta_0 + \beta_1 pop_i + \beta_2 rgdpch_i + \beta_3 grgdpch_i + \beta_4 openc_i \tag{9}$$

$$dmincer_i = \beta_0 + \beta_1 pop_i + \beta_2 rgdpch_i + \beta_3 grgdpch_i + \beta_4 openc_i \tag{10}$$

where, for each observation $i$, $dtheil_i$ is the annual change of Theil wage inequality, $dmincer_i$ is the annual change of Mincerian returns to education, $pop_i$ is population, $rgdpch_i$ is the real GDP per capita, $grgdpch_i$ is the annual growth of real GDP per capita, and $openc_i$ is the outcome level

[20] The same regressions with the Gastil index of civil liberties are run, and the results show lower level of significance over all specifications.

[21] The correlation between real GDP per capita and the Latin America dummy is -0.68.

Table 3 continued. Wage Inequality Regressions II (Part B)

| Inequality Measure : | Mincerian Returns to Education | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) |
| Population | 0.232*** | 0.189*** | 0.153** | 0.165*** | 0.197*** | 0.210*** | 0.183*** | 0.188*** | 0.167*** | 0.177*** |
| | (0.0543) | (0.0628) | (0.0626) | (0.0615) | (0.0571) | (0.0617) | (0.0580) | (0.0532) | (0.0576) | (0.0548) |
| Real GDP per Capita | −0.0372*** | −0.0280 | −0.00962 | 0.00307 | −0.0455*** | −0.0521*** | −0.0186 | −0.0393** | −0.0438** | −0.0561*** |
| | (0.00848) | (0.0179) | (0.0180) | (0.0210) | (0.0167) | (0.0195) | (0.0205) | (0.0169) | (0.0218) | (0.0200) |
| (Real GDP per Capita)$^2$ | 0.00605** | 0.00531 | 0.00105 | 0.000450 | 0.00843** | 0.00862** | 0.00349 | 0.00690* | 0.00623 | 0.00851** |
| | (0.00264) | (0.00394) | (0.00386) | (0.00422) | (0.00366) | (0.00406) | (0.00402) | (0.00350) | (0.00408) | (0.00385) |
| Annual Growth of | 0.0223** | 0.0166 | 0.00302 | 0.00792 | 0.00546 | 0.0171 | 0.00463 | 0.00212 | −0.00242 | −0.00195 |
| Real GDP per Capita | (0.00929) | (0.0108) | (0.0107) | (0.0110) | (0.0102) | (0.0108) | (0.0106) | (0.00967) | (0.0101) | (0.00960) |
| Openness | −0.00359 | −0.0130 | −0.00755 | −0.00896 | −0.0148 | −0.00564 | −0.00173 | −0.00695 | −0.00221 | −0.00659 |
| | (0.00989) | (0.0116) | (0.0111) | (0.0113) | (0.0106) | (0.0134) | (0.0126) | (0.0116) | (0.0119) | (0.0114) |
| 1 / Life Expectancy at Birth | | −5.338 | −2.940 | −4.224 | −1.194 | −12.30 | −11.65 | 2.065 | −8.209 | 2.756 |
| | | (7.066) | (7.461) | (6.949) | (6.497) | (7.534) | (7.172) | (6.961) | (7.606) | (7.577) |
| Log of Fertility Rate | | 0.0430*** | 0.0378*** | 0.0267 | 0.0513*** | 0.0496*** | 0.0322** | 0.0330** | 0.0398*** | 0.0394*** |
| | | (0.0137) | (0.0129) | (0.0161) | (0.0126) | (0.0142) | (0.0152) | (0.0126) | (0.0148) | (0.0127) |
| Government Consumption Share | | | −0.221*** | | | | | | −0.220*** | −0.171*** |
| | | | (0.0608) | | | | | | (0.0623) | (0.0624) |
| Inïation (Consumer Prices, Annual %) | | | −0.00438 | | | | | | 0.00641 | 0.00277 |
| | | | (0.00879) | | | | | | (0.00939) | (0.00882) |
| Democracy Index | | | 0.00656* | | | | | | −0.00718 | −0.00498 |
| | | | (0.00358) | | | | | | (0.00464) | (0.00404) |
| East Asia Dummy | | | | 0.0505*** | | | 0.0685*** | | 0.0617*** | |
| | | | | (0.0190) | | | (0.0184) | | (0.0209) | |
| Latin America Dummy | | | | 0.0377** | | | 0.0530*** | | 0.0478*** | |
| | | | | (0.0164) | | | (0.0170) | | (0.0181) | |
| OECD Dummy | | | | | 0.0478*** | | | 0.0956*** | | 0.0796*** |
| | | | | | (0.0108) | | | (0.0170) | | (0.0193) |
| LCR100km | | | | | | −0.0204* | −0.0192* | −0.0232** | −0.0138 | −0.0187* |
| | | | | | | (0.0119) | (0.0113) | (0.0102) | (0.0107) | (0.0100) |
| KGATRSTR | | | | | | −0.0298* | −0.0482*** | 0.0697*** | −0.0807*** | 0.0293 |
| | | | | | | (0.0153) | (0.0153) | (0.0221) | (0.0211) | (0.0267) |
| Linguistic Fractionalization | | | | | | 0.00574 | 0.00853 | 0.0192 | 0.0208 | 0.0266 |
| | | | | | | (0.0190) | (0.0177) | (0.0165) | (0.0172) | (0.0165) |
| Constant | 0.121*** | 0.162 | 0.145 | 0.114 | 0.0811 | 0.290** | 0.244** | −0.000308 | 0.275** | 0.0611 |
| | (0.0101) | (0.109) | (0.109) | (0.108) | (0.101) | (0.119) | (0.114) | (0.114) | (0.117) | (0.122) |
| Observations | 148 | 121 | 119 | 121 | 121 | 121 | 121 | 121 | 119 | 119 |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Adjusted $R^2$ | 0.390 | 0.494 | 0.549 | 0.526 | 0.581 | 0.521 | 0.585 | 0.647 | 0.629 | 0.661 |

