The Uncertainty of Academic Rent and Income Inequality: The OECD Panel Evidence

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Abstract: The paper presents an alternative view on the education – income inequality relationship, which calls into question the neoclassical claim that education increases labor productivity and hence contributes to a higher output, wage and consequently more even income distribution. In the context of public policies, education needs to be seen not only as a factor of income mobility, but also as a “positional good”, which benefits graduates at the expense of non-graduates. Education generates “academic rent”, by which we mean uneven remuneration of workers based on academic signs of distinctions that do not necessarily reflect differences in productivity. Using the robust panel model on a sample of OECD countries from 1980 to 2015, we show that investments in human capital lead to lower inequality, but overinvestments tends to increase income inequality, which may be related to academic rent. In discussing this result, we consider that uncertainty of academic rent under the condition of a rapid transformation of the workplace caused by the fourth industrial revolution.

Keywords: Academic rent, Income inequality, Uncertainty, Technological changes.

JEL: B52, I24.

Introduction

One of the key problems faced by developed countries over the last three decades is high and rising income inequality. Although there are divided opinions about the causes of deteriorating income distribution, there is more or less an agreement on how to improve income distribution.
Education is placed at the center of such academic and public debate. Backed by the dominant human capital theory, education is seen as a mechanism that not only improves individual welfare, but contributes to the welfare of the society.

However, it seems that the human capital theory approach fails the test of realism, since the developed countries are characterized by both high income inequality and high investments in education. It raises fundamental questions about the validity of this perspective, especially in the context of rising uncertainty in educational returns (academic rent), given the unpredictable impact of the fourth industrial revolution on the labor market.

1. Literature survey

The literature pertaining to the relationship between education and income inequality is large and growing, and includes a great variety of theoretical approaches, critiques and empirical studies, ranging from mainstream to radical perspectives. Therefore, here it is impossible to provide a comprehensive survey of different views and findings. Rather, we will focus on the neoclassical human capital theory, as a dominant approach, and its critiques from heterodox standpoints that inspire our research.

Considering the problem of poverty, John Kenneth Galbraith (1958; 1964) acknowledges the relevance of parts of both the neoclassical and the radical analyses, and emphasizes the central role of education, as a means of increasing individual capabilities and individual incomes (Dunn and Pressman 2005, 2006).

Since its appearance in the 1960s, human capital theory (Becker 1962; Schultz W. 1961) has been a dominant approach in understanding relationship between education and income that fits well with the market fundamentalism of neoliberal era (Klees 2008). The theory suggests that education increases the productivity of workers, which in turn leads to higher wages, since the wage is determined by the worker’s productivity (Marginson 1989). As a result, education is
seen as an investment that is not only crucial for individuals, but is also key to economic growth and the welfare of society (see, Barro, 1992; Keeley 2007).

Despite being the leading theory of education, few scholars from outside mainstream economics endorse human capital theory (Marginson 2017). Human capital theory rests on two core neoclassical paradigms: methodological individualism and agents’ rational action in making decisions (Bonal 2016), which are not immune to imperfections, therefore bounding human capital theory to imperfections as well (Tan 2014). The heterodox literature challenges this perspective by promoting the idea that the labor supply depends on many factors and is conditioned by the institutional and social context in which the individuals are embedded (Green 1992; Fernández-Huerga, García-Arias and Salvador 2017). Viewing production as a social, as well as a technical process, Samuel Bowles and Herbert Gintis (1975) argue that human capital theory is substantially misleading – it presents a very partial theory of production and does not offer the theory of reproduction at all. Considering the critiques of human capital theory that are discussed in the literature, Steven Klees (2016) point out three possible alternatives: human rights, human capabilities and human agency.

Since the pay-back period for human capital investment is longer, and results are more unpredictable than that of physical capital (Fontana and Srivastava 2009), the decision of an individual to invest in education is associated with uncertainty. Moreover, this uncertainty tends to increase as a result of changes in technologies, knowledges, and globalization (Galbraith 1977; Abbott 2005). In this context, special attention should be given to technological innovations, since they are an important source of the structural changeability of social reality, leading to fundamental uncertainty (Dequech 2011).

