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Education Expansion, Income Inequality and Structural Transformation: Evidence From OECD Countries

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Abstract

We study the relationship between educational inequality, income inequality and economic transformation using data of 20 OECD countries from 1870 to 2016. Our results show that educational expansion policies increase income inequality in the long run, while having no significant effect on the short run. The structural transformation suggested by Kuznets (1955) explains this potentially counter intuitive result, where contemporary policy, given its focus on the importance of increasing participation and expanding education, must be predicated on the notion that education expansion should decrease income inequality. We quantify the impact of educational inequality on employment in different sectors and find that education expansion promotes the structural transformation towards a higher wage disparity sector. Particularly, expanding education increases the employment in the service sector and reduces the employment in the agriculture sector. Overall, our findings suggest that educational expansion policies play an important role in economic development via promoting the structural transformation, though this leads to higher income inequality. That education expansion is ineffective in reducing income inequality, and instead exacerbates it in the long run, requires significant policy revision despite the popularity of such policies.

Keywords Economic transformation · Income inequality · Educational inequality

JEL Classification O15 · D31 · I24

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1 Introduction

Income inequality has long been a main concern for policymakers. Despite the absence of clear evidence on the effectiveness of education expansion[1] to reduce income inequality, it remains a major policy tool of governments within developed economies.[2] Political enthusiasm for such policies is to be expected as they are popular with voters, but beyond this point, the pursuit of these objectives suggests that governments, politicians and policy makers believe that the expansion of education to a wider audience will serve to address income inequality in some significant manner. These policies are also popular as they boost economic growth via structural transformation i.e. causing the movement of workers from a low productivity sector such as agriculture, to a high productivity sector like the service sector. However, this movement can exacerbate differences in the distribution of income as the income disparity of the former sector is low compared with the later (Kuznets, 1955).

The current literature provides mixed theoretical views and empirical evidence about the impact of educational inequality on income inequality. A portion of the literature (such as Becker and Chiswick, 1966; Knight and Sabot, 1983; Checchi, 2004) identifies support for a negative relationship between education expansion and income inequality. Their findings arguably are quite intuitive. One might logically assume that an expansion in education should give rise to a fall in income inequality. The widespread acquisition of education should raise skill levels within the economy and diminish differences in income that may have previously existed due to disparities in educational attainment. Furthermore, that the increase in the level of education required to complete jobs in an increasing technologically advanced and globalised world, requires a greater level of skills and formal qualifications than in the past.

While logically consistent, this perspective is subject to significant scrutiny. Colins (1979), posits that the most significant skills relevant to an occupation are learned on the job itself, and that education, rather than being necessary from a technical skills standpoint, instead represents a cultural capital tool through which, individuals compete for entry, position and power within organisations. Collins findings are consistent with earlier theory within labour economics relating to the signalling value of qualifications (Spence, 1978), which also suggests that education is not an indicator of occupational productivity, but rather a means to signal potential value and capabilities to an employer[3]. Collins states

[1] Education expansion and decreasing education inequality are used interchangeably based on an assumed a priori relationship. Expansionary education policies, which may impact all within society, though commonly target low participation groups, should cause an increase in participation and as such a decline in education inequality. While one is assumed to cause the other, depending on the context of the discussion we may either refer to education expansion (assumed to cause a decline in education inequality), or declining education inequality (an assumed product of expanding education). This relationship and the interchangeable terminology is consistent with similar literature in this area (Gregorio & Lee, 2002; Checchi, 2004; Castello-Climent and Doménech, 2014).

[2] In the UK the two most recent Labour party manifestos have pledged to remove university tuition fees on the basis that they limit participation, and therefore limit economic advancement, particularly for young people from poorer backgrounds. The same premise was a central policy promise of Bernie Sanders in his last two presidential bids in the US, which sought to make both junior colleges and state universities free. The enthusiasm for expanding participation in higher education is also prevalent across Europe, where low or zero fees are common. Where fees are still in place, the availability of cheap student loans are widespread in an attempt to ensure that cost does not prohibit participation.

[3] It should be noted that earlier research by Becker (1962) runs counter to both Collins and Spence as Becker proposes a more direct relationship between human capital accumulation and productivity.

that this misconstrued relationship between education and value within an occupation has led to credential inflation. This is where more people acquire education to meet the increasingly demanding criteria of employers, and in the process join a collectively more abundant population of qualified individuals. As a greater proportion of society become educated, the individual value of acquiring education may be expected to decline, though recent empirical evidence in the UK (O'Leary and Sloane, 2011) and US (Ashworth & Ransom, 2019) suggests the graduate wage premium has flattened, rather than declined. Research in the field of overeducation, serves as modern empirical evidence of the concerns raised by Collins. The growth of the so-called credential society has brought with it lower wages for mismatched employees[4] (Groot, 1996; Buchel and Mertens, 2004) and diminished job satisfaction and mobility for those who have failed to gain employment at a level commensurate with their education (Battu et al., 1999). It should be noted that the effects of the credential society expressed through the consequences of overeducation vary significantly across degree subject (Rossen et al., 2019). It is the variable returns to education across degree disciplines that might explain in part why income inequality increases with education expansion. While a greater portion of the population hold qualifications, significant returns may accrue to a small number of especially high skilled disciplines, thereby exacerbating income inequality for those outside of those fields of study.

Returning to the effects of education expansion on income inequality, both Ram (1984, 1989) and Castelló-Climent and Doménech (2014) find a positive relationship between education expansion and income inequality. Recently, Tasseva (2020) shows also that education expansion increases income inequality in Great Britain as high- and middle-income households receive a disproportionate fraction of income gains. Indeed, the positive nexus between education expansion and income inequality is more difficult to intuitively comprehend. They are not as immediately logically consistent compared to those proposing a negative relationship, and the evidence of a positive relationship contradicts contemporary education policy which is largely based around expanding education as a means of resolving income inequality. However, Kuznets (1955) stressed that there are at least two forces that lead to higher income inequality: a higher savings rate for higher earners, and the structural transformation towards sectors that have, inherently, a higher income disparity. Education expansion can lead to higher income inequality via the latter force. Figure 1, for example, shows a positive relationship between educational inequality and the employment share in the agriculture sector, while Fig. 2 shows a negative relationship between educational inequality and the employment share in the service sector, which may increase the income inequality. In this study, we examine the interdependencies between education expansion, income inequality and structural transformation.

We believe our findings contribute to the existing literature in two key areas. Most of relevant studies cited above and within the literature review are based on panel data and use static models such as OLS and fixed effect models, or dynamic panel models, particularly the GMM estimator. Unlike these approaches, we use an autoregressive distributed lag (ARDL) model, which allows us to distinguish between the short- and long-run relationship between educational inequality, income inequality and economic transformation. The intuition behind using this model is that the expansion of education can affect the structural transformation, and thereby the income distribution (Baymul & Sen, 2020), which is a long

[4] Mismatched in this context refers to gaining employment within an occupation for which your level of education is beyond that which is required for the job.

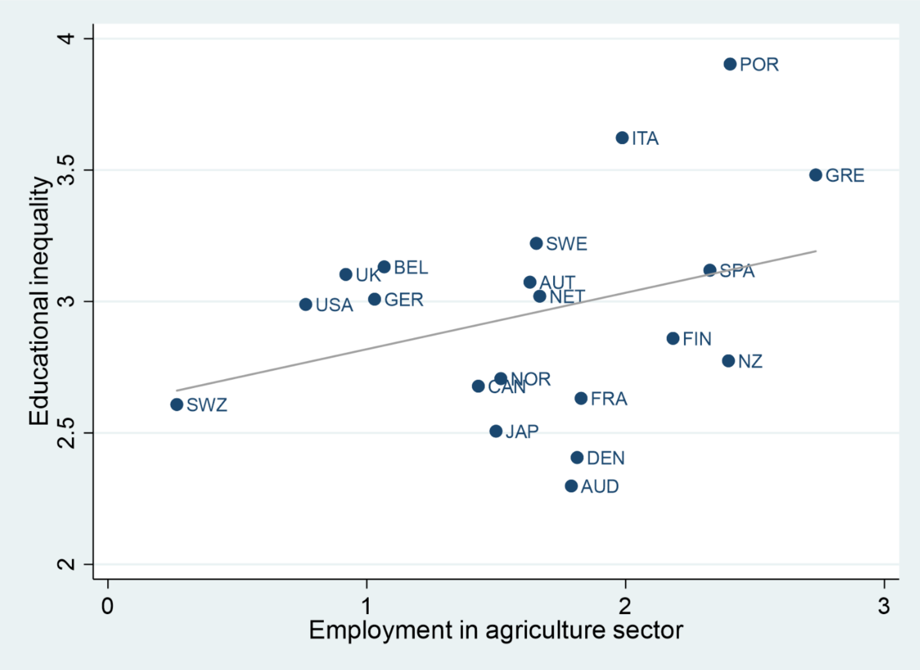

Fig. 1 Employment share in the Agriculture Sector (x-axis) and Educational inequality (y-axis) (averages over 1950–2016, in log)

run process. Effectively, while the much research has been conducted in this area, it has been produced using methodological approaches that do not consider the relative effects of education expansion between the short and long run. To estimate the long run relationship between educational inequality on income inequality, we collect data of 20 OECD countries over the period 1870–2016. Differentiating between the short and long run adds an additional layer of detail and granularity that is lacking from the existing research. Rather than ambiguously identify a positive or negative relationship between education inequality and income inequality, our approach considers the possibility that this relationship may not be static over time. Identifying either a consistent or variable relationship between the short and long run, may lead to wildly different policy implications from our results, thereby avoiding binary conclusions as to the efficacy of expansionary educational policies on income inequality.

