1. Introduction

The phenomenon of income inequality has become a widespread concern of economic thought in recent years. Income disparity analyses are not limited to Marxist or Keynesian economics anymore but are also intensively undertaken in mainstream economics. Most research in this area focuses on the consequences of the absolute level and dynamics of income inequality. Many scholars have attempted to explain the impact of the income distribution on economic processes through a variety of channels, including human capital (Galor, 2011a); political processes (Alesina and Rodrik, 1994; Acemoglu, 2003; Rajan and Zingales, 2006); incentives for working hard (Bell and Freeman, 2001; Kuhn and Lozano, 2008); physical capital accumulation (Kaldor, 1955), social capital (Alesina and Perotti, 1996; Uslaner and Brown, 2005; McKnight and Nolan, 2012), and most recently through financial stability channels (Fitoussi and Saraseno, 2010; Ranciere and Kumhof, 2010; Stiglitz, 2012; Tomkiewicz, 2012).

Although each of these problems provides many interesting research questions, the channel of human capital seems to require the most urgent inquiry. First of all, human capital is accepted by many as the main engine of economic development (Becker, 1994; Benhabib and Spiegel, 1994; Hanushek, 2013). Second, the theory behind income inequality and human capital relationships is well-grounded in economic thought. Nonetheless, this relationship is still not fully exploited in the empirical literature. Consequently, the aim of the present paper is to advance empirical research in this area and to provide evidence on the effects of income inequality on human capital accumulation in OECD countries.
The structure of the paper is as follows: Part 1 presents a theoretical background for the present inquiry. Part 2 focuses on empirical research methods, and Part 3 describes data sources and variable definitions. Part 4 presents the estimation results, followed by the conclusions.

2. Theoretical underpinnings

The most-prominent theoretical research on the interdependencies between income inequality and human capital was conducted by Galor (Galor and Zeira, 1993; Galor, 2011a, 2011b), who suggests that the impact of income inequality on human capital is clearly negative and stems from the fact that a high concentration of income and wealth empowers only a few to make human capital investments. While this is not a problem in the case of physical capital (as the high investments of a few rich individuals may compensate for the lack of these investments among the numerous poor), it makes an investment in human capital sub-optimal. Galor argues that individual human capital accumulation is subject to diminishing returns, as a human being’s capacity to learn is constrained by various physiological factors. Therefore, it is impossible for a few rich individuals to accumulate such a big stock of human capital that would compensate for the lack of human capital among the poor. The argument is at the core of the unified growth theory (Galor, 2011b), according to which income inequalities inhibit growth in those economies where human capital is the main engine of development.

Theoretically, the negative impact of wealth and income inequality on human capital can be mitigated by efficient credit markets, so that all individuals (including those poor) can borrow funds for investment. Under the conditions of perfectly competitive markets, it does not matter whether the investments in human capital are made from borrowed funds or from assets accumulated in previous periods. Economic reality shows, however, that there are significant market failures, particularly in the market of loans for human capital investments. The high costs of monitoring and difficulties in securing education loans boost the price of credit much above an efficient market price. As a result, many authors argue (Banerjee, 2004; Attanasio and Kaufmann, 2009; Kaufmann, 2014) that the costs of loans for education are so high that they discourage human capital investments.

Insufficient investments in human capital are undoubtedly offset by publicly subsidized schooling at all levels of education. This does not mean, however, that income inequalities do not play any role in countries offering such services free of charge, as individuals need to incur other types of expenses on human capital than tuition fees. The Polish example shows that, despite the large availability of public education offered, there are still significant constraints for investments in human capital among the poor. This is documented by, among others, educational
horizontal inequality (indicating the low share of students from poor families on
prestigious educational paths) and evidence of the impact of the financial situation
of a household on educational achievements (Herbst and Rok, 2014; Czarnecki,
2015; Rószkiewicz and Saczuk, 2015).