As our contribution to existing literature, we provide the empirical evidence on the relationship between income inequality and human capital. This evidence may provoke debate on the
uncertainty of benefits from education under the condition of rapid technological changes, which goes beyond neoclassical human capital theory.

2. Stylized facts and conceptual framework

Our conceptual framework is based on questioning the human capital theory’s assumption that education, productivity and income are in linear continuum (Marginson 2017). The claim that higher education drives higher productivity and wages leads to a justification for expanded investment in education as a mechanism which, more or less automatically, reduces income inequality. Education and hard work are seen as ways to create a fairer, and more efficient, society through the expansion of opportunity and upward social mobility.

Although human capital theory is widely accepted, it seems that the reality of the developed countries, manifested by parallel dynamics of educational expansion and rise in income inequality, does not perfectly fit into this mainstream model. Thus, average total enrolment in tertiary education in the OECD countries has increased more than 3 times over the period 1980-2015, whereas average market income inequality did not decrease. Moreover, income inequality rose about 1.2 times during the same period.

In considering the limitations of human capital theory, we note the specific role of technological changes, especially the distributional effects as a result of the concentration of innovations by corporate capital. A reduction of income inequality requires simultaneous improvements on both the supply side and demand side of the labor market. Automation and routinization of work tasks, as one of the key features of modern technological progress, devalues human capital acquired during education. Hence, automation reduces labor demand, while routinization hinders a worker’s creativity. Under these conditions, it may be expected that the supply of skilled workers, relative to unskilled workers, will gradually decrease, but in reality this ratio rises rapidly in favor of skilled workers.
Of the factors that can be associated with this phenomenon, special attention should be given to "mistaken identification". Based on the post-Keynesian perspective of uncertainty (Davidson 1991), we assume that, at the moment of choice, an individual's subjective probabilities regarding the future position of the labor market governs decisions on investment in education. These subjective probabilities do not necessarily coincide with objective probabilities, according to which past outcomes determine future decision. When assessing the benefits of education, an individual, as a rule and on average, identifies themselves with the good, rather than with the bad examples. Therefore, an individual makes the decision to enroll into faculty, even though the labor market signals the uncertainty of “academic premium” – an increase in earnings that is attributed to graduates over non-graduates.

An increase in the average level of human capital increases the total output to the point where there is a workplace that utilizes a more educated labor force. If there are no such jobs, additional education does not increase the total labor productivity. Since degrees are seen as a signal to employers of the qualities that workers had in order to get into a faculty, employers continue to hire workers with a degree rather than without degree. Education becomes a “positional good” that benefits graduates at the expense of non-graduates. Under the conditions of unchanged total labor productivity, the higher wage of skilled workers, relative to less-skilled workers, represents an “academic rent”. This leads to the conclusion that income inequality increases when the growth rate of highly educated workers is higher than the growth rate of total labor productivity.

Technological progress is a main driver of labor productivity, but its contribution to jobs creation is determined by dynamics of innovation and the spread of new technologies. Unlike the society that prefers democratization of innovations, in the sense that new technology becomes more available to all members of the society, corporate capital shows a preference to monopolize innovations (for more, see Josifidis and Supic 2018a, 2018b ). Thus, in 1981, the
average percent of gross domestic expenditure on research and experimental development (GERD) financed by government for 35 OEDC countries accounted for 44%, whereas in 2015 it had fallen to 27%. At the same time, the percent of GERD financed by the business enterprise sector rose from 52% in 1981 to 61% in 2015 (OECD 2018). As a result of this concentration of innovation by corporate capital, the rate of job creation is lower, and income inequality higher, than could be given the potential of new technologies.