Secondly, to the best of our knowledge, this is the first study empirical study of the trivariate of income inequality, education inequality and structural transformation, which is important to deepen our understanding of the impact of education expansion on income inequality. We use data of employment share in agriculture, industry and service sectors in these countries over the period 1950–2016 to investigate the structural transformation as a potential channel between educational inequality and income inequality in the long run. While a finding that structural transformation causing a migration of workers from primary to more advanced sectors of the economy is to be expected, our findings quantify this historical migration in a robust manner that may potentially give rise to a significant revision

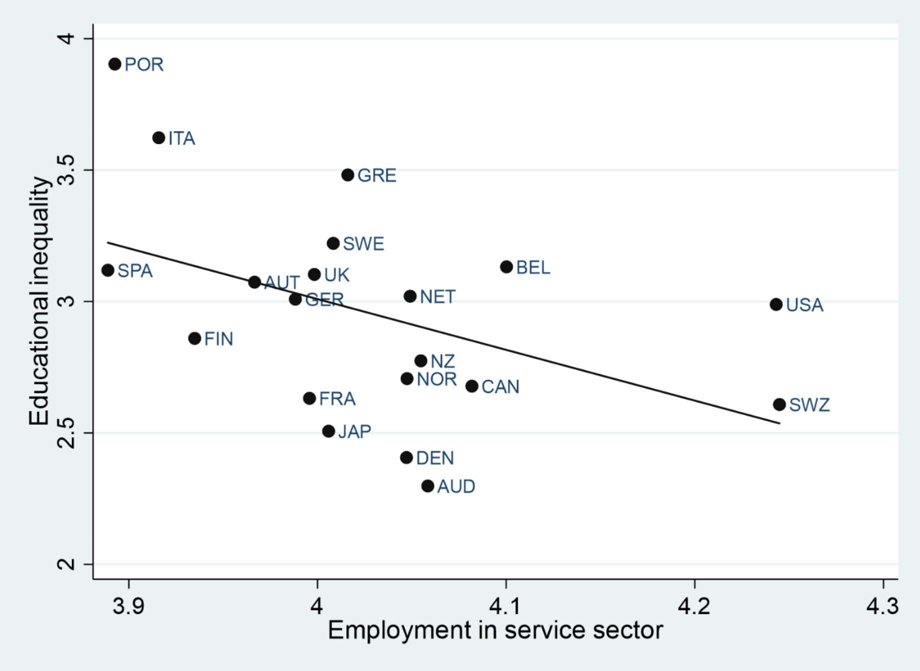

Fig. 2 Employment share in the Service Sector (x-axis) and Educational inequality (y-axis) (averages over 1950–2016, in log)

in this core element of education policy. The expansion of education is viewed as a major policy for the advancement of a series of economic objectives relating to development, increasing productivity and the reduction of poverty and inequality. Long term, quantifiable and robust evidence running counter to this assumption would represent a challenge to the policy trends within developed nations which tend to lean towards the expansion of education as a means to address poverty and inequality. Should the expansion of education, and the consequences with respect to structural transformation contribute to the increase in income inequality, then it is rigorous findings such as those we present that will be necessary to instigate a revised approach, where any change in policy will be challenging given the popularity of policies which promote education expansion. As before, the effects of structural transformation are differentiated between the short and long run, thereby providing a fuller overview for policy makers to consider when determining how to proceed with the expansion of education in the future.

Our empirical estimates indicate that while there is no significant relationship between education inequality and income inequality in the short run, there is a negative relationship in the long run. In practical terms this means that in the long run, the expansionary policies that have increased educational opportunities for a wider segment of the population, and as such decrease education inequality, have resulted in an increase in income inequality. Additionally, we find a negative impact of educational inequality on employment in the service sector and a positive impact in the agriculture sector in the long run which reasonably explains the negative long run impact of educational inequality on income inequality

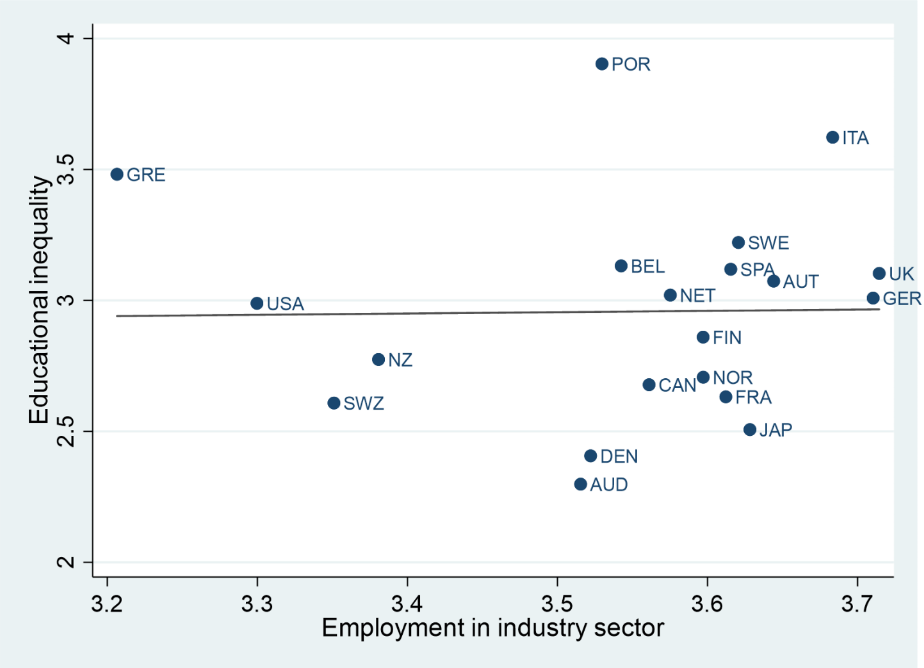

Fig. 3 Employment share in the Industrial Sector (x-axis) and Educational inequality (y-axis) (averages over 1950–2016, in log)

because the wage disparity, usually, is higher in the former compared to the later. These findings are robust using a different measure of education inequality, methods to deal with endogeneity, sub-periods and data frequency. Our results have significant implications, for evaluating and explaining the short and long run effectiveness of educational policies from a historical perspective, such as those relating to tuition fees, grants, lifelong learning schemes etc.

The paper is structured as follows: Immediately following the introduction is a review of relevant literature in this area. The next section summarises the data set used within our analysis, including definitions of the variables used, where necessary details of how variables were constructed/calculated and the presentation of summary and descriptive statistics. Following this is a discussion of the methodology, detailing the methods utilised in our empirical analysis. An empirical results section provides an econometric overview of our estimates, followed by a final discussion and concluding section that addresses the implications of our findings, limitations of our analysis and directions for future research.

2 Literature Review

The hypothesised impact of education expansion on income inequality is ambiguous. On the one hand, Knight and Sabot (1983) suggest that the expansion of education will initially lead to higher inequality due to the change in labour force composition i.e. the size of skilled workers cohort will relatively increase. Those acquiring education initially will be in the minority and as such will attain a wage premium relative to those who are less well educated, thereby initially exacerbating income inequality. The growing wage premium for educated labour will entice a greater number of individuals to participate in education, so they too can attain the greater wage premium. However, the growth in the supply of educated workers will inherently make educated individuals more common among the population and therefore less valuable. This will be reflected in a progressively declining wage premium for skilled workers in the long run which leads to a decline in income inequality. Graphically, the relationship between education inequality and income equality would take the form of an inverted U-curve, indicative of a Kuznets Curve. Since the empirical identification of this assumed relationship by Knight and Sabot (1983) other research has continued to examine this relationship. More recent studies, such as Rehme (2007), and Földvári and van Leeuwen (2014) have raised the issue of an evolving relationship between education inequality and income inequality over time. Rehme analyses the joint effect of education on growth and income equality, finding that an increase in education is initially characterised by an increase in income inequality, with a decrease following later in time. Rehme posits that this outcome is a function of the relationship between the interaction of human capital and production technology, stating that income inequality persists in part due to weak substitution between high and low skilled workers. In an environment where few have acquired the necessary level of education for better paying jobs, those who have will see their income increase. Those without education are not substitutable for those with higher levels of education and as such will see their income lag behind that of higher skilled workers, thereby resulting in growing inequality. Income inequality will however decline as the portion of the population becoming educated grows over time.