Note: The sample comprises 40 countries. Standard errors are indicated in parentheses.
Rescaling: Theil Wage Inequality is multiplied by 10; Micerian Returns to Education is divided by 100; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100; Inflation is divided by 1,000.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**TABLE 4.**

Growth of Wage Inequality

| Inequality Measure: | Annual Change of Theil Wage Inequality | | | | Annual Change of Mincerian Returns to Education | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Population | 0.955 | | | | 174.9 | | | |
| | (1.283) | | | | (151.0) | | | |
| Real GDP per Capita | $-0.297^{***}$ | $-0.265^{***}$ | $-0.256^{***}$ | | 7.714 | 13.56 | 14.97 | |
| | (0.0959) | (0.0856) | (0.0847) | | (11.28) | (10.11) | (10.02) | |
| Annual Growth of Real | 0.190 | 0.0975 | | 0.191 | 28.24 | 28.47 | | 33.25 |
| GDP per Capita | (0.229) | (0.228) | | (0.234) | (26.91) | (26.95) | | (26.80) |
| Openness | 0.219 | 0.115 | 0.152 | −0.00490 | −7.780 | −26.85 | −21.43 | −20.71 |
| | (0.250) | (0.207) | (0.202) | (0.211) | (29.46) | (24.47) | (23.94) | (24.12) |
| Constant | $0.333^{*}$ | $0.391^{**}$ | $0.390^{**}$ | 0.0894 | −16.60 | −5.927 | −6.054 | 9.498 |
| | (0.186) | (0.168) | (0.168) | (0.142) | (21.84) | (19.83) | (19.84) | (16.21) |
| Observations | 119 | 119 | 119 | 119 | 119 | 119 | 119 | 119 |
| Year FE | N | N | N | N | N | N | N | N |
| Adjusted $R^2$ | 0.051 | 0.054 | 0.057 | −0.016 | 0.009 | 0.006 | 0.005 | −0.001 |

Note: These regressions encompass 38 countries, with the same number of observations included in our first difference model. Standard errors are indicated in parentheses.

Rescaling: Annual Change of Theil Wage Inequality is multiplied by 100; Annual Change of Micerian Returns to Education is multiplied by 100; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100.