There is another aspect of this problem that deserves a comment. Skill-biased technical change is a relatively new phenomenon. Prior to the third industrial revolution, technological changes were unskill-biased. Technological innovation over that period was mainly associated with the replacement of highly-skilled artisans by the combination of machines and lower-skill workers. The third industrial revolution changed this trend in favor of higher-skilled workers. It is difficult to predict which occupations will be most affected by the fourth industrial revolution. However, based on its current trajectory, it is possible to argue that well-paid jobs, intensive in cognitive skills, will also be endangered by new technological advancements. As a result, it seems that the logic of capital to replace a more expensive factor of production by a cheaper one will be more expressed, and call into question the certainty of academic rent in the future.

3. Empirical model and discussion

Based on the presented conceptual framework, we propose two hypotheses: (1) education increases the level of human capital and contributes to a more even income distribution, but overeducation increases income inequality, and (2) income inequality increases when the growth rate of highly educated workers is higher than the growth rate of total labor productivity.

The first hypothesis suggests a nonlinear relationship between income inequality and human capital, which is controlled by including a squared term for human capital measure in the model (HC). To test the second hypothesis, we construct a variable that depicts the ratio of total

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1 Innovation that shifts demand from less skilled workers to more educated workers.
enrollment in tertiary education, as a measure of education, to GDP per hour worked, as a measure of labor productivity, \((\text{EdProd})\).

The baseline model is written as:

\[
\log \text{Gini}_{it} = \beta_0 + \beta_1 \log \text{Gini}_{it-1} + \beta_2 \text{TFP}_{it} + \beta_3 \text{HC}_{it} + \beta_4 \text{HC}^2_{it} + \beta_5 \text{EdProd}_{it} + \beta_6 \text{FDI}_{it} + \beta_7 \text{MinWage}_{it} + \beta_8 \text{GNIpc}_{it} + \beta_9 \text{Emp}_{it} + u_t + e_{it}
\]

\(i = 1, 2, ..., N; t = 1, 2, ..., T\).

where subscript \(i\) stands for the country, \(t\) is the time period; \(\text{Gini}_{it}\) is inequality in market income, measured by the Gini index before taxes and social transfers, and \(\text{Gini}_{it-1}\) is its lagged value; \(\text{TFP}_{it}\) is total factor productivity, as a measure of technological progress; \(\text{HC}_{it}\) is human capital index; \(\text{EdProd}_{it}\) is tertiary education to labor productivity ratio; \(\text{FDI}_{it}\) is foreign direct investment outflow; \(\text{MinWage}_{it}\) is minimum wage setting regimes; \(\text{GNIpc}_{it}\) is gross national income per capita; \(\text{Emp}_{it}\) is employment rate; \(u_t\) represents time specific effects, and \(e_{it}\) is an idiosyncratic error term. Variable definitions, data sources and descriptive statistics are presented in Table 1 (Appendix).

The hypothesis is tested using unbalanced panel data from a sample of 35 OECD countries over the period 1980–2015. Given that income inequality is persistent over time, we prefer a dynamic to static model specification. The model is estimated using the system Generalized Method of Moments (GMM) estimation method (Arellano and Bond 1991).

The results of the baseline specification are shown in Table 1, and are consistent with our expectations. We will consider the results one by one. The estimated coefficient of \(\text{Gini}_{it-1}\) suggests that the current level of market income inequality is strongly positively determined by its previous level. This suggests that there is an inertia in income inequality dynamics in developed countries, which tends to maintain an unchanged income distribution, and opposes the effort and effects of redistributive policies.
Technological progress, measured by the total factor productivity index, is negatively associated with income inequality. This finding is in line with our conceptual framework, since technological progress is seen as a primary driver of labor productivity and job creation. What has a negative effect on income distribution is not technological progress in of itself, but the concentration of innovations that does not allow the full utilization of available human capital.

The effect of human capital on income inequality is statistically significant, but the relationship is not linear over the whole range of the human capital index. The minimum of this function is at $HC_it=2.9$, which is within range of the observed values of human capital index in our sample. This means that an increase in human capital reduces income inequality at a decreasing rate to human capital index below 2.9. However, further increases in human capital is accompanied by a worsening income distribution.