On the other hand, the dual sector model introduced by Lewis (1954) suggests that economic development is associated with movement of the workers from the agricultural sector, where the marginal productivity is zero and workers get equal wages, to a more productive, modern sector. Kuznets (1955) also illustrates the role of structural transformation toward higher income disparity sectors as main cause of higher income inequality. Education expansion can accelerate this shift and increase the income inequality as the wage disparity is higher in modern sector. Lin (2006) highlights how the expansion in higher education exacerbates income inequality due to a rising supply of educated workers. Tasseva (2020) confirms the positive impact of education expansion on wage disparity, and thereby income inequality. Galor and Moav (2004) rather than discussing the extent, to which differences in skills drive income inequality, present a theoretical model on the relationship between the movement from physical to human capital, and the impact this transition has on income inequality. In the early stages of the industrial revolution, physical capital was the prime driver of growth, giving rise to an increase in industrial sector jobs and instigating the migration of labour away from the agricultural sector as hypothesised by the dual sector model. This created inequality generally between owners of capital, but also between skilled and unskilled labour, as only productive workers were retained as the less productive are replaced by capital. As time progressed, human capital became a more prominent driver of growth. As human capital began to garner greater value, the incentive to invest in education grew, resulting in more educated individuals. Galor and Moav (2006), highlight that as the focus shifted from physical to human capital that it was in the interests of capital owners to promote policies relating to the free provision and expansion of education as the increase in educated workers increased productivity and therefore benefits capital owners. In this case, the wage premium, and thereby income inequality, tends to increase as the demand for educated workers grows faster than the supply (Atkinson, 2015). While focused on the transition from physical to human capital, this transition is effectively analogous to the changing relationship between income and education inequality over time.

The empirical studies also provide mixed evidence about the educational and income inequality nexus. While some studies suggest a positive association between income and educational inequality (Becker & Chiswick, 1966; Checchi, 2004; Rodríguez-Pose & Tselios, 2009; Checchi & van de Werfhorst, 2014), others find either a negative or insignificant impact of educational inequality on income inequality (Ram, 1984, 1989; De Gregorio and Lee, 2002; Castelló-Climent and Doménech, 2014, and Tasseva, 2020). Therefore, there is a need to further examine this relationship in an attempt to shed greater light on direction and extent of the effect between these two variables.

3 Data

This study is based on panel data covering 20 OECD countries over the period 1870–2016, to examine the dynamic relationship between educational and income inequality. This sample includes all OECD countries that have the required variables for our analysis. Table 1 presents the countries included in our sample.

The dependent variable is income inequality, proxied by the post-tax, post-transfer, i.e. net Gini coefficient. Higher values of this index indicate higher income inequality and is commonly used as a measure of inequality in the empirical literature (e.g., Gregorio and Lee, 2002; Checchi, 2004; Castelló-Climent and Doménech, 2014; Madsen et al., 2018). The index covers the entire spectrum of the income distribution, which is important to investigate the impact of education inequality on income disparity across different groups (Madsen et al., 2018).

Next, we follow the literature in the measurement of educational inequality. In particular, we use the Gini coefficient of educational inequality estimated from average education data using the method as suggested by Thomas et al. (2000), Checchi (2004) and Castelló-Climent and Doménech (2014) and Földvári and van Leeuwen (2014)[5]. The Gini coefficient of educational inequality measures the relative inequality of schooling distribution. It is a

Table 1 Sample of countries

Australia	Japan
Austria	Netherlands
Belgium	New Zealand
Canada	Norway
Denmark	Portugal
Finland	Spain
France	Sweden
Germany	Switzerland
Greece	United Kingdom
Italy	United States

[5] The Gini coefficient of educational inequality is calculated as, $G^h = \frac{1}{2\bar{H}} \sum_{i=0}^{3} 0 \sum_{j=0}^{3} 0 \left| \widehat{x}_i - \widehat{x}_j \right| n_i n_j$ Where $\bar{H}$ is average years of schooling in the population aged 15 and over, i and j are different levels of

superior measure of educational distribution than alternatives such as the standard deviation of schooling, which only measures dispersion in absolute terms (Thomas et al., 2000 op-cit). We do however utilise standard deviation of schooling in additional estimates to test the robustness of our findings. The Gini coefficient of educational inequality is also preferable to more simplistic measures such as enrolment ratios, and quality of education, both of which suffer from issues relating to measurement quality, availability of data and the ability to compare metrics over time.

We control also for GDP per capita, education attainment and trade openness as suggested by other studies such as Gregorio and Lee (2002), Checchi (2004), Földvári and van Leeuwen (2011). Furthermore, we consider other income inequality determinants such as R&D, as a proxy of technology, (Castelló-Climent, & Doménech, 2014), age dependency ratio (Checchi & van de Werfhorst, 2014), inflation and urbanisation (Coady & Dizioli, 2018). Finally, to assess the impact of educational inequality on structural transformation, we use the ratio of employment in agriculture, industry and service sectors over the period 1950–2016 from Szirmai (2017). This data is available from 1950 to 2016, however, for most countries the data is available until 2008. Therefore, we estimate this impact using WDI data over the period 1991–2016.[6] Appendix A provides details about the definitions and sources of our variables whilst Appendix B presents summary statistics.

4 Methodology

Several empirical studies test the relationship between education expansion and income inequality using static panel models, such as pooled OLS, or fixed and random effects models (see, for example, Checchi, 2001; Földvári and van Leeuwen, 2011, 2014; Castelló-Climent and Doménech, 2014). However, income inequality is highly persistent (see Delis et al., 2013) and these static models are unable to capture the dynamic nature of inequality which may lead to biased results. Additionally, these models do not differentiate between short and long run effects. Some studies employ dynamic GMM-type procedures (e.g. Teulings and Van Rens, 2008; Rodríguez-Pose and Tselios, 2009; Coady and Dizioli, 2018). Although these procedures can address the dynamic issue, they model only the short run. Furthermore, these procedures can lead to spurious results the number of cross sections (N), is relatively small compared with the number of years (T) (Roodman, 2006).

In this study, we specify a panel-based Autogressive Distributed Lag (ARDL) model as it allows for a separate distinction between short and long run effects. There are three estimators typically used in the literature (Pesaran et al., 1999; Asteriou & Monastiriotis, 2004; Samargandi et al., 2015) to estimate ARDL models; the mean group (MG), dynamic fixed effects (DFE), and pooled mean group (PMG). The main difference between them is their assumptions about the heterogeneity of short and long run coefficients. More specifically, Pesaran and Smith (1995) MG estimator allows all coefficients to be heterogeneous whilst DFE estimator assumes short and long run coefficients are homogenous across sections. The PMG estimator of Pesaran et al. (1999) is between these two extreme estimators as it

education, n_i and n_j are the shares of the population with a given level of education, and $\widehat{x}_i$ and $\widehat{x}_j$ are the cumulative average years of schooling at an education level.

[6] This data is available for short period but provides more observations for the last decade comparing with Szimai (2017).

assumes that the long run coefficients are homogenous across sections, but allows for heterogeneity in the short run coefficients. In this study, we focus on MG and PMG estimators as DFE is very restrictive i.e. assuming that the impact of educational inequality on income inequality is same across countries in both short and long run might be seen as a rather unrealistic assumption.

To test the impact of educational inequality on income inequality, we employ the following ARDL (*p*, *q*) approach as suggested by Pesaran and Smith (1995), Pesaran (1997) and Pesaran et al. (1999), where *p* and *q* are the lags of the dependent variable and the independent variables respectively:

$$\Delta Gini_{i,t} = \lambda_i \left[Gini_{i,t-1} - \{\beta_{i,0} + \beta_{i,1}X_{i,t-1}\}\right] + \sum\nolimits_{j=1}^{p-1}\theta_{i,j}\Delta Gini_{i,t-j} + \sum\nolimits_{j=0}^{q-1}\eta_{i,j}\Delta X_{i,t-j} + \epsilon_{i,t} \quad (1)$$

where $Gini$ is the Gini coefficient (in logs) for country *i* at year *t* and X is a group of candidate income inequality determinants including the educational Gini and other control variables (see data section, above). θ and η refer to the short run coefficients of the lagged dependent variable and the regressors respectively, while β represents the long run parameters. λ is the coefficient of speed of adjustment to the long run equilibrium. The first term on the right-hand side of Eq. (1) aims to capture any long run relationship between educational and income inequality. As the system is expected to return to the long run equilibrium, λ is expected to be negative and statistically significant.

We follow the same procedure to investigate the impact of the educational Gini on structural transformation, measured by the employment ratio by sectors. More superficially, we estimate the following ARDL (*p*, *q*) model;

$$\Delta SEmp_{i,t} = \gamma_i \left[SEmp_{i,t-1} - \{\alpha_{i,0} + \alpha_{i,1}X_{i,t-1}\}\right] + \sum\nolimits_{j=1}^{p-1}\vartheta_{i,j}\Delta SEmp_{i,t-j} + \sum\nolimits_{j=0}^{q-1}\varphi_{i,j}\Delta X_{i,t-j} + \xi_{i,t} \quad (2)$$

where $SEmp$ is the employment in agriculture, industry or service sector in country *i* at year *t*. The control variables in this model include educational attainment, GDP per capita and R&D.

We follow the literature (e.g. Samargandi et al., 2015 and Makhlouf et al., 2020) by using the Hausman test to compare and choose the most appropriate estimator. The null hypothesis of the Hausman test is that the difference between a pair of estimators is not significant and we employ a 5% level of significance. Finally, we impose an ARDL lag structure as follows; $p=1$ and $q=1$ (for all regressors) based on the Schwartz Bayesian criterion. In fact, this specification, $p=q=1$, is not surprising as it has been widely used in past studies that employ ARDL models to test a variety of economic issues (see for example, Li et al., 2016; Samargandi et al., 2015 and Makhlouf et al., 2020).

