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Title: The Role of R&D Intensity and Education in a Model of Inequality, Growth and Risk of Poverty: Evidence from Europe

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Abstract
Reducing inequality and risk of poverty has become a global challenge for sustainable development and improving quality of life because economic growth has not translated into inequality and risk of poverty alleviation. Therefore, the extent to which inequality, economic growth, and risk of poverty interact has been a serious concern. However, previous studies have failed to incorporate the effects of R&D and education into the model of inequality, growth and risk of poverty. The purpose of this study was to contribute to the understanding of the role of R&D and education in the model by examining the dynamics of causal relationships. Consideration was given to heterogeneity and cross-sectional dependence across European Union countries over the period 2000 to 2018. Our findings provide evidence for the central importance of R&D intensity and education level in the model of inequality, growth and risk of poverty. Notably, our results argue for the feedback hypothesis between economic growth and R&D intensity for both old and new EU country samples. In addition, our results revealed the bidirectional favourable effect between R&D and inequality for old EU countries, while the adverse effect of R&D on risk of poverty was observed for new EU countries, implying that national and EU-wide policies for research and innovation should shift from an orientation towards economic growth to one towards societal challenges.

Keywords: economic growth, inequality, risk of poverty, R&D, education.

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Code availability: IBM SPSS Statistics 25, Stata 13, and EViews 10 program environments

JEL codes: O15, O32, I25

The Role of R&D Intensity and Education in a Model of Inequality, Growth and Risk of Poverty: Evidence from Europe

Abstract

Reducing inequality and risk of poverty has become a global challenge for sustainable development and improving quality of life because economic growth has not translated into inequality and risk of poverty alleviation. Therefore, the extent to which inequality, economic growth, and risk of poverty interact has been a serious concern. However, previous studies have failed to incorporate the effects of R&D and education into the model of inequality, growth and risk of poverty. The purpose of this study was to contribute to the understanding of the role of R&D and education in the model by examining the dynamics of causal relationships. Consideration was given to heterogeneity and cross-sectional dependence across European Union countries over the period 2000 to 2018. Our findings provide evidence for the central importance of R&D intensity and education level in the model of inequality, growth and risk of poverty. Notably, our results argue for the feedback hypothesis between economic growth and R&D intensity for both old and new EU country samples. In addition, our results revealed the bidirectional favourable effect between R&D and inequality for old EU countries, while the adverse effect of R&D on risk of poverty was observed for new EU countries, implying that national and EU-wide policies for research and innovation should shift from an orientation towards economic growth to one towards societal challenges.

1. INTRODUCTION

The issue of ensuring sustainable economic growth and reducing inequality and risk of poverty has become a major development goal and constitutes the core part of the international sustainable development agenda. This is because inequality and risk of poverty have exacerbated problems such as hunger, illness, and poor sanitation, which not only make people vulnerable to disease but also have harmful effects on social relations and political participation (Mood and Jonsson 2016). Moreover, persistent poverty is seen as a self-reinforcing phenomenon that hinders the growth of individual wealth (Barrett and Carter 2013). It can be persistent due to the problem associated with wealth dynamics that is inconsistent with local thresholds as well as increasing returns (Mirza et al. 2019). Likewise, inequalities in income or an unfair distribution of income affects economic parameters, and the presence of a poverty gap may lead to poor economic decision making, social exclusion and a lack of educational opportunities (Adamkovič and Martončik 2017). The impact of economic growth on the reduction of poverty has been reported to be lessened under such conditions (Škare and Družeta 2016). Regarding the present-day factors of inequality and risk of poverty, the direction is affected by the altered conditions for development cooperation. It is influenced by economic integration, demographic changes, mounting pressures on national resources, global epidemics and changing patterns of disease, a shift of power from the West to emerging economies, and the re-emergence of digital technology (which widens the gap between those who benefit from globalization and those who do not) (Akoum 2008; Bergh and Nilsson 2014; Kaidi and Mensi 2019; Wade 2004). All these factors are bound to redesign the future for developing and developed countries and regions (Lin et al. 2020).

Much evidence in the literature supports the theory that the growth–inequality relationship is real (Voitchovsky 2005) and that economic growth and the equitable distribution of income are essential for poverty risk reduction (Fosu 2017; Ravallion 2001). The main tenet is that unfavourable income distribution limits the effectiveness of growth policies in reducing poverty risk (Cunguara and Hanlon 2012; De Magalhães and Santaeulàlia-Llopis 2018). Moreover, inequality in income may cause an absence of basic freedom, as well as opportunity, and this absence is, in turn, considered a major impediment to poverty alleviation (Beker 2016). According to the latest World Inequality Report[1], the richest 10% of the world's population presently earns 52% of global income, while the poorer half of the global population makes 8.5% of that income. In Europe, the income share of the richest 10% stands at around 36%. This demonstrates the magnitude of the gap that exists between the rich and the poor.

Several studies have produced causality estimates of the relationships in the model of inequality, growth and poverty risk (Akanbi 2016; Janvry and Sadoulet 2000; Khemili and Belloumi 2018). However, previous work has failed to incorporate the effects of R&D and education into the nexus.