Figure 1 shows this relationship more clearly. As it can be seen, the findings strongly confirm the first hypothesis. The plot line first slopes downward, revealing the reducing influence of human capital on income inequality for low and middle levels of human capital, and then upward, indicating increasing effect of human capital on income inequality for very high levels of human capital.

The estimated coefficient of EdProd$it$ suggests that the faster growth in the number of highly educated workers, as compared to labor productivity, exacerbates income distribution. Although this result is consistent with the second hypothesis, the absolute amount of the effect does not seem to be strong.

The effects of FDI outflow and minimum wage settings are clear. Investments that go to other countries are pro-income inequality, as this outflow reduces the number of jobs in the domestic economy. A shift in in minimum wage settings towards a more rigid regime is anti-income inequality. Namely, the upward adjustment of minimum wage, which is typically associated with
more government interventions, distributes income to low-paid workers and improves income
distribution.

A somewhat surprising finding is that GNI per capita growth reduces income inequality,
implying that economic growth would raise the incomes of the poor. An explanation to this can
be found in famous Simon Kuznets’ hypothesis (1955), according to which at the low levels of
GDP/pc, inequality increases with rising GDP/pc, but that at the higher levels of GDP/pc,
further increases in GDP/pc is associated with declining inequality.

To demonstrate the robustness of our results, we performed extensive checks. First, the model is
re-estimated by excluding one country/year after another from the model². In this way, we make
sure that observed patterns are not caused by an outlier country or deviant year. Second, we
reduce the model to a parsimonious form that includes only statistically significant variables.
The robustness tests show that our results are robust to a variety of sensitivity analyses.

**Conclusion**

The reality of the OECD countries, manifested by a parallel increase in income inequality and an
expansion in high education, creates doubts about the validity of the human capital theory
assumption according to which education, productivity and income are seen in a linear way.
Given the social dimension of production, and the unpredictable impact of technological
changes on the labor market, workers are faced with an increasing uncertainty of academic rent.
This leads us to a hypothesis of the non-linear relationship between education and income
inequality, in which the turning point reflects the education/productivity ratio.

The results of the empirical analysis, based on panel data for OECD countries over the period
1980 – 2015, reveal the reduced influence of human capital on income inequality for low and
middle levels of human capital, while this effect is positive for very high levels of human capital.

² Constrained by a page limit, the result of this robustness test is available upon request.
We find that technological progress in of itself doesn’t have a negative effect on income distribution, and that the impact could be related to the concentration of innovations by corporate capital, which does not allow the full utilization of human capital. In a given condition, the faster growth in the number of highly educated workers, as compared to labor productivity, exacerbates income distribution. These results suggest that human capital theory provides a necessary, but not sufficient, framework to explain the real world complexity of the education – income inequality relationship in the OECD countries.
References


**Table 2** Income Inequality and Human Capital in OECD countries: The System GMM Estimates (1980–2015, Three-Year Averages)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Baseline Model (3-year averages)</th>
<th>(2) Parsimonious Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gini (lagged)</td>
<td>0.942***</td>
<td>0.929***</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>TFP</td>
<td>-0.356***</td>
<td>-0.366***</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.119)</td>
</tr>
<tr>
<td>HC</td>
<td>-1.068*</td>
<td>-0.927*</td>
</tr>
<tr>
<td></td>
<td>(0.571)</td>
<td>(0.562)</td>
</tr>
<tr>
<td>HC²</td>
<td>0.179*</td>
<td>0.155*</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.093)</td>
</tr>
<tr>
<td>EdProd</td>
<td>0.034**</td>
<td>0.032**</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>FDI</td>
<td>0.001***</td>
<td>0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>MinWage</td>
<td>-0.007**</td>
<td>-0.007**</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>GNIpc</td>
<td>-0.0212**</td>
<td>-0.022**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Empl</td>
<td>0.026</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.255)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.84</td>
<td>0.84</td>
</tr>
<tr>
<td>AR(1) (p-value)</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>AR(2) (p-value)</td>
<td>0.229</td>
<td>0.225</td>
</tr>
<tr>
<td>Hansen J-test (p-value)</td>
<td>0.770</td>
<td>0.565</td>
</tr>
<tr>
<td>Observations</td>
<td>289</td>
<td>293</td>
</tr>
<tr>
<td>Number of instruments</td>
<td>26</td>
<td>24</td>
</tr>
<tr>
<td>Countries</td>
<td>35</td>
<td>35</td>
</tr>
</tbody>
</table>