5 Empirical Results

Table 2 shows the results of estimating Eq. (1). The first part of the table presents the long run coefficients while the second shows the short run coefficients. The error-correction coefficients, λ, are negative and statistically significant at 1% level in both estimators which indicates that the null hypothesis (of no long run relationship) can be rejected. The Hausman

Table 2 Educational Inequality and Income Inequality (ARDL Models)

	(1)	(2)
	PMG	MG
Long-run coefficients		
Educational inequality	-0.050**	-0.292***
	(-2.37)	(-2.85)
Educational attainment	-0.233***	-0.593
	(-4.18)	(-1.22)
Real GDP per capita	-0.027	-0.013
	(-0.70)	(-0.13)
Urbanization	-0.212***	0.171
	(-2.64)	(0.45)
R&D intensity	0.00617	0.105***
	(0.29)	(2.90)
Trade openness	0.088***	-0.023
	(5.97)	(-0.70)
Age dependency ratio	-0.039	-0.074
	(-0.49)	(-0.34)
Inflation	-0.008***	-0.004**
	(-5.89)	(-2.30)
Short-run coefficients		
Error-correction coefficient	-0.052***	-0.196***
	(-4.05)	(-7.17)
Δ Educational inequality	-0.006	0.013
	(-0.42)	(0.48)
Δ Educational attainment	-0.157	-0.446
	(-1.22)	(-1.01)
Δ Real GDP per capita	0.067***	0.056***
	(3.31)	(2.97)
Δ Urbanization	0.409*	0.329
	(1.92)	(1.32)
Δ Trade openness	-0.006	0.000
	(-0.86)	(0.02)
Δ R&D intensity	-0.017**	-0.036***
	(-2.12)	(-5.35)
Δ Age dependency ratio	-0.091	-0.057
	(-1.11)	(-0.63)
Δ Inflation	0.000*	0.000***
	(1.71)	(2.73)
Constant	0.281***	1.061***
	(3.95)	(4.70)
Observations	2672	2672
Hausman test (p-value)	0.002	

Notes: *t*-statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The lag structure is $p=1$ and $q=1$ based on SBC. *p*-value represents the *p*-value of the Hausman test for poolability. PMG is more efficient estimation than MG under the null hypothesis

test assesses whether the PMG estimator is significantly different from the MG. Given the null cannot be rejected at 5% level, we might prefer the MG given it is efficient. Both estimators generate analogous results regarding the effect of educational inequality on inequality in both the short and long run, however we focus on the findings of MG estimator in this case.

Table 2 shows that the impact of educational inequality is statistically insignificant in the short run which indicates that education expansion is ineffective at impacting income inequality. The long run coefficient, on the other hand, suggests that educational inequality has a negative and statistically significant impact on income inequality. Additionally, the differential impact in the short and long run may explain the mixed evidence provided by relevant literature and illustrates the importance of distinguishing between the short and long run effects of educational inequality.

Our results reveal that the relationship between educational inequality and income inequality is insignificant in the short run. In practical terms this means that an expansion in education has no effect on income inequality in that time period. To an extent this is to be expected[7]: any change in education policy which gives rise to a change in educational inequality may be subject to an extended lag before the time which it begins to influence income inequality. For instance, a policy may seek to increase educational participation and attainment among underrepresented groups to decrease income inequality. One must consider that the policy may not yield immediate returns. It will take some time for participants to attain the higher level of education, with a further delay in individuals gaining suitable employment to the extent that income inequality declines between specific groups within society. Once suitable employment is attained, sticky wages set by contracts within institutions means that the short-term payment schedule for employees is fixed. This effectively prevents the extent to which significant progress in diminishing income inequality via wages attained through employment as a result of increased education is possible in the short run. This issue may persist even within environments where workers exercise collective bargaining rights via unions.

In the long run, the increase in income inequality, despite increasing education participation, may reflect substantial differences in the returns to education. For example, while most developed countries have seen increased participation in higher education, there exists considerable evidence of the different financial value of these qualifications, with substantial gaps by level and qualification. While society has become collectively more educated, the increase in inequality may reflect a concentration of higher returns among more valuable disciplines, studied by relatively few people.

An alternative explanation for our findings may be a function of the relationship between the comparative returns captured by labour relative to the returns from owning capital. The inequality observed may be in part a function of diverging wage premia among skilled and less skilled workers, but also as a result of the variable returns from output captured by labour relative to those who own capital. As Piketty and Zucman (2014) have shown, the rate of return to capital, held by a relatively smaller portion of the population, has grown over time. At the same time the educated population has grown, leading to a decline in the wage premium achieved among groups such as graduates. Simply, while owners of capital have seen their returns and wealth grow, educated labour have seen their premium from education decline. Beyond these potential explanations, the growth of the educated worker group can enhance the transformation towards more sophisticated, high wage disparity sectors such as the service sector. Of course, this transformation is a lengthy process.

[7] For instance, Castelló-Climent and Doménech (2014) Illustrate that the change in education between t and t+1 can lead to higher income, however the income of those with high education will increase as well in the same rate due to skill-biased technological change. Therefore, the income inequality does not change despite the reduction in educational inequality.

We will focus on this explanation later by testing the impact of educational inequality on the employment in different sectors.

Turning to the control variables, GDP per capita has a positive impact in the short run and a negative impact in the long run. However, the latter impact is statistically insignificant. These results support other studies such as Kuznets (1955) because economic growth increases income inequality and then decreases it by shifting labour from low productivity sectors to high productivity sectors (more recent studies of the relationship include, *inter alia*, Dollar et al., 2016 and Makhlouf et al., 2020). The effect of inflation is analogous with GDP impact given that both variables are usually positively associated (see Makhlouf et al., 2020). On the other hand, the impact of technology, as proxied by R&D, is negative in the short run and positive in the long run. Technology can lead to higher inequality in the long run via increasing the skill premium, which widens the wage gap between skilled and unskilled workers (Jaumotte et al., 2013) and the unemployment by increasing the use of labour-saving capital. The effects of the remaining control variables are statistically insignificant as suggested by recent studies such as Coady and Dizioli (2018) and Makhlouf et al. (2020).

The nexus between educational and income inequalities may present some time-variation. Therefore, our next exercise is to test the stability of this nexus over different time periods. To do so, we split our sample into two sub-samples before and after WWII (see Madsen et al., 2018 and Makhlouf et al., 2020). The results of the PMG estimator, the efficient estimator according to the Hausman test at the 5% level, confirm our previous findings i.e. insignificant impact of educational inequality in the short run and positive and significant negative impact in the long run (see Table 3). This shows that our findings are not sensitive to the choice of estimation period.

Moving on, we check the robustness of our main findings for using different lag structures. More specifically, we re-estimate our results presented in Table 2 using additional lags of dependent and independent variable i.e. $p=2$ and $q=2$. Note that although the lag structure, $p=1$ and $q=1$, is selected based on SBC and used in Table 2, allowing for more lags of the dependent and independent variable is a useful practice to check the robustness of our results to potential types of endogeneity (Pesaran et al., 1999). For example, some studies like Checchi (2001) illustrate that the causality can work in opposite direction i.e. higher income inequality can limit the access to education. To address this issue, we follow Checchi (2001) by using additional lag of the educational inequality. The new findings, see Table 4, show robustness of our results to using different model specifications.

We also test the robustness of our findings using a different measure of educational inequality by using the 3-year standard deviation of schooling years attained in the population age 15 and over (see Ehrlich and Kim, 2007). Additionally, we use 2SLS method as an alternative approach to test the robustness of our findings of reverse causality. We treat educational inequality, education attainment and real GDP per capita as endogens variables and use their first lag, we use also second and third lag lags, as instrumental variables (see Table 5). The findings confirm our previous results that educational inequality has a negative impact on income inequality.

Finally, the results in Table 5 not only show the robustness of our results of education inequality measurement and endogeneity but also for using 3-year observations. Using 3-year intervals reduces the degrees of freedom however it allows us to abstract somewhat from business cycle fluctuations (see Delis et al., 2013 and Makhlouf et al., 2020).