The main contributions of this study to the literature are twofold. Firstly, despite the considerable impact that R&D and complementary factors may have on the interactions among inequality, growth and risk of poverty, this study examines the dynamics of causal effects of R&D and education in the model of inequality, growth and poverty risk. Examining such causal effects in this model is challenging because of the complex relationships between the variables considered. For example, R&D intensity tends to create a short-term employment adjustment problem and is negatively linked to economic performance after the 2008 recession (Crescenzi et al. 2016). This is attributed to the fact that R&D-intensive economies do not have good short-

[1] https://wir2022.wid.world/

run response capacity, which, rather than technological processes supported by R&D investment, results from a skilled workforce enabling rapid non-technological (organisational and process) innovation. However, in the long run, high growth rates in R&D intensity tend to lift individuals out of the risk of poverty or out of the poverty trap because it creates jobs, increases economic productivity, and equips workers with the skills that are necessary for their jobs (Lee and Rodríguez-Pose 2016; Nakamura et al. 2019). It has also been demonstrated that developing countries cannot exploit R&D for economic growth and that middle-income countries have the highest rates of return (Goñi and Maloney 2017). For low-income countries, this finding indicates the critical role of factors that complement R&D, such as education and the quality of the innovation system. In other words, these countries must have sufficient absorptive capacity to exploit technological advances (Donou-Adonsou 2019). As a consequence, economies can be stuck in an equilibrium poverty trap if there are non-optimal dynamics between the intensity of R&D and the level of complementary human capital (Accinelli and Sanchez Carrera 2011; Arunachalam and Shenoy 2017). Moreover, technology was also found to fuel inequality, which in turn could lead to resource depletion and increased risk of poverty (Mao et al. 2020; Mirza et al. 2019).

Our second contribution is to empirically evaluate the effects of R&D intensity and education on the model of inequality, growth, and risk of poverty in old and new EU countries while considering cross-sectional dependence and heterogeneity in the data. The EU, as one of the most developed regions on planet Earth, has not been entirely spared the scourge of inequality and risk of poverty. Its at-risk-of-poverty rate was almost 17 per cent in 2018, with more than 8 per cent of the population lifted above the poverty threshold by social transfers (Eurostat 2020). What is most striking is that these rates have remained relatively stable over the last 10 years despite significant economic growth. Considerable variations exist across the EU countries, and inequality in income distribution has steadily increased in the last 10 years (Eurostat 2020). Therefore, reducing the at-risk-of-poverty rate was considered one of the top priorities for Europe 2020 in the initiatives set in 2010 (i.e., getting at least 20 million people out of poverty risk by the year 2020); it remains difficult to achieve this initiative because at-risk-of-poverty rate has continued to grow in the last 10 years (Madama and Jessoula 2018). Indeed, previous studies indicated that the gaps have widened in EU countries, with the new countries being the most disadvantaged (Weziak-Bialowolska 2016). Here, we study new and old EU member countries separately to model diverse living conditions. Some new EU countries are still considered transitional economies and will continue to experience reductions in poverty risk as a result of rapid growth in their GDPs. In addition to substantial variations in poverty risk and the effectiveness of governmental policies between new and old EU countries, the economic and welfare state strategies also differ (Bosco and Poggi 2020). Institutional quality, income distribution and education also had significantly different effects on the reduction of poverty risk in EU countries, according to recent findings (Bosco 2019). Compared to the old countries, new EU countries also lag behind in terms of wages, social protection expenditures, and levels of satisfaction with life (Aidukaite 2011). Unlike most of the previous work, we show that the panel data on the model of inequality, growth, and risk of poverty for EU countries over the period 2000 to 2018 are cross-sectionally dependent and heterogeneous. Therefore, to obtain consistent and reliable empirical results, we used appropriate modifications of traditional panel estimation methods that are robust for these problems.

The rest of the article is organized as follows. Section 2 reviews related studies on the model of inequality, growth and risk of poverty. Section 3 introduces the data used for empirical experiments. Section 4 outlines the proposed econometric model. The results of the empirical experiments are presented in Section 5. Section 6 discusses the results and their policy implications. Section 7 presents the conclusions.

2. RELATED LITERATURE

Over the last decade, there has been considerable debate on how growth, inequality and risk of poverty interact with each other (Basu and Subramanian 2020). While there is no consensus among economists on these relationships, the prevailing empirical evidence suggests that economic growth reduces risk of poverty and inequality increases risk of poverty (Soava et al. 2020; Škare and Družeta 2016). If it is true that growth reduces poverty risk, then by how much and how fast, for whom, and under what circumstances does this occur? Previous studies have agreed that an unfavourable income distribution is associated with a restricted effect of growth on poverty risk reduction (Adams 2004; Sumner 2019). As presented in Table I, empirical evidence suggests that bidirectional causality exists between growth and inequality (Akanbi 2016; Sehrawat and Giri 2018). However, the direction of the growth-to-inequality effect depends on the stage of economic development; growth increases inequality in low-income countries (Juknys et al. 2017). The bidirectional link between inequality and income / non-income poverty has also been studied, and is usually ascribed to the relationships of the factors to economic growth (Akanbi 2016).

The results of an empirical study on Malaysia suggested that economic growth was essential for but not sufficient for reducing the poverty rate, especially when the goal was a rapid reduction in the poverty rate (Mulok et al. 2012). Similarly, the results for Swaziland showed that economic growth did not reduce poverty (measures as consumption per capita); the poverty level was attributed to a high level of income inequality in this country (Nindi and Odhiambo 2015). Growth was found to have no significant effect on income distribution in South Africa, but increased equality was found to promote economic growth (Akanbi 2016). A bidirectional causality between economic growth and inequality was observed for Tunisia, a finding that suggested that the effect of growth on consumption per capita could be strengthened by reducing inequality (Khemili and Belloumi 2018).