**Notes:** The variables: Gini, Gini (lagged). It is assumed that the variables: Gini (lagged), TFP, HC, GNIpc and Empl are endogenous, because causality may run in both directions simultaneously. Robust two-step standard errors are in parentheses. Level of significance: *** for p-value <0.01, ** for p-value <0.05, * for p-value p<0.1. AR(1): The Arellano–Bond test for the serial correlation. The null hypothesis is that there is no first-order autocorrelation in the first differences equation. AR(2): The Arellano–Bond test for the autocorrelation. The null hypothesis is that there is no second-order autocorrelation in the first differences equation. The Hansen J-test is used to test the null hypothesis of instrument validity and the validity of the additional moment restrictions required by the system GMM, respectively. To avoid the problem of instrument proliferation, the matrix of instruments is collapsed and the number of lags is limited at 2. GMM regressions are conducted using the xtabond2 package in Stata 14. **Source:** Authors’ calculation (2018). STATA 14 software.
**Figure 1** Income Inequality and Human Capital

![Graph showing the relationship between Log Gini Index and Human Capital Index with 95% Confidence Interval]

**Source:** Authors’ illustration (2018). STATA 14 software.

### Appendix

**Table 1 Variable Description (Three-Year Averages)**

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Source</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gini</td>
<td>Income inequality in market (pre-tax, pre-transfer) income</td>
<td>The world wealth and income database</td>
<td>405</td>
<td>2.97</td>
<td>0.31</td>
<td>1.52</td>
<td>3.45</td>
</tr>
<tr>
<td>TFP</td>
<td>Penn World Table 9.0</td>
<td>Total factor productivity (constant national prices)</td>
<td>398</td>
<td>0.94</td>
<td>0.12</td>
<td>0.50</td>
<td>1.51</td>
</tr>
<tr>
<td>HC</td>
<td>Penn World Table 9.0</td>
<td>Human capital index</td>
<td>398</td>
<td>3.03</td>
<td>0.44</td>
<td>1.51</td>
<td>3.73</td>
</tr>
<tr>
<td>EdProd</td>
<td>Labor force with tertiary education (% of total) to GDP per hour worked</td>
<td>World Bank - World Development Indicators, 2018 and OECD 2018,</td>
<td>360</td>
<td>1.89</td>
<td>0.97</td>
<td>0.08</td>
<td>7.19</td>
</tr>
<tr>
<td>FDI</td>
<td>Foreign direct investment, inward outflows (% of GDP)</td>
<td>World Bank - World Development Indicators, 2018.</td>
<td>372</td>
<td>3.52</td>
<td>7.88</td>
<td>-14.6</td>
<td>73.33</td>
</tr>
<tr>
<td>MinWage</td>
<td>Minimum wage setting</td>
<td>Quality of Government OECD dataset 2018</td>
<td>377</td>
<td>4.63</td>
<td>2.88</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>GNIpc</td>
<td>Gross national income per capita growth (annual %)</td>
<td>World Bank - World Development Indicators, 2018.</td>
<td>358</td>
<td>2.06</td>
<td>2.42</td>
<td>-6.21</td>
<td>11.32</td>
</tr>
<tr>
<td>Empl</td>
<td>Employment to population ratio</td>
<td>World Bank - World Development Indicators, 2018.</td>
<td>371</td>
<td>54.99</td>
<td>7.79</td>
<td>31.92</td>
<td>80.67</td>
</tr>
</tbody>
</table>