Table 3 Educational Inequality and Income Inequality (ARDL Models) Before and After the WWII

	Pre WWII		Post WWII	
	(1)	(2)	(3)	(4)
	PMG	MG	PMG	MG
Long-run coefficients				
Educational inequality	-0.076***	-0.376	-0.195***	-0.564*
	(-3.98)	(-1.06)	(-7.55)	(-1.67)
Educational attainment	-0.211***	-0.414	0.208	1.706
	(-6.27)	(-0.84)	(1.33)	(1.03)
Real GDP per capita	0.081***	0.137	-0.259***	-0.087
	(2.66)	(1.57)	(-4.61)	(-0.50)
Urbanization	-0.307***	1.815	-0.263**	2.001
	(-5.48)	(0.70)	(-2.11)	(1.63)
R&D intensity	0.101***	0.065**	0.111***	0.105*
	(5.08)	(1.96)	(3.49)	(1.68)
Trade openness	0.023***	-0.010	0.040***	-0.049
	(2.64)	(-0.41)	(2.64)	(-1.06)
Age dependency ratio	0.515***	0.962**	-0.288***	0.689
	(6.39)	(2.01)	(-4.03)	(0.82)
Inflation	0.000	-0.001*	-0.002**	0.149
	(1.02)	(-1.68)	(-2.02)	(0.95)
Short-run coefficients				
Error-correction coefficient	-0.277***	-0.443***	-0.097***	-0.285***
	(-2.87)	(-5.56)	(-4.10)	(-9.21)
Δ Educational inequality	-0.074	0.043	-0.008	0.068*
	(-0.82)	(0.27)	(-0.29)	(1.80)
Δ Educational attainment	-0.270	-1.455	-0.139	-0.200
	(-0.38)	(-0.84)	(-0.76)	(-0.33)
Δ Real GDP per capita	0.062**	0.040	0.090***	0.057
	(2.51)	(1.22)	(3.13)	(1.10)
Δ Urbanization	1.096**	0.419	-0.108	-0.069
	(2.48)	(0.64)	(-0.46)	(-0.14)
Δ Trade openness	-0.016	-0.005	-0.005	0.005
	(-1.42)	(-0.32)	(-0.88)	(0.43)
Δ R&D intensity	-0.053***	-0.054***	-0.007	-0.028*
	(-4.19)	(-5.14)	(-0.59)	(-1.90)
Δ Age dependency ratio	0.066	-0.519	-0.099	0.002
	(0.22)	(-1.56)	(-0.77)	(0.01)
Δ Inflation	0.001	0.000	0.001	-0.026
	(1.09)	(1.02)	(0.72)	(-1.00)
Constant	0.708***	-5.477	0.791***	0.240
	(2.90)	(-0.80)	(4.13)	(0.36)
Observations	1265	1265	1407	1407
Hausman test (p-value)	0.650		0.385	

Notes: *t*-statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *p*-value represents the *p*-value of the Hausman test for poolability. PMG is more efficient estimation than MG under the null hypothesis

Table 4 Educational and Income Inequality (ARDL Models), Different Lag Structures

	(1)	(2)
	PMG	MG
Long-run coefficients		
Educational inequality	-0.051**	-0.222***
	(-2.47)	(-3.00)
Educational attainment	-0.242***	-0.421
	(-4.41)	(-0.96)
Real GDP per capita	-0.038	-0.067
	(-0.96)	(-0.84)
Urbanization	-0.189**	0.014
	(-2.41)	(0.04)
R&D intensity	0.011	0.098***
	(0.52)	(2.98)
Trade openness	0.089***	-0.009
	(6.11)	(-0.39)
Age dependency ratio	-0.059	-0.133
	(-0.77)	(-0.81)
Inflation	-0.008***	-0.002
	(-5.81)	(-0.64)
Short-run coefficients		
Error-correction coefficient	-0.053***	-0.213***
	(-4.08)	(-7.58)
Δ Gini index (-1)	0.067*	0.081**
	(1.84)	(2.29)
Δ Educational inequality	-0.00549	0.012
	(-0.37)	(0.58)
Δ Educational inequality (-1)	0.007	0.013
	(0.21)	(0.38)
Δ Educational attainment	-0.173	-0.477
	(-1.26)	(-1.03)
Δ Real GDP per capita	0.066***	0.056***
	(3.19)	(3.28)
Δ Urbanization	0.364*	0.386
	(1.71)	(1.47)
Δ Trade openness	-0.006	-0.001
	(-0.82)	(-0.17)
Δ R&D intensity	-0.015*	-0.034***
	(-1.88)	(-5.18)
Δ Age dependency ratio	-0.075	-0.044
	(-0.91)	(-0.49)
Δ Inflation	0.000	0.000*
	(0.93)	(1.79)
Constant	0.299***	1.165***
	(3.99)	(5.44)
Observations	2652	2652
Hausman test (p-value)	0.04	

Notes: *t*-statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. p-value represents the p-value of the Hausman test for poolability. This estimation takes place over the whole sample period

Table 5 Educational and Income Inequality (2SLS) 3-observations

	(1)	(2)	(3)
Instrumental variables	one-year-lag	2-year-lag	3-year-lag
Educational inequality[a]	-2.170*	-2.629**	-2.572*
	(-1.92)	(-2.01)	(-1.75)
Educational attainment	-0.014	-0.020	-0.020
	(-0.55)	(-0.67)	(-0.58)
Real GDP per capita	-0.111***	-0.106***	-0.101***
	(-7.90)	(-7.01)	(-6.18)
Inflation	-0.000*	-0.000*	-0.000*
	(-1.75)	(-1.76)	(-1.74)
R&D intensity	0.050***	0.048***	0.047***
	(7.23)	(6.86)	(6.48)
Urbanization	-0.149***	-0.149***	-0.150***
	(-7.09)	(-7.00)	(-6.87)
Trade openness	0.005	0.004	0.003
	(0.88)	(0.73)	(0.49)
Age dependency ratio	0.273***	0.265***	0.252***
	(4.30)	(4.07)	(3.79)
Constant	3.994***	3.993***	4.000***
	(14.12)	(13.51)	(13.02)
Observations	877	857	837

t statistics in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$. [a] in this table we use the Gini coefficient of educational inequality as suggested by Thomas, Wang, and Fan (2000), Checchi (2004) and Castelló and Doménech (2002). The 2SLS model accounts for endogeneity of educational inequality, educational attainment and real GDP per capita. First-, second-, and third-year lag are used as instrument of these variables in columns 1, 2 and 3, respectively

In Table 6 we use 3-observations with our benchmark approach, ARDL Models, and also use 5-year intervals. All estimators generate analogous results regarding the effect of educational inequality on income inequality and these results support our annual observation findings (see Table 6).

6 Discussion and Further Results

Given the relationship identified between education inequality and income inequality, we must seek to find explanations for what we observe. In the long run, we observe that a decrease in educational inequality is associated with an increase in income inequality. As with the short run relationship, there are several possible reasons as to why this is the case, some of which were discussed earlier. In the case of the long run, we test the impact of educational inequality on employment in different sectors as a partial explanation for our long run findings. Kuznets (1955) illustrates that economic transformation can lead to higher economic growth yet higher income inequality as workers move from a low-income disparity sector such as the agricultural sector to a high- income disparity sector like the service sector (see Baymul and Sen, 2020). The expansion of education may accelerate the economic transformation thereby increasing income inequality in the long run.

Table 7 presents the results over the period 1950–2016. The results of PMG estimator, the efficient estimator according to Hausman test at 5% level, show that educational inequality

Table 6 Educational Inequality and Income Inequality (ARDL Models) 3- and 5-year observations

	3-year obs.		5-year obs.	
	(1)	(2)	(3)	(4)
	PMG	MG	PMG	MG
Long-run coefficients				
Educational inequality	-0.058***	-0.373**	-0.054***	-0.345**
	(-2.99)	(-2.47)	(-3.33)	(-2.44)
Educational attainment	-0.214***	-0.223	-0.205***	-1.481
	(-4.19)	(-0.26)	(-4.69)	(-1.29)
Real GDP per capita	-0.028	-0.011	0.007	0.249
	(-0.72)	(-0.10)	(0.23)	(0.98)
Urbanization	-0.087	0.119	-0.056	1.335
	(-1.23)	(0.28)	(-1.08)	(1.13)
R&D intensity	-0.012	0.071*	-0.039**	0.040
	(-0.59)	(1.89)	(-2.12)	(0.56)
Trade openness	0.093***	-0.052*	0.078***	-0.022
	(6.40)	(-1.82)	(6.55)	(-0.29)
Age dependency ratio	0.043	-0.053	-0.038	0.128
	(0.60)	(-0.22)	(-0.73)	(0.42)
Inflation	-0.014***	-0.004	-0.014***	-0.010**
	(-7.27)	(-1.54)	(-8.05)	(-1.99)
Short-run coefficients				
Error-correction coefficient	-0.144***	-0.548***	-0.259***	-0.962***
	(-4.23)	(-10.67)	(-3.95)	(-9.72)
Δ Educational inequality	0.043	0.121	0.073	0.272**
	(1.09)	(1.36)	(1.37)	(2.31)
Δ Educational attainment	-0.374*	-0.214	-0.359*	1.244
	(-1.70)	(-0.26)	(-1.75)	(1.12)
Δ Real GDP per capita	0.052	0.019	0.080*	0.043
	(1.45)	(0.50)	(1.66)	(1.10)
Δ Urbanization	0.237	0.600	0.304	0.682
	(1.20)	(1.42)	(1.35)	(1.17)
Δ Trade openness	0.002	0.022	0.000	0.053*
	(0.16)	(1.59)	(0.00)	(1.84)
Δ R&D intensity	-0.006	-0.029***	-0.013	-0.043**
	(-0.64)	(-3.18)	(-0.53)	(-2.01)
Δ Age dependency ratio	-0.156	-0.065	-0.176	-0.256
	(-1.48)	(-0.56)	(-1.31)	(-0.98)
Δ Inflation	0.001*	0.001*	0.002	0.002**
	(1.70)	(1.85)	(1.27)	(2.10)
Constant	0.679***	2.321***	1.170***	3.862**
	(4.17)	(3.97)	(3.88)	(2.02)
Observations	882	882	531	531
Hausman test (p-value)	0.007		0.994	