Note that the concept of monetized and consumption-based poverty traditionally used for developing countries, such as the international poverty line of $2.15, is not suitable for developed countries, such as EU countries. Therefore, the EU definition is based on the proportion of the population living at risk of poverty, this is the share of households whose total equivalized income falls below 60 percent of the median national equivalized household income for the reference year. This measure considers purchasing power standard and relative, as there are differences in cost of living and median national equivalised household income across EU countries. Most EU countries experienced risk of poverty being elastic to economic growth (Dudzeviciute and Prakapiene 2018). More precisely, significant relationships were found between economic growth and risk of poverty in half of the EU countries. Indeed, countries with a higher economic level exhibited a relatively low share of the population living below the national poverty line. However, the relationship between growth and inequality substantially varied across EU countries, with economically developed countries showing relatively high income inequality while lower inequality was observed for economically weaker EU countries. Furthermore, risk of poverty and inequality tended to move in the same direction in most EU countries (Dudzeviciute and Prakapiene 2018). Different broad categories of EU countries with different rates of development were detected (Michálek and Výbošťok 2019). Across the broad categories, economic growth was found to be connected with a decrease in risk of poverty, while risk of poverty increased with greater inequality. The highly developed and emerging EU were studied separately to find opposite effects of GDP on inequality (Soava et al. 2020). This finding is consistent with the Kuznets hypothesis that early economic development tends to increase income inequality, whereas the inequality tends to decrease at a certain level of economic development. For highly developed EU countries, risk of poverty promoted income inequality, while economic growth decreased income inequality. Inverse effects were obtained for the emerging EU countries (Soava et al. 2020).

Recent evidence revealed that additional factors must be considered in the inequality, growth and risk of poverty model because growth is not a sufficient condition for reducing poverty risk (Agasisti and Bertoletti 2020; Burzynski et al. 2020; Lee and Clarke 2019).

The role of R&D and technology is attracting growing attention in the model of inequality, growth and poverty. The findings for cities in the United States indicated that high-technology industries increased wages for workers who did not have a college degree, but no real impact was found on the reduction of the poverty rate (Lee and Rodríguez-Pose 2016). Similarly, a positive job multiplication effect was observed for local labour markets in the United Kingdom, but the presence of high-technology industries resulted in lower wages for low-skilled workers and an increase in inequality (Lee and Clarke 2019). The positive role of technology in enhancing overall quality of life (human development index decomposed into GDP, education and life expectancy) was also demonstrated (Ibrahim et al. 2021).

Education has also been considered one of the instruments for reducing poverty risk and inequality by increasing the productivity of the poor, allowing vertical mobility, and improving chances to get better-paid jobs (Bourguignon and Morrisson 1998; Burzynski et al. 2020). The effect of human capital on economic growth was reportedly significantly higher than that of physical capital (Garza-Rodriguez et al. 2018). Previous studies also suggest that human capital should be developed to ensure inclusive economic growth (Alia 2017). In contrast to R&D intensity, human capital is arguably positively affecting short-term economic growth (Crescenzi et al. 2016).

place Table I here

Collectively, earlier research found strong relationships among inequality, economic growth, and risk of poverty. Different strengths of these links can be attributed to varying levels of economic development and social transfers and different capacities of economies to exploit R&D and human capital for economic growth. To evaluate these effects on the model of inequality, growth and risk of poverty, we examined the causal relationships in old and new EU countries. In modelling these effects, we thought that the data would likely be subject to cross-sectional dependence and heterogeneity. Therefore, we used appropriate modifications of traditional econometric methods to overcome these problems in the data and produce more consistent results and accurate policy implications for the countries.

3. DATA

This study encompasses the following set of variables: (1) risk of poverty (measured as the at-risk-of-poverty rate, where the at-risk-of-poverty threshold is set at 60 per cent of the national median equivalised disposable income); (2) inequality (income quintile share ratio S80/S20 for disposable income by sex and age group; based on the data in the EU Statistics on Income and Living Conditions survey); (3) GDP (real GDP in Euro per capita); (4) R&D intensity (employment in high-technology and medium-high-technology manufacturing and knowledge-intensive services, in percentage of total employment); and (5) education (percentage of the population aged 30 to 34 years who have completed tertiary studies).

For empirical experiments, we used panel time-series data for old and new EU countries from 2000 to 2018 obtained from the Eurostat database. To replace missing data and reach more valid conclusions, we employed a multiple imputation method in the IBM SPSS Statistics 25 program environment. More precisely, linear regression was used to produce five parameter estimates and then these estimates were pooled to obtain the final parameter estimates. This study considered 15 old EU countries (before the largest EU enlargement in 2004), Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom, and 13 new EU countries (joining the EU in 2004 and later), Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia. In total, the data for the new and old EU countries comprised 247 and 285 observations, respectively.

Following previous studies (Akanbi 2016; Sehrawat and Giri 2018), we converted all variables (except those measured in percentages) using logarithmic transformation to reduce heteroscedasticity. Another advantage of this transformation is that the coefficients of the models can be interpreted as the elasticities of the dependent variables with respect to the independent variables. Fig. I depicts the yearly averages from 2000 to 2018 in both country samples. Figure 1 shows that although structural changes in the economies and education systems of new EU countries have resulted in significant reductions in poverty risk and educational attainment, significant income inequality and a persistent R&D activity gap are still evident.