$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

of trade openness.[22] Because of how $dtheil_i$ and $dmincer_i$ are constructed, regressions are run with the levels at the beginning of the period. Table 4 presents that the coefficients on real GDP per capita are negative and significant in the first model, but turn insignificant in the second model. Notably, the second model exhibits very low adjusted R-squared values.[23]

In summary, the hypothesis that the coefficients on the level of real GDP per capita or the squared real GDP per capita should be negative is not rejected, but the results are somewhat mixed across regressions. The second hypothesis that the coefficients on the annual growth of real GDP per capita should be positive is also not rejected in the regressions using levels of inequality. We conclude that the "inverted U-curve" is present in our wage inequality data, and that rapid income growth is generally associated

[22]The fixed effect method was also tried, but 23 countries in the data have fewer than four observations, and variables other than the fixed effects did not have statistically significant coefficients.

[23]Regressions with regional dummies and democracy index are also run, but the coefficients are not significant except for one specification with East Asia dummy. Semiparametric PLR formation with real GDP per capita in the non-linear part is also employed, but there is no significant change other than changes in the magnitude of coefficients and standard errors.

with greater inequality. Furthermore, we find that regional heterogeneity and cultural differences are important factors in cross-country regression analysis, consistent with Durlauf, Kourtellos and Tan (2008).

### 4.2. The Effect of Globalization of Trade: Openness

Utilizing the same models as mentioned earlier, this section examines the impact of trade openness on wage inequality and its growth. Although the literature suggests that openness could influence wage inequality, it does not provide a definitive hypothesis regarding the direction of this effect. Epifani and Gancia (2008) propose a positive relationship, which serves as the hypothesis for this section.[24] We consider the same set of control variables in the analysis, and the results are reported in Tables 2, 3, and 4.

Table 2 displays the results of regressions on Theil wage inequality, with models specified by equation (6), both including and excluding control variables. Almost all regression results indicate that trade openness has a positive and statistically significant effect on wage inequality, demonstrating robustness. This finding remains consistent in semiparametric PLRs presented in columns (11) and (12).

Table 3, which comprises regression results using Mincerian returns to education as an inequality measure, reveals that coefficients on openness occasionally have negative values but are primarily insignificant. When significant, these coefficients tend to be positive. The coefficients on openness are insignificant in semiparametric PLRs in columns (11) and (12).[25]

Table 4 includes regression results from the models depicted in equations (9) and (10). Openness is consistently insignificant in regressions analyzing the growth of wage inequality.[26]

The hypothesis that trade openness positively affects wage inequality is not rejected, as the results demonstrate that trade openness has a positive impact on Theil wage inequality in numerous specifications, particularly when considering the levels of Theil wage inequality and Mincerian returns to education.

[24]In an earlier section of this paper (openness approach in income inequality analysis), we discussed Wood's hypothesis, which posits that openness reduces inequality at low income levels while increasing inequality at high income levels. To test this hypothesis, we added an interaction term between real GDP per capita and openness to the model. However, the resulting interaction coefficient was consistently found to be insignificant.

[25]In our dataset, we found a moderate positive correlation of 0.34 between real GDP per capita and openness.

[26]The hypothesis examines the impact of openness levels on subsequent shifts in wage inequality. Alternatively, one could investigate the effects of changes in openness. Additional regressions (not reported) indicate a positive relationship with changes in Theil wage inequality, consistent with the findings in Table 2. Regional dummies and the democracy index are also incorporated, and a semiparametric PLR model with real GDP per capita in the nonlinear component is employed. However, these modifications do not lead to any significant alterations in the results.

### 4.3. The Effect of Returns to Skill and Skill-biased Technological Change (SBTC) on Levels and Changes in Wage Inequality

This section examines the influence of returns to skill on wage inequality, using Mincerian returns to education as a proxy for returns to skill and changes in these returns as a measure of skill-biased technological change (SBTC).[27] If returns to skill affect wage inequality fluctuations, then the changes in Theil wage inequality and Mincerian returns to education should exhibit a strong correlation.

**TABLE 5.**

Wage Inequality Regressions III (Part A)