The mechanism described above is believed to be magnified by fertility dif-
ferentials between the poor and the rich (Becker et al., 1994; Dahan and Tsid-
don, 1998; De La Croix and Doepke, 2003). If poor families choose to have many
children (who will receive little education), then the supply of unskilled labor
will increase. Accordingly, this will further lower the wages of low-skilled workers
and hinder investments in human capital in the next generation. Such a conclu-
sion is based on the negative correlation between fertility and income, which
has been observed in the overwhelming majority of modern economies (Kremer
and Chen, 2002). Recent evidence shows, however, that this argument may lose
its significance, as the pattern of this relationship is rather U-shaped than linear.
This means that both poor and rich families decide to have more children than
middle-class households (Hazan and Zoabi, 2015).

The economic literature also indicates the indirect impact of inequalities on
human capital accumulation through the channel of social capital. Many scholars
argue that social capital reduces the investment costs of education, facilitating
the spill-over effects of human capital at the family and local community levels,
and provides additional incentives for education (Coleman, 1988; Schuller, 2001;
Piazza-Georgi, 2002; Acar, 2011). Thus, low social capital is believed to be a barrier
to the development of human capital (Wosiek, 2014). At the same time, there are
compelling theoretical and empirical arguments pointing to the negative impact
of income inequality on social capital, resulting from a lack of trust inherent to
unequal societies (Uslaner and Brown, 2005; Greiner et al., 2012) and from sta-
tus anxiety that pushes individuals to compete for status (Pickett and Wilkinson,
2009). Therefore, by hindering social capital, income inequalities are believed to
block the development of human capital.

All of the above arguments suggest the strong impact of income inequality
on human capital. In particular, it can be assumed that low income inequalities
tend to facilitate human capital accumulation and that an unequal distribution of
income is a barrier to the development of this production factor.

3. Empirical strategy

In order to verify the effects of income inequality on the accumulation of human
capital in OECD countries, estimates of the dynamic panel model were conducted.
The model was estimated by means of the System Generalized Method of Moments
(SGMM), a method developed by Arellano and Bover (Arellano and Bover, 1995).
This method was chosen for several reasons. First of all, theoretical considerations indicate that the accumulation of human capital depends on various factors, not just on income inequalities. Therefore, one should look for the appropriate control variables. Yet, some human capital determinants (such as institutional solutions in the educational sphere that determine the quality of the schooling system) are extremely difficult to measure. The lagged dependent variable may serve as a proxy for these determinants. The inclusion of such a variable among the regressors reduces the risk of omitted-variable bias; but at the same time, it gives concerns about the endogeneity of this variable. Moreover, the endogeneity problem also applies to other explanatory variables, which makes the static panel models the incorrect choice. In addition, the available data forms a short panel, which makes using a static model with fixed effects (as a solution to omitted-variable bias) inappropriate. Therefore, it seems reasonable to use SGMM, which was designed to address the above-mentioned econometric issues. SGMM combines equations based on variables in the first differences (where explanatory variables are instrumented with lagged values of those variables) with equations based on variables in absolute levels (which are instrumented with lagged first-differenced variables). Instrumenting explanatory variables allows us to reduce the problem of endogeneity. What is more, for short panels, SGMM is preferred to its sister method (FDGMM – First Difference GMM), as it increases the efficiency of estimation (Dańska-Borsiak, 2009, p. 30; Brzezinski, 2013, p. 14). Consequently, SGMM was chosen as an estimation method. To check the consistency of the SGMM estimator, the Sargan-Hansen test (testing the joint validity of instruments) and AR(2) test (testing if the error term is not second-order serially correlated) were conducted and reported.

The regression model of human capital inflow adopted in this paper is as follows:

\[ H_{i,t} = \alpha_1 H_{i,t-1} + \alpha_2 \text{Ineq}_{i,t-1} + \alpha_3 X_{i,t-1} + \eta_{i,t} \]  

(1)

where:

- \( H_{i,t} \) – inflow of human capital in \( i \)-country in \( t \) time period,
- \( H_{i,t-1} \) – inflow of human capital in \( i \)-country in \( t-1 \) time period,
- \( \text{Ineq}_{i,t-1} \) – income inequality in \( i \)-country in \( t-1 \) time period,
- \( X_{i,t-1} \) – set of control variables in \( i \)-country in \( t-1 \) time period,
- \( \eta_{i,t} \) – residual factor,
- \( \alpha_1, \alpha_2, \alpha_3 \) – regression equation parameters.