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4. ECONOMETRIC MODEL

4.1 Theoretical model

The intense debate hovering around the effects of R&D intensity and human capital on inequality, economic growth and risk of poverty, presented above makes it plausible to assume that there are long-run relationships between these variables. To test the validity of this interaction framework, we developed an econometric model combining the panel fully modified ordinary least squares (FMOLS) and the panel vector error correction model (VECM). We wish to detect causalities among the following variables: risk of poverty (POVR), inequality (INEQ), economic growth (EG), R&D intensity (R&D), and education level (EDU).

Section 2 provided the theoretical basis for the model of inequality, growth and risk of poverty. This study adds two core variables to the model, namely R&D intensity and education level.

The theoretical rationale for including R&D intensity in the model is that it has been theorized that R&D intensity not only stimulates economic growth but can also contribute to reducing poverty risk reduction by increasing the employment rate (Moretti 2010) and consumption expenditure (Biru et al. 2020). Increased R&D activity is assumed to stimulate economic activity and the adoption of new technologies has the capacity to increase economic efficiency (Shahbaz et al. 2020). R&D activity is recognised to lead to technological innovations, which in turn contribute to economic growth (Nair et al. 2020). A theoretical link between R&D activity and inequality can be based on neoclassical economic models of knowledge diffusion and creation (Asongu and Odhiambo 2019). In addition, the reverse effect can also be assumed since poor economies face a number of barriers to research activities, such as greater risk aversion and information failure (Mobarak and Sldanha 2022).

Following Dhrifi et al. (2021), we introduce education level as another variable in the model of inequality, growth and risk of poverty. According to the economic growth theories, education level promotes economic growth. More precisely, three mechanisms through which education affects economic growth can be found in the literature (Hanushek and Woessmann 2020): (1) by increasing labour productivity and thus the equilibrium level of output in line with neoclassical growth theories (Ogundari and Awokuse 2018); (2) by increasing the innovation capacity of the economy, leading to economic growth in accordance with endogenous growth theories (Romer 1994); and (3) by facilitating knowledge diffusion and sharing that foster endogenous innovation and enhance productivity (Bretschger et al. 2017).

Previous research also justifies examining the impact of education level on poverty and inequality. People with higher levels of education have higher earning potential than people with lower levels of education. Moreover, the opposite effect can also be expected, as people living in poverty are more likely to leave school early in order to work (Dhrifi et al. 2021). In addition, an indirect effect of education on poverty risk was found to be mediated by economic growth (Agasisti and Bertoletti 2020; Janvry and Sadoulet 2000). A negative impact of the increase in educational level on the poverty risk level was demonstrated for both EU countries (Mihai et al. 2015) and OECD (Organisation for Economic Co-operation and Development) countries (Paraschiv 2017). Education was found to be a possible mediator of the relationship between economic growth and income inequality (Berg et al. 2018). An evolving role of higher education was observed, with increasing returns to education promoting income inequality (Mishra and Bhardwaj 2020).

4.2 Empirical methodology

4.2.1 Cross-sectional dependence and heterogeneity tests

Prior to the analysis of stationary properties of the above variables, it is crucial to investigate the characteristics of the panel time-series data to select the appropriate panel unit root tests. Indeed, the use of traditional panel unit root tests may result in unreliable and inconsistent estimates in the case of cross-sectional dependence and heterogeneity.

To address the problem of inter-dependent observations across sample countries, we investigated the characteristic of error terms using the residual cross-sectional dependence Pesaran test (M. H. Pesaran 2004). We opted for this test because it is valid for dynamic heterogeneous panel data even when the dimension of cross section dimensions is large relative to the time dimension of the panel. The test uses the scaled average pairwise correlation coefficient statistic, which applies to shorter panel time-series data and smaller numbers of cross-sectional units. Addressing the problem of cross-sectional dependence was essential in this study because the sample countries from which data were gathered were strongly economically interconnected.

Another critical problem to overcome in the case of panel time-series data is the heterogeneity across individual units. To obtain more reliable estimates, econometric approaches to causal modeling assume that the information from the time-series dimension can be selectively pooled with the cross-dimensional information (Blomquist and Westerlund 2013). In other words, there is an assumption of homogeneity of the parameters (slope coefficients) of interest. To test for this assumption, we used the Blomquist and Westerlund slope homogeneity test (Blomquist and Westerlund 2013) because it allowed us to identify the problems of heteroscedasticity and serial correlation in the data (M. H. Pesaran and Yamagata 2008).

4.2.2 Panel unit root tests

The stationarity properties of the variables were investigated using panel unit root tests robust to the issues of cross-sectional dependence and heterogeneity. Because our panel data were expected to suffer from problems with cross-sectional dependence and heterogeneity, we chose to perform the CIPS (cross-sectionally augmented Im–Pesaran–Shin) panel unit root test (M. H. Pesaran 2007), which produces consistent and reliable estimates robust to these issues.