Notes: *t*-statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *p*-value represents the *p*-value of the Hausman test for poolability. PMG is more efficient estimation than MG under the null hypothesis

Table 7 Educational Inequality and Employment by Sectors (ARDL Models) 1950–2016

Employment in:	Agriculture		Industry		Service	
	(1)	(2)	(3)	(4)	(5)	(6)
	PMG	MG	PMG	MG	PMG	MG
Long-run coefficients						
Educational inequality, Gini	0.559***	0.806*	0.122**	0.447*	-0.078**	-0.299***
	(9.03)	(1.70)	(2.26)	(1.67)	(-2.53)	(-2.64)
Educational attainment	-1.764***	-2.049	-0.755***	1.042	-0.056	-0.006
	(-12.09)	(-1.45)	(-7.05)	(0.63)	(-0.41)	(-0.01)
Real GDP per capita,	-0.413***	-0.417	0.267***	-0.094	0.288***	0.153
	(-7.30)	(-1.02)	(5.39)	(-0.59)	(7.59)	(1.56)
R&D intensity	-0.062**	-0.072	-0.084***	-0.295	-0.051***	0.072
	(-2.50)	(-0.64)	(-3.75)	(-1.44)	(-3.94)	(1.60)
Short-run coefficients						
Error-correction coefficient	-0.172***	-0.383***	-0.093***	-0.222***	-0.119***	-0.307***
	(-5.11)	(-8.18)	(-3.84)	(-8.95)	(-4.20)	(-7.99)
Δ Educational inequality	0.278	0.183	0.004	-0.071	-0.023	0.031
	(1.58)	(1.02)	(0.06)	(-0.84)	(-0.66)	(0.88)
Δ Educational attainment	2.606	-1.873	0.835	0.327	0.257	0.536
	(1.27)	(-0.75)	(1.16)	(0.36)	(0.41)	(1.19)
Δ Real GDP per capita	0.261**	0.338**	0.318***	0.336***	-0.250***	-0.241***
	(1.98)	(2.34)	(4.57)	(4.39)	(-6.58)	(-5.64)
Δ R&D intensity	0.010	0.012	0.009	0.026*	0.013*	-0.008
	(0.28)	(0.36)	(0.83)	(1.84)	(1.91)	(-0.98)
Constant	1.360***	4.117***	0.179***	0.501*	0.190***	0.994***
	(5.00)	(3.73)	(3.68)	(1.73)	(4.42)	(3.25)
Observations	1157	1157	1157	1157	1157	1157
Hausman test (p-value)	0.97		0.18		0.07	

t statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *p*-value represents the *p*-value of the Hausman test for poolability. PMG is more efficient estimation than MG under the null hypothesis. Agriculture is the primary sector i.e. Agricultural, Forestry and Fisheries. The industry sector includes both manufacturing and non-manufacturing industry, the latter comprises of mining, utilities and construction. The services sector consists of the following sectors; trade, restaurants and hotels, transport, storage and communication, finance, insurance, real estate and business services and government services, community, social and personal services reduces the employment in service sector and increases the employment in both industry and agriculture sectors in the long run. These results support our conjecture that educational expansion can lead to higher income inequality by promoting the structural transformation toward higher wage disparity sector. These findings are in line with Tasseva (2020) which shows that education expansion exacerbates income inequality by raising the wage disparity. All control variables show the expected effect e.g. education attainment reduces the employment in both the agriculture and industry sectors whilst economic development, proxied by GDP per capita, increases (decreases) the service (agriculture and industry) sector share of employment in the long run. Technology decreases the employment in all sectors in the long run, which may reflect the impact of technological progress on labour-saving capital accumulation. Considering the limitation of this sectoral employment data over the last decade (see data section for more details), we use data of the employment share of these three sectors from WDI dataset over the period 1991–2016. The PMG is the efficient estimator according to Hausman test at 5% level. The results of this estimator confirm our previous findings. Particularly, that educational inequality has a negative effect on the employment in the service sector and positive impact on the employment in the agriculture sector in the long run, see Table 8.

Overall, our findings reflect a shift in employment across agricultural, industrial, and service sectors and the impact this has had over time. Before the widespread availability of education, the majority of people were working in the agricultural sector. Most people working in this sector combined with the low skills level required resulted in an equal, though low paid equality among many workers. With advances in technological development, combined with increasing availability of education, the sectoral composition of economies diversified to include more service sector jobs, requiring education, but offering higher real wages in return. In the pursuit of higher wages in the higher paying sectors, individuals acquired more education, thus causing migration between the sectors. As evidenced in Table 6, we can observe the impact of this migration as education levels increased. As people left the agricultural sector, we see inequality fall within the sector, reflecting an increased parity among those who remain within the sector, who likely are receiving better wages than before due to their relative scarcity and improvements in industrial agriculture. Conversely the migration of educated labour to the service sector has caused increased income inequality within such occupations. This could reflect vastly different returns to education within the sector based on education level and discipline, a finding consistent with aforementioned returns to education literature.

Several studies suggest that educational expansion can increase inequality of educational opportunities, which leads to higher income inequality (Raftery & Hout, 1993). For example, Haim and Shavit (2013) find that educational expansion enhanced the inequality of opportunity for both tertiary secondary education. For a deeper understanding of the effect of educational inequality on income inequality, we test whether the level of inequality of educational opportunities exacerbates this effect[8]. The main challenge of this exercise is to find an appropriate measure of inequality of educational opportunities. We address this challenge by using the degree of intergenerational mobility. A growing strand of literature shows that the degree of intergenerational (im)mobility can capture inequality of opportunity (see Aiyar and Ebeke, 2020).

[8] We thank our anonymous reviewer for this important point.

Table 8 Educational Inequality and Employment by Sectors (ARDL Models) 1991–2016 (WDI data)

Employment in:	Agriculture		Industry		Service	
	(1)	(2)	(3)	(4)	(5)	(6)
	PMG	MG	PMG	MG	PMG	MG
Long-run coefficients						
Educational inequality, Gini	0.170***	1.408	-0.033	0.032	-0.015***	-0.017
	(7.78)	(1.13)	(-0.94)	(0.34)	(-2.68)	(-0.77)
Educational attainment	-1.256***	3.996	-2.670***	-1.915**	0.030	0.446***
	(-9.58)	(0.88)	(-11.64)	(-2.39)	(0.81)	(3.80)
Real GDP per capita,	-0.317***	-0.932*	0.253***	0.093	0.093***	0.019
	(-6.83)	(-1.82)	(5.44)	(0.74)	(7.86)	(0.45)
R&D intensity	-0.120***	0.973	0.051	-0.042	0.030***	0.009
	(-4.22)	(0.91)	(1.28)	(-0.60)	(3.35)	(0.61)
Short-run coefficients						
Error-correction coefficient	-0.222***	-0.557***	-0.0825**	-0.438***	-0.124***	-0.379***
	(-5.02)	(-10.23)	(-2.15)	(-4.82)	(-4.17)	(-6.09)
Δ Educational inequality	-0.028	-0.041	0.040	-0.036	0.001	0.021*
	(-1.26)	(-0.56)	(0.53)	(-0.92)	(0.56)	(1.68)
Δ Educational attainment	-0.009	-0.266	0.490	1.229	-0.007	-0.248**
	(-0.02)	(-0.38)	(0.94)	(1.23)	(-0.12)	(-1.98)
Δ Real GDP per capita	0.052	0.258***	0.181***	0.089	-0.072***	-0.042***
	(0.79)	(2.66)	(5.39)	(1.45)	(-5.10)	(-3.23)
Δ R&D intensity	-0.059	-0.075	-0.005	0.010	0.003	-0.001
	(-1.15)	(-1.31)	(-0.63)	(0.72)	(0.95)	(-0.14)
Constant	1.460***	3.205***	0.445**	0.944**	0.104***	0.562*
	(4.91)	(3.99)	(2.06)	(2.02)	(4.32)	(1.80)
Observations	488	488	488	488	488	488
Hausman test (p-value)	0.81		0.26		0.08	

Notes: *t*-statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *p*-value represents the *p*-value of the Hausman test for poolability. PMG is more efficient estimation than MG under the null hypothesis

We use two indices of intergenerational mobility (with higher values corresponding to less mobility) from the Global Database on Intergenerational Mobility (GDIM). The GDIM offers more than one observation per country by estimating intergenerational mobility (IGM) in education by 10-year cohorts, covering individuals born between 1940 and 1989. The first index (denoted CAT) measures the share of respondents that have attained a higher educational category than their parents, conditional on the parents not having obtained tertiary education, such that all included individuals have a chance of surpassing their parents.

The second index, denoted YOS, measures the share of respondents with greater years of schooling completed than their parents, conditional on parents not having obtained the highest year of schooling observed in the sample (see Van der Weide et al., 2021). Whilst some studies use father-son observations, we use parents average-all children observations for a more comprehensive measure of intergenerational mobility. We follow other studies such as Aiyar and Ebeke (2020) by using the average of all 10-year cohorts by country. Given that Intergenerational Mobility indices are time invariant, their impact will be fully absorbed by the country fixed effects. To address this issue, we classify the countries into two groups, high and low mobility, based on the average of these indices, and re-estimate the effect of educational inequality on income inequality on these two groups.