Set of control variables \( X_{i,t-1} \) includes additional determinants of human capital inflow, such as:

- \( \text{Dev}_{i,t-1} \) – GDP per capita in \( i \)-country in \( t-1 \) time period,
- \( \text{Edu}_{i,t-1} \) – Stock of human capital in \( i \)-country in \( t-1 \) time period,
- \( \text{Urban}_{i,t-1} \) – share of urban population \( i \)-country in \( t-1 \) time period.
Does income inequality hamper human capital accumulation in OECD countries

It is assumed that the effects of income inequality (and other variables) on human capital accumulation do not manifest year-to-year but over a longer period. Thus, the model is based on data divided into 5-year periods. The explanatory variables are delayed by one (5-year) period.

The independent variable in the model represents the inflow of human capital associated with the skills and competences of young generations. Modeling the inflow of human capital provides a way of omitting the issues related to changes in the stock of human capital associated with cohort differences and aging.

The model contains a set of control variables. Controlling the stock of human capital (i.e., aggregated human capital accumulated during previous periods) results from the recognition of positive externalities of human capital that facilitates further investment in this production factor (Barro, 1989; Azariadis and Drazen, 1990; Romer, 1993); meanwhile, controlling GDP per capita stems from theoretical findings that imply complementarities of human and physical capital and the importance of the demand for human capital that is greater in advanced economies (Caballé and Santos, 1993; Redding, 1996; Reinert, 2005, p. 7). Finally, including the urbanization variable in the model enables us to control the relatively high cost of education in countries that are sparsely populated. Including these control variables (next to the lagged dependent variable) increases the probability that the estimated coefficient of the inequality variable truly reflects the distributional effects and is not merely picking up another type of human capital determinant.

The specification of the regression equation is close to the related empirical research in this area. Perotti (Perotti, 1996), whose work is a pioneering attempt in this field, included among the control variables the level of economic development, the stock of human capital, and a dichotomous variable indicating poor countries. In turn, Battisti, Fioroni, and Lavezzi (Battisti et al., 2014) control only for the stock of human capital. In her attempt to estimate the impact of the inequality of education for human capital accumulation among the control variables, Castello-Climent (Castelló-Climent, 2010) included the stock of human capital, the level of economic development, the degree of urbanization, public educational expenditure, and a dichotomous variable indicating the least-developed countries. All of the above studies were based on cross-sectional data. The novelty of the present paper is, thus, the estimation of the income inequality – human capital relationship in the dynamic panel set.

4. Data sources

The present paper utilizes recent developments in human capital and income inequality indicators. First of all, the dependent variable is measured by the average adjusted test scores that were retrieved from the Global Education Achievement
World Bank Dataset (Angrist et al., 2013). Skills-test scores are believed to capture the human capital of young generations much better than purely quantitative measures such as enrollment rates. This is documented by, among others, a comparison of the growth regressions that use quantitative indicators of human capital with those using qualitative indicators. Such a comparison reveals that qualitative measurements of human capital are much better predictors of economic growth rates than measurements of school attainment (Hanushek, 2013, p. 8). Therefore, it is justified to believe that the use of *average adjusted test scores* reduces the measurement errors connected with the complex task of human-capital quantification.

Income inequality was measured by the Gini coefficient of net disposable income derived from the SWIID (Standardized World Income Inequality Database) developed by F. Solt (Solt, 2016). According to many authors, the SWIID provides the most-reliable data on income inequality (Ostry et al., 2014; Sequeira et al., 2017; Solt, 2015).