4.2.3 Cointegration tests

For variables that are not stationary at levels, reliable long-run parameter estimates must be cointegrated (i.e., the presence of a long-term equilibrium among variables is required). We used the combined Johansen–Fisher panel cointegration test (Maddala and Wu 1999) to check whether the variables were cointegrated. We chose this test because it allowed us to examine cointegration relationships among the five non-stationary time series in our panel, and compared to traditional cointegration tests, this test allowed us to examine more than one cointegration relationship.

4.2.4 Testing long-run and short-run effects

In the next step, this study used FMOLS with a weighted panel method to obtain long-term parameter estimates (Pedroni 2000). FMOLS was used because it is robust to heterogeneity and allows for the correction of simultaneity and residual correlation bias (Kamoun et al. 2019; Kasman and Duman 2015). The panel FMOLS model is given as follows:

$$Y_{i,t} = \alpha_i + \sum_{k=1}^{n} \beta_k X_{i,t}^{k} + \varepsilon_{i,t}, \text{ where} \tag{1}$$

$$\hat{\beta}_{FMOLS}^{*} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T}\left(X_{i,t}-\bar{X}_i\right)^2\right)^{-1}\left(\sum_{t=1}^{T}\left(X_{i,t}-\bar{X}_i\right)Y_{i,t}^{*}-T\hat{\gamma}_i\right)\right], \tag{2}$$

$$Y_{i,t}^{*} = Y_{i,t} - \bar{Y}_i \quad - (\widehat{\Omega}_{2,1,i}/\widehat{\Omega}_{2,2,i})\Delta X_{i,t}, \tag{3}$$

$$\hat{\gamma}_i = \widehat{\Gamma}_{2,1,i} + \widehat{\Omega}_{2,1,i}^{0} - (\widehat{\Omega}_{2,1,i}/\widehat{\Omega}_{2,2,i})(\widehat{\Gamma}_{2,2,i} + \widehat{\Omega}_{2,2,i}), \tag{4}$$

where $i = 1, 2, \ldots, N$ are cross-sectional units, t is time, $t = 1, 2, \ldots, T$, α_i is a constant term, β_k denotes a coefficient of independent variable X^k, $\varepsilon_{i,t}$ is an error term, Ω denotes the covariance matrix, and Γ_i represents the weighted sum of autocovariances. For robustness check, we also used the panel dynamic ordinary least squares (DOLS) model that incorporates lags and leads to compensate for small-sample bias and simultaneity. Both FMOLS and DOLS models also overcome the problem of serial correlation and endogeneity.

Lastly, the traditional Granger causality test for panel data was performed to reveal both long-run and short-run causality among the variables (Esen and Çelik Keçili 2021). The test is based on the estimates of VECM given as follows:

$$\Delta POVR_{i,t} = \alpha_{1,i} + \sum_{j=1}^{q} \beta_{1,0,i,j} \Delta POVR_{i,t-j} + \sum_{j=1}^{q} \beta_{1,1,i,j} \Delta INEQ_{i,t-j} + \sum_{j=1}^{q} \beta_{1,2,i,j} \Delta EG_{i,t-j} + \sum_{j=1}^{q} \beta_{1,3,i,j} \Delta R\&D_{i,t-j} + \sum_{j=1}^{q} \beta_{1,4,i,j} \Delta EDU_{i,t-j} + \gamma_{1,i} ECT_{i,t-1} + \varepsilon_{1,i,t}, \quad (5)$$

$$\Delta INEQ_{i,t} = \alpha_{2,i} + \sum_{j=1}^{q} \beta_{2,0,i,j} \Delta INEQ_{i,t-j} + \sum_{j=1}^{q} \beta_{2,1,i,j} \Delta POVR_{i,t-j} + \sum_{j=1}^{q} \beta_{2,2,i,j} \Delta EG_{i,t-j} + \sum_{j=1}^{q} \beta_{2,3,i,j} \Delta R\&D_{i,t-j} + \sum_{j=1}^{q} \beta_{2,4,i,j} \Delta EDU_{i,t-j} + \gamma_{2,i} ECT_{i,t-1} + \varepsilon_{2,i,t}, \quad (6)$$

$$\Delta EG_{i,t} = \alpha_{3,i} + \sum_{j=1}^{q} \beta_{3,0,i,j} \Delta EG_{i,t-j} + \sum_{j=1}^{q} \beta_{3,1,i,j} \Delta POVR_{i,t-j} + \sum_{j=1}^{q} \beta_{3,2,i,j} \Delta INEQ_{i,t-j} + \sum_{j=1}^{q} \beta_{3,3,i,j} \Delta R\&D_{i,t-j} + \sum_{j=1}^{q} \beta_{3,4,i,j} \Delta EDU_{i,t-j} + \gamma_{3,i} ECT_{i,t-1} + \varepsilon_{3,i,t}, \quad (7)$$

$$\Delta R\&D_{i,t} = \alpha_{4,i} + \sum_{j=1}^{q} \beta_{4,0,i,j} \Delta R\&D_{i,t-j} + \sum_{j=1}^{q} \beta_{4,1,i,j} \Delta POVR_{i,t-j} + \sum_{j=1}^{q} \beta_{4,2,i,j} \Delta INEQ_{i,t-j} + \sum_{j=1}^{q} \beta_{4,3,i,j} \Delta EG_{i,t-j} + \sum_{j=1}^{q} \beta_{4,4,i,j} \Delta EDU_{i,t-j} + \gamma_{4,i} ECT_{i,t-1} + \varepsilon_{4,i,t}, \quad (8)$$