According to aforementioned discussion, we expect that the effect will be stronger on low mobility group. The results in Table 9 show that educational inequality has a stronger impact on income inequality on the low mobility group comparing with the high inequality group i.e. the inequality of educational opportunities exacerbates the impact of educational expansion on income inequality.

7 Conclusion

Inequality in any form is a natural and not completely avoidable outcome of a competitive environment. Income inequality has received much attention, as have the potential methods for addressing and minimising this issue that has widespread knock-on effects that impact other socially important factors such as crime and health within a given area. Despite the many negatives that come with a degree of inequality, it is not strictly a negative. The opportunity to earn more, and in the process create an inequality in income relative to others, acts as an incentive for economic development, either individually or on a larger scale from a business perspective. Despite the inevitability of inequality in a competitive environment, income inequality is ultimately perceived as socially harmful and it is in part the responsibility of government to attempt to reduce its presence. Education is viewed as one of main tools for addressing income inequality. By educating more people it enhances occupational opportunities and social mobility across society, and in theory should result in a decline in income inequality as the availability and consumption of education increases. Conversely, an increase in educated individuals leads to higher income inequality by incentivising the migration of skilled workers to more sophisticated sectors which, are characterised by greater wage disparities. Our findings support the second hypothesis. Specifically, we employ panel ARDL model on a sample of 20 OECD countries over the period 1870–2016 to estimate the short and long run effect of education inequality on income inequality. Our estimates indicate that in the short run, expanding education yields no statistically significant effect on income inequality, while causing an increase in income inequality in the long run. We find also that education inequality reduces the employment in the service sector while it raises the employment in the agriculture sector which explains the negative effect of educational inequality on income inequality as the wage disparity is higher in the former sector. While the aforementioned relationship between expanding education, structural transformation and income inequality has been hypothesised before in earlier literature, it is despite this assumed relationship, that the countries within our sample have largely pro-

Table 9 Educational Inequality and Income Inequality, different level of Mobility

	High Mobility		Low Mobility	
	(1)	(2)	(3)	(4)
	CAT	YOS	CAT	YOS
Long-run coefficients				
Educational inequality, Gini	-0.199**	-0.186*	-0.433**	-0.399**
	(-2.23)	(-1.74)	(-1.97)	(-2.28)
Educational attainment	-0.902*	-0.827	-0.129	-0.358
	(-1.78)	(-1.37)	(-0.13)	(-0.45)
Real GDP per capita	-0.027	-0.031	0.008	0.0042
	(-0.27)	(-0.26)	(0.04)	(0.02)
Urbanization	0.457	0.364	-0.259	-0.022
	(0.75)	(0.50)	(-0.94)	(-0.08)
R&D intensity	0.116**	0.105**	0.089	0.105*
	(2.45)	(2.27)	(1.49)	(1.80)
Trade openness	-0.003	0.004	-0.053	-0.050
	(-0.13)	(0.14)	(-0.70)	(-0.83)
Age dependency ratio	-0.367	-0.472	0.365	0.324
	(-1.37)	(-1.52)	(1.15)	(1.27)
Inflation	-0.002*	-0.003*	-0.005	-0.005*
	(-1.92)	(-1.72)	(-1.55)	(-1.66)
Short-run coefficients				
Error-correction coefficient	-0.206***	-0.201***	-0.181***	-0.190***
	(-5.01)	(-4.11)	(-5.62)	(-6.97)
Δ Educational inequality, Gini	0.000	0.014	0.032	0.012
	(0.00)	(0.29)	(1.47)	(0.47)
Δ Educational attainment	-0.0395	0.106	-1.055	-0.997
	(-0.13)	(0.37)	(-1.05)	(-1.22)
Δ Real GDP per capita	0.066***	0.055***	0.0410	0.0564*
	(3.41)	(2.86)	(1.07)	(1.69)
Δ Urbanization	0.355	0.462	0.289	0.195
	(1.07)	(1.18)	(0.73)	(0.61)
Δ Trade openness	0.003	0.006	-0.004	-0.005
	(0.22)	(0.36)	(-0.56)	(-0.96)
Δ R&D intensity	-0.032***	-0.032***	-0.041***	-0.040***
	(-3.65)	(-2.97)	(-3.86)	(-4.74)
Δ Age dependency ratio	-0.053	0.016	-0.063	-0.131
	(-0.55)	(0.17)	(-0.35)	(-0.85)
Δ Inflation	0.000***	0.000**	0.000	0.000*
	(2.61)	(2.29)	(1.52)	(1.77)
Constant	1.149***	1.256***	0.928***	0.865***
	(3.53)	(3.27)	(3.06)	(3.56)
Observations	1626	1385	1046	1287

t statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

ceeded with policies that increase education expansion, and therefore exacerbate income inequality through the channel of structural transformation.

Our findings raise some serious questions regarding the conventional wisdom of using education as one of the primary methods for addressing income inequality. A multitude of policies geared towards increasing educational participation and attainment have been utilised in developed countries to improve inequality within society. Our findings directly contradict the prevailing wisdom of this approach. Our results should serve as a major contribution to the literature in that they directly challenge the current educational policy trajectory of many developed countries. What we have identified not only provides evidence that their current approach to education is ineffective in diminishing income inequality, but that a policy revision is necessary to stop the continuing compounding of this problem. This will be especially challenging for governments to address due the prior acknowledgement that expanding educational is very popular, and even the mere mention of limiting access is dreadfully unpopular with the electorate. Governments will be faced with a delicate trade-off in balancing their desire to address the social consequences that come with growing income inequality, while not sacrificing the economic growth that has occurred during the same period.

We believe that our findings reveal two key points that should be considered by policy makers when devising educational policy as a means of addressing income inequality. In the first instance, policy makers should be aware that the expansion of education will not serve as a quick fix for income inequality. As our findings indicate, the relationship between expanding education and income inequality in the short run was insignificant. Therefore, neither policy makers nor the electorate should be seduced by populist options relating to the rapid expansion of education as an immediate cure all to disparities between rich and poor within society. Secondly, our findings indicate that the current means in which education expansion policies are utilised is having the opposite of the desired effect with regards to income inequality. Our solution is not to argue for a wholesale reversal of current policies but rather for a re-evaluation of existing initiatives and the consideration of supplementary policy, both within and outside education to help address income inequality. Revisions to current policy could focus not only on expanding education, but also diversifying the type of education made available to potentially avoid the bottlenecking of individuals into similar types of education (i.e. the excessive number of university graduates), which diminishes the returns to education one can attain, and thereby the extent to which education can address inequality. Diversification could take the form of reinvestment into other forms of post-secondary education which are at times underfunded relative to higher education, such as tertiary education aimed at vocations. Diversification of education alone is unlikely to suffice in properly addressing inequality but could be combined with the expansion of other policies that seek to minimise inequality such as the expansion of the minimum wage or revisions in progressive taxation. The combined effectiveness and the interaction of these policies in addressing income inequality falls outside the remit of this paper.

Appendix

Appendix A Data sources

Variable	Definition	Source
Gini	The post-tax, post-transfer Gini coefficient	Madsen et al. (2018), and Solt (2019) (after 2011)
GDP per capita	Real GDP per capita	Madsen and Ang (2016) and WDI (after 2009)

Appendix A Data sources

Variable	Definition	Source
Inflation	The change in Consumer Price Index	Coppedge et al. (2018), Jordà et al. (2017) and WDI (after 2010)
openness	The sum of imports and exports to GDP ratio	Churchill et al. (2018) and WDI (post 2014)
Age dependency ratio	Age dependency ratio computed as the fraction of the population outside working age (15–64)	Madsen et al. (2018) and WDI (after 2011)
Urbanization	Ratio of people living in urban areas to overall population	Coppedge et al. (2018), UN World Urbanization Prospects 2018 (post 2000) and National Material Capabilities
Educational attainment	Years of education for the population of working age	Madsen et al. (2018) and Human Development Reports (after 2011)
Educational inequality	Gini coefficient of educational inequality estimated from average education data	Coppedge et al. (2018), and Human Development Reports (after 2010)
R&D	The ratio of R&D to nominal GDP	Madsen et al. (2018) and OECD: Main Science and Technology Indicators (after 2011)
Employment in industry	The industry sector includes both manufacturing and non-manufacturing industry, the latter comprises of mining, utilities and construction.	Szirmai (2017)
Employment in service	The services sector consists of the following sectors; trade, restaurants and hotels, transport, storage and communication, finance, insurance, real estate and business services and government services, community, social and personal services	Szirmai (2017)
Employment in agriculture	Agriculture is the primary sector i.e. Agricultural, Forestry and Fisheries.	Szirmai (2017)
Employment in industry WDI	The share of people working in industry sector to overall employment	WDI
Employment in service WDI	The share of people working in service sector to overall employment	WDI
Employment in agriculture WDI	The share of people working in agriculture sector to overall employment	WDI

Appendix B Summary Statistics

	Obs.	Mean	S.D
Net Gini coefficient (in log)	2692	3.469	0.229
Educational inequality, Gini (in log)	2693	2.964	0.613
Educational attainment (in log)	2693	1.992	0.479
Real GDP per capita (in log)	2693	9.331	0.895
Urbanization (in log)	2693	3.403	0.379
R&D intensity (in log)	2693	-0.409	1.391
Trade openness to GDP (in log)	2693	-2.800	1.821
Age dependency ratio (in log)	2693	4.025	0.132
Inflation	2693	6.441	56.261
Employment in agriculture (in log)	1177	1.678	0.869
Employment in industry (in log)	1177	3.551	0.206
Employment in service (in log)	1176	4.021	0.189
Employment in industry (in log) WDI [a]	508	1.391	0.076

Appendix B Summary Statistics

	Obs.	Mean	S.D
Employment in agriculture (in log) WDI [a]	508	0.592	0.285
Employment in service (in log) WDI [a]	508	1.844	0.041

[a] The source of this data is WDI and available form 1991 to 2016.