Measures representing other control variables include:

– the average number of years spent in formal education as a measurement of human capital stock (*Edu*), which was retrieved from the Barro and Lee dataset (Barro and Lee, 2013);
– the natural logarithm of GDP per capita in constant dollars from 2005 (*Dev*), retrieved from the World Bank dataset (World Bank, 2016);
– the percentage of the population living in cities as a measurement of urbanization (*Urban_pop*), retrieved from the World Bank (World Bank, 2016).

Due to data availability restrictions, the analysis was conducted for the time period of 1990–2010.

5. Estimation results

The estimation results suggest a statistically significant and negative impact of income inequalities on the accumulation of human capital (see Table 1 for the estimation results and robustness check). Estimate No. 1 shows that income inequalities help to explain the average test scores even when controlling for these scores achieved in the previous period. These results are not sensitive to the inclusion of other control variables (Estimation 3). Adding variables representing the level of development (*Dev*), stock of human capital (*Edu*), and share of the urban population (*Urban_pop*) does not significantly alter the results. All others being equal, high income inequality was, on average, accompanied by a lower inflow of human capital. This result is statistically significant and the SGMM estimation seems to be consistent, as indicated by Hansen-Sargan and the AR(2) tests.
Table 1
System GMM estimates of model (1) with robustness check to choice of instruments and outlier exclusion

<table>
<thead>
<tr>
<th>Sample</th>
<th>OECD</th>
<th>OECD</th>
<th>OECD</th>
<th>OECD</th>
<th>OECD (excluding Mexico, Chile, and Turkey)</th>
<th>OECD (excluding Mexico, Chile, and Turkey)</th>
<th>OECD (excluding Mexico, Chile, and Turkey)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sGMM (1)</td>
<td>sGMM (2)</td>
<td>sGMM (3)</td>
<td>sGMM (4)</td>
<td>sGMM (5)</td>
<td>sGMM (6)</td>
<td>sGMM (7)</td>
</tr>
<tr>
<td>Ineq t-1</td>
<td>-0.374*** (0.061)</td>
<td>-0.212** (0.098)</td>
<td>-0.268*** (0.100)</td>
<td>-0.333*** (0.104)</td>
<td>-0.219* (0.118)</td>
<td>-0.159 (0.140)</td>
<td>-0.247* (0.134)</td>
</tr>
<tr>
<td>H t-1</td>
<td>0.285 ** (0.112)</td>
<td>0.346*** (0.113)</td>
<td>0.285** (0.124)</td>
<td>0.291 ** (0.121)</td>
<td>0.321*** (0.114)</td>
<td>0.358*** (0.123)</td>
<td>0.291** (0.132)</td>
</tr>
<tr>
<td>Dev t-1</td>
<td>-</td>
<td>-</td>
<td>1.704* (0.924)</td>
<td>1.269 (0.9536)</td>
<td>-</td>
<td>-</td>
<td>0.855 (0.830)</td>
</tr>
<tr>
<td>Edu t-1</td>
<td>-</td>
<td>-</td>
<td>-0.373 (0.358)</td>
<td>-0.556 (0.389)</td>
<td>-</td>
<td>-</td>
<td>-0.636 (0.520)</td>
</tr>
<tr>
<td>Urban_pop t-1</td>
<td>-</td>
<td>-</td>
<td>0.004 (0.057)</td>
<td>-0.016 (0.069)</td>
<td>-</td>
<td>-</td>
<td>-0.003 (0.073)</td>
</tr>
<tr>
<td>Observations</td>
<td>181</td>
<td>181</td>
<td>179</td>
<td>179</td>
<td>168</td>
<td>168</td>
<td>166</td>
</tr>
<tr>
<td>Countries</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td>31</td>
<td>31</td>
<td>31</td>
</tr>
<tr>
<td>Instruments collapsed</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hansen-Sargan</td>
<td>0.268</td>
<td>0.152</td>
<td>0.999</td>
<td>0.522</td>
<td>0.412</td>
<td>0.099</td>
<td>0.661</td>
</tr>
<tr>
<td>AR (2)</td>
<td>0.795</td>
<td>0.915</td>
<td>0.772</td>
<td>0.777</td>
<td>0.844</td>
<td>0.880</td>
<td>0.777</td>
</tr>
</tbody>
</table>