$$\Delta EDU_{i,t} = \alpha_{5,i} + \sum_{j=1}^{q} \beta_{5,0,i,j} \Delta EDU_{i,t-j} + \sum_{j=1}^{q} \beta_{5,1,i,j} \Delta POVR_{i,t-j} + \sum_{j=1}^{q} \beta_{5,2,i,j} \Delta INEQ_{i,t-j} + \sum_{j=1}^{q} \beta_{5,3,i,j} \Delta EG_{i,t-j} + \sum_{j=1}^{q} \beta_{5,4,i,j} \Delta R\&D_{i,t-j} + \gamma_{5,i} ECT_{i,t-1} + \varepsilon_{5,i,t}, \quad (9)$$

where $\beta_{i,j}$ and γ_i denote the short-run and long-run coefficients, respectively; ECT is the error correction term; and j represents the hysteresis length. To determine whether coefficients $\beta_{i,j}$ are statistically significant, the Wald test was performed. To further explore the magnitudes of the effects in the VECMs, we applied the variance decomposition method (H. H. Pesaran and Shin 1998).

5. EMPIRICAL RESULTS

To choose the appropriate panel unit root and causality tests, the residual cross-sectional dependence Pesaran test and the Blomquist and Westerlund slope homogeneity test were performed. The results in Table II indicate cross-sectional dependence in both country samples. No cross-sectional dependence was observed for risk of poverty and inequality in the sample of old EU countries. Table III shows the empirical results of the Blomquist and Westerlund slope homogeneity test, indicating that the data were heterogeneous. Overall, both the cross-sectional independence and slope homogeneity hypotheses were rejected at $P = 0.01$.

To overcome the problems of cross-sectional dependence and heterogeneity, the CIPS panel unit root test was performed, as presented in Table IV. The results show that most variables include unit root at levels. However, all the variables became stationary at first differences, indicating that the variables were integrated at I(1).

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To test whether the levels of the underlying variables were cointegrated, we used the combined Johansen–Fisher panel cointegration test. The results in Table V indicate that for both country samples, there were at least four (one) cointegrated relationships between the variables based on the trace (maximum eigenvalue) test. We can conclude that the variables cointegrated and, therefore, that there may exist long-run relationships among the variables for both country samples.

place Table V here

The results of the FMOLS models are presented in Table VI, indicating that there was a negative long-run relationship between risk of poverty and economic growth for both country samples. The negative elasticity of poverty risk with respect to economic growth also implies that an increase in GDP led to a lower at-risk-of-poverty rate in EU countries. A significant effect of inequality on risk of poverty was also found for both categories of EU countries. A significant positive long-run relationship was detected between economic growth and inequality for new EU countries, while economic growth significantly reduced inequality in old EU countries.

Concerning the effects of R&D intensity and human capital (tertiary education level) on poverty, the results indicated different effects for both country samples. For old EU countries, a 1 per cent increase in educational level resulted in a 0.098 per cent decrease in risk of poverty; while a significant positive effect of R&D intensity on poverty was observed for the other sample. A consistently positive (negative) impact of R&D intensity (educational level) on economic growth was found for both country samples. R&D intensity and educational level also decreased inequality for old EU countries. Concerning the effect of poverty risk on these two indicators, risk of poverty had a significantly negative impact on educational level in old EU countries, but it had no significant impact in new EU countries. In contrast, inequality had more serious consequences, significantly reducing the educational level in both samples. Notably, a 1 per cent increase in the risk of poverty level led to a more than 1 per cent decrease in the educational level. Similarly, a 1.082 per cent reduction in R&D intensity was observed as a result of a 1 per cent increase in the equality level for old EU countries. Note that we also performed DOLS to ensure the robustness of the long-run coefficient estimates (see Appendix A). Furthermore, we considered the Gini coefficient of the equivalised disposable income, an alternative measure of inequality commonly used in previous studies (Janvry and Sadoulet 2000) (see Appendix B for the results of FMOLS). In the final set of validation experiments, to check the robustness of the model to imputed values, we also performed experiments on the original data with missing values (see Appendix C). Overall, the results of the robustness checks validate the obtained results.

place Table VI here

The long-run estimates presented in Table VI indicate the existence of relationships among the underlying variables. Therefore, we further investigated the directions of the causalities using the panel short-run and long-run Granger causality tests. The results in Table VII indicate the presence of a long-term equilibrium among all variables for new EU countries. At the same time, this relationship was found among the variables risk of poverty, inequality, R&D intensity, and education for old EU countries.

place Table VII here

Table VII also reports short-run relationships among the variables using the Wald test. For old EU countries, we found evidence for a short-run bidirectional relationship between R&D intensity and economic growth; a unidirectional relationship ran from economic growth to inequality, from inequality to risk of poverty, and from R&D to inequality and education. In new EU countries, we could conclude that there was a short-run bidirectional relationship between educational level and inequality; a unidirectional relationship ran from risk of poverty to economic growth, from risk of poverty to inequality, from R&D to risk of poverty, inequality, and education, and from economic growth to R&D.