| Inequality Measure: | Theil Wage Inequality | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Population | 1.6010*** | | | | |
| | (0.3391) | | | | |
| Real GDP per Capita | −0.1939*** | −0.1426*** | −0.1430*** | | |
| | (0.0220) | (0.0205) | (0.0203) | | |
| Annual Growth of Real | −0.0074 | −0.0093 | | −0.0555 | |
| GDP per Capita | (0.0494) | (0.0528) | | (0.0600) | |
| Openness | 0.2433*** | 0.1086** | 0.1063** | 0.0191 | |
| | (0.0519) | (0.0463) | (0.0444) | (0.0510) | |
| Mincerian Returns to Education | 0.1639 | 1.1956*** | 1.1867*** | 1.7195*** | 1.6714*** |
| | (0.4742) | (0.4498) | (0.4455) | (0.5083) | (0.5008) |
| Constant | 0.3577*** | 0.3388*** | 0.3398*** | 0.1439** | 0.1492*** |
| | (0.0577) | (0.0615) | (0.0610) | (0.0628) | (0.0509) |
| Observations | 155 | 155 | 155 | 155 | 155 |
| Year FE | N | N | N | N | N |
| Adjusted $R^2$ | 0.3701 | 0.2807 | 0.2853 | 0.0547 | 0.0618 |

Note: The sample comprises 40 countries. Standard errors are indicated in parentheses.
Rescaling: Theil Wage Inequality is multiplied by 10; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100; Micerian Returns to Education is divided by 100.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

First, we conduct regressions to explore the relationship between Theil wage inequality and Mincerian returns to education. The models take the

[27]In the literature, skill-biased technological change has been measured "residually" using a factor-biased version of Solow's aggregate total factor productivity (TFP). Additionally, several proxies have been employed to measure skill-biased technological change, including changes in computer use, R&D expenditure, the amount of IT capital, the number of IT workers, high-tech capital share, and changes in returns to schooling (Violante, 2008; Sanders and ter Weel, 2000).

form:

$$theil_i = \beta_0 + \beta_1 pop_i + \beta_2 rgdpch_i + \beta_3 grgdpch_i + \beta_4 openc_i + \beta_5 mincer_i \quad (11)$$

where, for each observation $i$, $theil_i$ is the Theil wage inequality, $popi$ is population, $rgdpch_i$ is the real GDP per capita, $grgdpch_i$ is the annual growth of real GDP per capita, $openc_i$ is the outcome level of trade openness, and $mincer_i$ is the Mincerian returns to education.

Various models are tested, including and excluding control variables such as population, real GDP per capita, annual growth of real GDP per capita, and openness. The results are reported in Table 5 (Part A). The coefficient on Mincerian returns to education is consistently positive and significant across all specifications and datasets, except when population is included.[28] The correlation between population and Mincerian returns to education is 0.37 in the data. These results suggest that while Theil wage inequality and Mincerian returns to education are not identical, given their fairly low raw correlation of 0.26, they seem to be related.

When regional dummies and the democracy index are considered in columns (6) through (13), coefficients on Mincerian returns to education remain consistently positive and generally significant. However, they become insignificant when Latin America dummies are added.[29] Column (14) presents the results of a semiparametric PLR model where real GDP per capita is treated as a nuisance variable, and the coefficient on Mincerian returns to education becomes insignificant, while openness and the OECD dummy remain significant. Column (15) displays the results of a semiparametric PLR model where Mincerian returns to education is treated as a nuisance variable. In the semiparametric PLR models shown in columns (14) and (15), coefficients on real GDP per capita, openness, and the OECD dummy remain significant, but the fit of the PLR model does not improve compared to the OLS model specifications. Overall, the results support a positive relationship between returns to education and wage inequality, although this relationship is sensitive to population and the Latin America dummy.

We examine the relationship between changes in Theil wage inequality and changes in Mincerian returns to education by conducting regressions on the annual change of Theil wage inequality. The models take the form:

$$dtheil_i = \beta_0 + \beta_1 pop_i + \beta_2 rgdpch_i + \beta_3 grgdpch_i + \beta_4 openc_i + \beta_5 dmincer_i \quad (12)$$

[28]One hypothesis posits that coefficients on population should be positive, as larger countries typically have a more diverse economic base. In the data, the observed coefficients on population are indeed positive and significant, which supports this hypothesis.

[29]The data reveals a correlation of 0.41 between Mincerian returns to education and the Latin America dummy variable.