Source: Author’s own research
Notes: *, **, and *** indicate statistical significance at the 10-, 5- and 1-percent levels, respectively. Robust standard errors in parentheses. Time dummies are included but not reported. Hansen-Sargan denotes the p-values of the Sargan-Hansen test of the over-identifying restrictions with the null hypothesis that the instruments are valid instruments. AR(2) denotes the p-values for second-order serial correlation with the null hypothesis that the error term is not second order serially correlated. Row ‘Instruments collapsed’ indicates whether horizontal squeezing of the instrument matrix was applied (see: [Roodman, 2009, p. 148]). All calculations made in R (R Core Team, 2015) with the use of the plm package (Croissant and Millo, 2008).
Estimations No. 2 and 4 provide a robustness check to the choice of instruments. As suggested in the econometric literature (Roodman, 2009) a large number of instruments may weaken the Sargan-Hansen test of instrument validity. This might especially be the case in Estimation 3, where adding a set of control variables increases the number of instruments and where the Sargan-Hansen test \( p\)-value is suspiciously high. Therefore, the instruments were collapsed (Roodman, 2009, p. 148), and the equation was re-estimated. As indicated in Columns 2 and 4, the results turned out to be insensitive to such a procedure; i.e., they suggest that income inequalities negatively influence human capital accumulation.

Among the OECD countries (which constitute the research sample of this paper), there are countries where income inequalities and educational test scores clearly stand out from the rest. In particular, Chile, Mexico, and Turkey are characterized by exceptionally high income inequalities (their Gini Indexes in 2005 amounted to 0.49, 0.46, and 0.40, respectively, while the average for the OECD was equal to 0.31). At the same time, these countries achieved the weakest educational test scores among all OECD countries (in 2010, Mexican students scored only 41.6 points, 42.3 points for students in Chile, and 47.7 points for those in Turkey, while the OECD average equaled 51.7 points). Therefore, one may suspect that the results of Estimations 1 through 4 were driven primarily by these countries. Thus, other estimations were conducted on a sample of OECD countries excluding Mexico, Chile, and Turkey. The results for the basic equation (Estimation 5) show that, although the estimated impact of income inequities on human capital accumulation is lower than in corresponding equation No. 1, it is still significant and negative. Similar conclusions can be derived from Estimation 7, where additional control variables are included. Only in Estimation 6 (where the instruments were collapsed) did the inequalities coefficient turn out to be statistically insignificant. It should be noted, therefore, that the sample restriction did not fundamentally determine the outcomes of the estimations; however, as it reduced cross-sectional variation in the data, it also weakened the results of the estimation.

6. Conclusions

Economic theory provides convincing arguments for the harmful effects of inequality in income distribution on human capital accumulation. The aim of the present paper is to verify these theoretical predictions in the sample of OECD countries during the years of 1990–2010.

Based on the research conducted in this paper, it can be concluded that the data confirms the theoretical findings and that income inequalities indeed
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constitute barriers for human capital accumulation. The estimation results show that, on average, high income inequalities precede a low inflow of human capital. The results do not change if the additional control variables that could potentially determine the pace of human capital accumulation are included. Income inequalities have proven to be better predictors of average adjusted test scores than the GDP per capita, average years of schooling, and share of urban population. These results are also robust with different instrument specifications. Through the use of the dynamic panel model, it was possible to mitigate the problems associated with the omitted variable bias and endogeneity of regressors. The results turned out to be modestly sensitive to the sample modifications. Exclusion from the sample of the most-unequal economies in the OECD (Chile, Mexico, and Turkey) did not change the direction of the estimated relationships between income inequalities and the inflow of human capital. Yet, these results tend to be weaker in such a limited sample size. On this basis, it is possible to indicate research areas for future work connected with further sample manipulation. In particular, it would be interesting to search for patterns of income inequalities, human capital, and economic growth relationships in groups of countries with inclusive and exclusive educational institutions, as this could possibly determine the direction and strength of these relationships.

References


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