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Declarations

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References

Aiyar, S., & Ebeke, C. (2020). Inequality of opportunity, inequality of income and economic growth. *World Development*, *136*, 105115.

Ashworth, J., & Ransom, T. (2019). Has the college wage premium continued to rise? Evidence from multiple US surveys. *Economics of education review*, *69*, pp.149–154.

Asteriou, D., & Monastiriotis, V. (2004). What do unions do at the large scale? Macro-economic evidence from a panel of OECD countries. *Journal of Applied Economics*, *7*(1), 27–46.

Atkinson, A. B. (2015). *Inequality: What can be done?* Harvard University Press.

Battu, H., Belfield, C. R., & Sloane, P. J. (1999). Overeducation among graduates: a cohort view. *Education economics*, *7*(1), pp.21–38.

Baymul, C., & Sen, K. (2020). Was Kuznets right? New evidence on the relationship between structural transformation and inequality. *The Journal of Development Studies*, *56*(9), 1643–1662.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of political economy*, *70*(5, Part 2), pp.9–49.

Becker, G. S., & Chiswick, B. R. (1966). Education and the distribution of earnings. *The American Economic Review*, *56*(1/2), 358–369.

Castelló-Climent, A., & Doménech, R. (2002). Human capital inequality and economic growth: some new evidence. *The Economic Journal*, *112*(478), C187-C200

Castelló-Climent, A., & Doménech, R. (2014). Human capital and income inequality: Some facts and some puzzles. Retrieved from BBVA Research https://www.bbvaresearch.com/wp-content/uploads/migrados/WP_1228_tcm348-430101

Checchi, D. (2001). Education, inequality and income inequality. LSE STICERD Research Paper, (52).

Checchi, D. (2004). Does educational achievement help to explain income inequality?. Inequality, growth and poverty in an era of liberalization and globalization.

Checchi, D., & van de Werfhorst, H. (2014). Educational policies and income inequality.

Churchill, S. A., Inekwe, J., Ivanovski, K., & Smyth, R. (2018). The environmental Kuznets curve in the OECD: 1870–2014. *Energy Economics*, *75*, 389–399.

Coady, D., & Dizioli, A. (2018). Income inequality and education revisited: Persistence, endogeneity and heterogeneity. *Applied Economics*, *50*(25), 2747–2761.

Collins, R. (1979). *The credential society: An historical sociology of education and stratification*. Columbia University Press.

Coppedge, M., Gerring, J., Knutsen, C. H., Lindberg, S. I., Skaaning, S. E., Teorell, J., & Stepanova, N. (2018). V-Dem Organization and Management V8.

Delis, M. D., Hasan, I., & Kazakis, P. (2013). Bank regulations and income inequality: Empirical evidence. *Review of Finance*, *18*(5), 1811–1846.

Dollar, D., Kleineberg, T., & Kraay, A. (2016). Growth still is good for the poor. *European Economic Review*, *81*(C), 68–85.

Ehrlich, I., & Kim, J. (2007). The evolution of income and fertility inequalities over the course of economic development: A human capital perspective. *Journal of Human Capital*, *1*(1), 137–174.

Földvári, P., & van Leeuwen, B. (2011). Should less inequality in education lead to a more equal income distribution? *Education Economics*, *19*(5), 537–554.

Földvári, P., & van Leeuwen, B. (2014). Educational and income inequality in Europe, ca. 1870–2000. *Cliometrica*, 8(3), 271–300.

Galor, O., & Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development. *The Review of Economic Studies*, *71*(4), 1001–1026.

Galor, O., & Moav, O. (2006). Das human-kapital: A theory of the demise of the class structure. *The Review of Economic Studies*, *73*(1), 85–117.

Gregorio, J. D., & Lee, J. W. (2002). Education and income inequality: New evidence from cross-country data. *Review of Income and Wealth*, *48*(3), 395–416.

Groot, W. (1996). The incidence of, and returns to overeducation in the UK. *Applied Economics*, *28*(10), 1345–1350.

Haim, E. B., & Shavit, Y. (2013). Expansion and inequality of educational opportunity: A comparative study. *Research in Social Stratification and Mobility*, *31*, 22–31.

Jaumotte, F., Lall, S., & Papageorgiou, C. (2013). Rising income inequality: Technology, or trade and financial globalization? *IMF Economic Review*, *61*(2), 271–309.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2017). Macrofinancial history and the new business cycle facts. *NBER Macroeconomics Annual*, *31*(1), 213–263.

Knight, J. B., & Sabot, R. H. (1983). Educational Expansion and the Kuznets Effect. *American Economic Review*, *73*(5), 1132–1136.

Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, *45*(1), 1–28.

Lewis, W. A. (1954). Economic Development with unlimited supplies of labour. *The Manchester School*, *22*(2), 139–191.

Li, T., Wang, Y., & Zhao, D. (2016). Environmental Kuznets curve in China: New evidence from dynamic panel analysis. *Energy Policy*, *91*, 138–147.

Madsen, J. B., & Ang, J. B. (2016). Finance-led growth in the OECD since the nineteenth century: How does financial development transmit to growth? *Review of Economics and Statistics*, *98*(3), 552–572.

Madsen, J. B., Islam, M. R., & Doucouliagos, H. (2018). Inequality, financial development and economic growth in the OECD, 1870–2011. *European Economic Review*, *101*, 605–624.

Makhlouf, Y., Kellard, N. M., & Vinogradov, D. V. (2020). Finance-Inequality Nexus: The Long and the Short of it. *Economic Inquiry*, *58*(4), 1977–1994.

O'Leary, N. C., & Sloane, P. J. (2011). The wage premium for university education in Great Britain During a decade of change. *The Manchester School*, *79*(4), pp.740–764.

Pesaran, H. (1997). The role of econometric theory in modelling the long run. *Economic Journal*, *107*(440), 178–191.

Pesaran, H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, *68*(1), 79–113.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, *94*(446), 621–634.

Piketty, T., & Zucman, G. (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly Journal of Economics*, *129*(3), 1255–1310.

Raftery, A. E., & Hout, M. (1993). Maximally maintained inequality: Expansion, reform, and opportunity in irish education, 1921-75. *Sociology of education*, 41–62.

Ram, R. (1984). Population increase, economic growth, educational inequality, and income distribution: Some recent evidence. *Journal of Development Economics*, *14*(3), 419–428.

Ram, R. (1989). Can educational expansion reduce income inequality in less-developed countries? *Economics of Education Review*, *8*(2), 185–195.

Rehme, G. (2007). Education, economic growth and measured income inequality. *Economica*, *74*(295), 493–514.

Rodríguez-Pose, A., & Tselios, V. (2009). Education and income inequality in the regions of the European Union. *Journal of Regional Science*, *49*(3), 411–437.

Roodman, D. (2006). How to do xtabond2: An introduction to difference and system GMM in stata. *Center for Global Development Working Paper*, (103).
Rossen, A., Boll, C., & Wolf, A. (2019). Patterns of overeducation in Europe: The role of field of study. *IZA Journal of Labor Policy*, *9*(1).
Samargandi, N., Fidrmuc, J., & Ghosh, S. (2015). Is the relationship between financial development and economic growth monotonic? Evidence from a sample of middle-income countries. *World Development*, *68*, 66–81.
Solt, F. (2019). Measuring income inequality across countries and over time: The standardized world income inequality database. SWIID Version 8.2, November 2019.
Spence, M. (1978). Job market signaling. *Uncertainty in economics* (pp. 281–306). Academic Press.
Szirmai, A. (2017). Structural Change Database, 1950–2016, v.1.2., November 2017.
Tasseva, I. V. (2020). The changing education distribution and income inequality in Great Britain. *The Review of Income and Wealth*
Teulings, C., & Van Rens, T. (2008). Education, growth, and income inequality. *The Review of Economics and Statistics*, *90*(1), 89–104.
Thomas, V., Wang, Y., & Fan, X. (2000). *Measuring education inequality: Gini coefficients of education*. The World Bank.
Van der Weide, R., Lakner, C., Mahler, D. G., Narayan, A., & Ramasubbaiah, R. (2021). Intergenerational mobility around the world. *Available at SSRN 3981372*.