Table 5 continued. Wage Inequality Regressions III (Part B)

| Inequality Measure : | Theil Wage Inequality | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14)PLR | (15)PLR |
| Real GDP per Capita | −0.1430*** | −0.1643*** | −0.1481*** | −0.0966*** | −0.1044*** | −0.0559** | −0.1184*** | −0.0578* | | −0.0648* |
| | (0.0203) | (0.0263) | (0.0204) | (0.0267) | (0.0290) | (0.0250) | (0.0324) | (0.0307) | | (0.0391) |
| Openness | 0.1063** | 0.1230*** | 0.1060** | 0.0940** | 0.0953** | 0.0824** | 0.1158** | 0.1030** | 0.1088** | 0.1621*** |
| | (0.0444) | (0.0466) | (0.0441) | (0.0438) | (0.0439) | (0.0412) | (0.0458) | (0.0426) | (0.0506) | (0.0521) |
| Mincerian Returns | 1.1867*** | 1.3568*** | 1.2170*** | 0.6947 | 0.7663 | 1.1109*** | 0.8532* | 1.2167*** | 0.1300 | |
| to Education | (0.4455) | (0.4676) | (0.4434) | (0.4767) | (0.4881) | (0.4110) | (0.5077) | (0.4262) | (0.6027) | |
| Democracy Index | | −0.0156 | | | | | −0.0140 | −0.0026 | 0.0005 | 0.0082 |
| | | (0.0161) | | | | | (0.0165) | (0.0148) | (0.0200) | (0.0188) |
| East Asia Dummy | | | −0.1294* | | −0.0594 | | −0.0425 | | | |
| | | | (0.0782) | | (0.0842) | | (0.0896) | | | |
| Latin America Dummy | | | | 0.1363*** | 0.1203** | | 0.1392** | | | |
| | | | | (0.0525) | (0.0573) | | (0.0616) | | | |
| OECD Dummy | | | | | | −0.2434*** | | −0.2698*** | −0.3094*** | −0.2409*** |
| | | | | | | (0.0463) | | (0.0487) | (0.0701) | (0.0663) |
| Constant | 0.3398*** | 0.3800*** | 0.3505*** | 0.2875*** | 0.2985*** | 0.4133*** | 0.3250*** | 0.4256*** | | |
| | (0.0610) | (0.0736) | (0.0610) | (0.0632) | (0.0652) | (0.0580) | (0.0755) | (0.0675) | | |
| Observations | 155 | 155 | 155 | 155 | 155 | 155 | 155 | 155 | 155 | 155 |
| Year FE | N | N | N | N | N | N | N | N | N | N |
| Adjusted $R^2$ | 0.2853 | 0.2998 | 0.2934 | 0.3114 | 0.3091 | 0.3926 | 0.3267 | 0.4204 | 0.1959 | 0.3832 |

Note: The sample comprises 40 countries. Real GDP per Capita and Mincerian Returns to Education are taken as non-linear components of the partially linear regression model (PLR) (14) and (15), respectively. Smoothing parameters are 0.8 for the PLRs, and the results are highly robust across various values of smoothing parameter. Standard errors are indicated in parentheses.

Rescaling: Theil Wage Inequality is multiplied by 10; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100; Micerian Returns to Education is divided by 100.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

where, for each observation $i$, $dtheil_i$ is the annual change of Theil wage inequality, $pop_i$ is population, $rgdpch_i$ is the real GDP per capita, $grgdpch_i$ is the annual growth of real GDP per capita, $openc_i$ is the outcome level of trade openness, and $dmincer_i$ is the annual change of Mincerian returns to education. Because of how $dtheil_i$ and $dmincer_i$ are constructed, the regressions are run with $dtheil_i$, $dmincer_i$, $grgdpch_i$, and the levels of the other variables at the beginning of the period.

**TABLE 6.**

Regressions on Annual Change of Theil Wage Inequality

| Inequality Measure : | Annual Change of Theil Wage Inequality | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6)PLR |
| Population | 0.6423 | | | | | 1.6215 |
| | (1.4154) | | | | | (2.2550) |
| Real GDP per Capita | $-0.2836^{***}$ | $-0.2619^{***}$ | $-0.2556^{***}$ | | | |
| | (0.1037) | (0.0917) | (0.0919) | | | |
| Annual Growth of Real | 0.3177 | 0.3238 | | 0.2846 | | $0.5412^{**}$ |
| GDP per Capita | (0.2539) | (0.2525) | | (0.2609) | | (0.2414) |
| Openness | 0.1707 | 0.0979 | 0.1710 | $-0.0552$ | | 0.1411 |
| | (0.2752) | (0.2227) | (0.2160) | (0.2237) | | (0.2724) |
| Annual Change of Mincerian | $-0.3597^{***}$ | $-0.3613^{***}$ | $-0.3244^{**}$ | $-0.3781^{***}$ | $-0.3451^{**}$ | $-0.4083^{***}$ |
| Returns to Education | (0.0013) | (0.0013) | (0.0013) | (0.0014) | (0.1344) | (0.1382) |
| Constant | $0.3291^{*}$ | $0.3701^{**}$ | $0.3781^{**}$ | 0.0900 | 0.1109 | |
| | (0.1991) | (0.1767) | (0.1772) | (0.1521) | (0.0743) | |
| Observations | 105 | 105 | 105 | 105 | 105 | 105 |
| Year FE | N | N | N | N | N | N |
| Adjusted $R^2$ | 0.0997 | 0.1069 | 0.1012 | 0.0436 | 0.0511 | 0.1116 |