The results of variance decomposition for old EU countries, as depicted in Fig. II, indicate that the shocks of poverty risk itself explained almost 98 per cent of poverty risk. The results also show that of the remaining variables, economic growth and inequality contributed the most to the risk of poverty. Still, it can also be seen that a shock in these three variables was reflected in future changes in the risk of poverty only after six periods. A similar pattern can be observed for economic growth, with almost 96 per cent of variance accounted for by the shocks of economic growth itself. A shock in education and inequality was only slowly reflected in a change in economic growth. In contrast, fluctuations in economic growth and R&D were quickly reflected in structural changes in inequality. Fig. II also shows the impulse responses of poverty risk, economic growth, and inequality aftershocks to the independent variables. Risk of poverty responded mainly to economic growth shocks. Consistent with the results of variance decomposition, shocks to risk of poverty and education caused a response of economic growth after four periods. The response of inequality to risk of poverty shocks increased substantially after three periods.

place Figure II here

For new EU countries, risk of poverty responses to economic growth took place after three periods, while a shock in R&D intensity was reflected in the change in risk of poverty only after eight periods (Fig. III). In contrast to old EU countries, a large proportion of variance in the economic growth of new EU countries could be explained by changes in equality and R&D intensity, respectively. After five periods, the shocks in risk of poverty and education level were reflected in a change in inequality. In terms of impulse responses, poverty responded quickly to economic growth and slowly to R&D intensity. After three periods, poverty increased mainly in response to shocks in economic growth. Future changes in economic growth were primarily caused by shocks in R&D intensity and inequality. A different pattern can be observed for inequality, which increased in response to shocks in risk of poverty. In contrast, a change in economic growth and education level caused a decrease in inequality.

place Figure III here

6. DISCUSSION AND POLICY IMPLICATIONS

The inequality-led poverty hypothesis was substantiated for both samples of EU countries, supporting earlier research (Khemili and Belloumi 2018). In other words, the feedback hypothesis between risk of poverty and inequality, suggested in most prior literature (Akanbi 2016; Sehrawat and Giri 2018), was not detected in either of the country samples. These findings may be explained by the Kuznets hypothesis, which states that income inequality tends to increase for low-income countries and tends to decrease for highly developed countries. The findings are also in line with the results for emerging and highly developed EU countries showing that income inequality has a tendency to grow in emerging EU countries (Soava et al. 2020).

In addition, poverty was found to be the main obstacle to economic growth for new EU countries, corroborating findings in another study (Nakabashi 2018). In contrast, the absence of causality between risk of poverty and economic growth in the short run suggests the neutrality hypothesis for old EU countries. Moreover, in consistence with the empirical studies on low- or medium-income countries (Akanbi 2016; Khemili and Belloumi 2018), we found an adverse impact of economic growth on inequality for new EU countries. For high-income old EU countries, we observed the opposite effect, that inequality is reduced by economic growth. Hence, we evidenced that this relationship depends on the stage of economic development.

We showed that an increase in R&D intensity has an unfavorable effect on poverty risk reduction in new EU countries. This finding indicates that new EU economies do not have enough capacity to exploit R&D. For old EU countries, the absence of a relationship between R&D intensity and risk of poverty is consistent with the results observed for high-income economies (Lee and Rodríguez-Pose 2016). We also confirmed the feedback hypothesis between economic growth and R&D intensity. In other words, we found a Granger bidirectional causality running from R&D intensity to economic growth, and vice versa. This finding is in agreement with earlier research (Hong 2017; Maradana et al. 2017). However, we found significant differences in the dynamics of this relationship between the sample countries. For old EU countries, short-run bidirectional causality was observed, but economic growth caused R&D intensity in the short run for new EU countries and the feedback hypothesis was only confirmed in the long run. The slower response of the economic system can be attributed to the ongoing process of technological and structural catching-up in new EU countries, which is also reflected in a slower knowledge diffusion and application.

The bidirectional favourable effect between R&D and inequality was found for old EU countries, and it is a relationship supported by previous studies in the literature (Lee and Clarke 2019; Mirza et al. 2019). In addition to the effect knowledge diffusion and spillovers (Asongu and Odhiambo 2019), the bidirectional effect can be explained through an increase in the employment of skilled workers (Moretti 2020) and increased labour productivity (Ogundari and Awokuse 2018). The weak effect for new EU countries may be attributed to a wage increase in high-technology industries, while there is no substantial effect on wages in low-technology industries. Another explanation may be that the increase in living costs affects low-income workers in particular (Kemeny and Osman 2018).

The feedback hypothesis between educational level and inequality was substantiated for old EU countries. Like R&D intensity, educational level had a negative causal relationship with inequality for old EU countries.

On the one hand, the results for new EU countries indicate a beneficial effect of inequality reduction on education, but, on the other hand, an increase in educational level had a favourable effect on inequality only in old EU countries. This relationship can be attributed to a relatively low level of tertiary education in new EU countries. Hence, our results confirm the crucial role of the knowledge absorptive capacity complementary to R&D intensity for new EU countries. Moreover, the neutrality hypothesis between education and risk of poverty suggests that new

EU economies, unlike old EU countries, suffer from non-optimal dynamics between R&D intensity and educational level (Accinelli and Sanchez Carrera 2011).