Note: These regressions encompass 38 countries. Real GDP per Capita is taken as non-linear component of the partially linear regression model (PLR). Smoothing parameter is 0.8 for the PLR, and the results are highly robust across various values of smoothing parameter. Standard errors are indicated in parentheses. Rescaling: Annual Change of Theil Wage Inequality is multiplied by 100; Annual Change of Micerian Returns to Education is not rescaled; Population is divided by 1,000,000; Real GDP per Capita is divided by 10,000; Growth of Real GDP per Capita is divided by 10; Openness is divided by 100.
$^{***}$ $p < 0.01$, $^{**}$ $p < 0.05$, $^{*}$ $p < 0.1$

We test various models by including and excluding control variables such as population, real GDP per capita, annual growth of real GDP per capita, and trade openness, with the results reported in Table 6.[30] The coefficient on the annual change of Mincerian returns to education is negative and statistically significant at the 1∼5% level, demonstrating robustness across

[30] We also conducted regressions that included regional dummies and democracy index. However, the coefficients were not found to be significant in these cases. Furthermore, semiparametric PLR formation with Mincerian returns to education in the nonlinear part was employed, but it did not yield any significant results.

different specifications. Column (6) displays the results of the semiparametric PLR with real GDP per capita in the nonlinear part. The fit of the PLR model improves, and the coefficients on the annual change of Mincerian returns to education are statistically significant, while the coefficient on annual changes of Mincerian remains negative.

The findings from Table 5 and Table 6 indicate that returns to education increase wage inequality, but changes in returns to education reduce changes in wage inequality. Considering that changes in Mincerian returns to education serve as a proxy for skill-biased technological change, the results in Table 6 reveal an intriguing phenomenon: an acceleration of skill-biased technological change leads to a deceleration of the wage gap widening process. A possible explanation is that the speed of technological change may surpass the speed of workers' skill acquisition. This concept aligns with Acemoglu (1998)'s theory that the "induced" increase in the relative demand for skills can potentially overshoot the increase in the relative supply of skills.

## 5. CONCLUSIONS

This paper presents a comprehensive dataset enabling the study of wage inequality and returns to education across 40 countries. Using this dataset, we explore hypotheses concerning wage inequality, focusing on the effects of the Kuznets curve, trade openness, and returns to skill. The key findings from our data analysis are as follows:

First, we discover that Kuznets' "inverted U-curve" is evident in our wage inequality data. Moreover, we observe that accelerated income growth typically correlates with increased inequality. Furthermore, our findings highlight the significance of regional heterogeneity and cultural distinctions in cross-country regression analyses, in alignment with Durlauf, Kourtellos and Tan (2008).

Second, trade openness exhibits a positive relationship with the level of both Theil wage inequality and Mincerian returns to education in numerous specifications, consistent with the conventional openness hypothesis.

Third, regressions analyzing the annual change of Theil wage inequality and the annual change of Mincerian returns to education generally lack explanatory power and do not yield robust results. Developing a more extensive dataset may enable the application of dynamic panel techniques to uncover more robust relationships.

Fourth, while Theil wage inequality and Mincerian returns to education are not identical, they are related. We find a positive relationship between returns to education and wage inequality, but this relationship is sensitive to population and the Latin America dummy.

Fifth, changes in wage inequality and changes in Mincerian returns to education exhibit a negative relationship. This finding can serve as evidence for Acemoglu (1998)'s theory that the "induced" increase in the relative demand for skills may even overshoot the increase in the relative supply of skills. This relationship warrants further investigation when a more complete dataset becomes available.

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