The implications for policy making are that the governments of EU countries can boost economic growth by supporting research and innovation. However, this support should be targeted at countries at risk of poverty in order to offset the negative impact of R&D on poverty risk with an indirect positive impact on poverty risk reduction through economic growth. That is, our results imply that the absorptive capacity of new EU countries should be strengthened in order to accelerate the effect of R&D on economic growth. Therefore, the capacities for learning and research infrastructure facilities should be enhanced. The absence of causality for old EU countries suggests that economic and R&D policies are more effective in reducing risk of poverty. Hence, we argue for a new research and innovation policy linked to social challenges, as represented by the Sustainable Development Goals of the United Nations. In other words, to address societal challenges, both individual government and EU policymakers should shift from emphasizing the traditional role of research and innovation policy to boosting economic growth. Moreover, the absence of the impact of educational policies on poverty reduction in new EU countries implies the need for effective education without increasing inequality. Therefore, we provide empirical support for recent EU policy responses, including equal opportunities, access to quality education and the labour market, and social inclusion and protection. These efforts should be directed in particular to new EU countries. This is in line with Keynesian/neoliberal schools emphasizing that equal access to public goods, especially to education, tends to reduce poverty (Davis and Sanchez-Martinez 2015). Overall, we advocate for policies aimed at facilitating market access for the poor, rather than redistributive policies.

7. CONCLUSIONS

This study was designed to investigate the effect of R&D intensity and education on the model of inequality, growth and risk of poverty. By addressing these causal relationships for the first time, this study has shown that R&D and education level intensity interact significantly with the model, indicating the central importance of R&D and educational instruments in the risk of poverty reduction. To demonstrate this effect, we analysed a panel of old and new EU countries over the period 2000 to 2018. We employed heterogeneous panel estimation methods with cross-sectional dependence to overcome the problems detected in the data. A long-run relationship among the underlying variables was found using the panel cointegration test. The results of the panel causality test suggest that the feedback hypothesis can be affirmed between economic growth and R&D intensity for both country samples. In addition, the results indicate one-way causality running from R&D to risk of poverty for new EU countries. These findings have important implications for both country samples, arguing for policies on research and innovation of individual nations and the EU that are oriented toward societal challenges rather than economic growth only.

Finally, several important limitations should be presented. The current study found spatial dependencies within country samples, thus confirming the importance of spatial distribution in risk of poverty and inequality. Therefore, further experimental investigations are needed to estimate the spatio-temporal effects by using advanced exploratory and dynamic models. Future studies should also be conducted as a longer time series becomes available in the Eurostat database to address the issue of the relatively short time span of the data in the current study. Furthermore, we recommend the investigation of other national innovation performance indicators promoting economic growth, such as patent-based indicators, indicators of technological and nontechnological innovation activities (Antonelli and Gehringer 2017), total factor productivity (You et al. 2020), foreign direct investment inflow (Das and Chatterjee 2020), and indicators of the capability of accessing innovative work and other types of knowledge (Perez-Trujillo and Lacalle-Calderon 2020). Finally, new multidimensional poverty measures should be considered to overcome the limitations of the traditional income poverty measures, such as different consumption patterns, different prices and functionings. This is an important future research direction also because the poverty measure used by the EU was critisized for measuring relative poverty and income inequality, rather than absolute poverty (Darvas 2019).

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Table I: Summary of previous studies on the model of inequality, growth and risk of poverty

Study	Period	Methodology	Country	Causality
(Mulok et al. 2012)	1970-2009	ARDL bound test, Granger causality test	Malaysia	GDP→Poverty rate
(Akanbi 2016)	1995-2012	Granger causality test	South Africa	Inequality↔GDP, GDP↔Poverty (income: private household consumption per capita, non-income: human poverty index), Inequality↔Poverty
(Khemili and Belloumi 2018)	1970-2013	ARDL bound test, Granger causality test	Tunisia	GDP→Consumption per capita, Inequality→ Consumption per capita, Inequality↔GDP
(Nakabashi 2018)	1980-2015	OLS, DPD model	Brazil	Poverty (proportion of individuals and households living in poverty)→GDP
(Sehrawat and Giri 2018)	1970-2015	ARDL bound test, Granger causality test	India	GDP→Poverty headcount rate, Financial development→Poverty headcount rate, Inequality↔Poverty headcount rate
(Dudzeviciute and Prakapiene 2018)	2005-2016	OLS	28 EU countries	GDP→Risk of poverty, GDP↔Inequality, Inequality→Risk of poverty
(Michálek and Výbošťok 2019)	2005-2015	Growth incidence curve	28 EU countries	GDP→Risk of poverty, Inequality→Risk of poverty
(Dhrifi et al. 2020)	1990-2017	3SLS	108 countries	Education↔GDP
(Soava et al. 2020)	2005-2016	Granger causality test	Highly developed and emerging EU countries	GDP→Inequality, Risk of poverty →Inequality, GDP→Inequality
This study	2000-2018	FMOLS, VECM Granger causality test	old and new EU countries	old EU countries: Risk of poverty↔GDP, GDP→Inequality, Inequality→Risk of poverty, R&D↔GDP, R&D→Inequality, R&D→Education, Education→Inequality new EU countries: Risk of poverty↔GDP, Inequality→Risk of poverty, R&D→Risk of poverty, GDP→R&D, GDP↔Inequality, Inequality→Education, R&D→Inequality, R&D→Education

Notes: ≠ no causality, → unidirectional causality, ↔ bidirectional causality, 3SLS – three-stage least squares, ARDL – autoregressive distribution lag model, FMOLS – fully modified ordinary least squares, OLS – ordinary least squares, and VECM – vector error correction model.

Table II: Results of residual cross-sectional dependence Pesaran test

variable	old EU countries	new EU countries
POV	-1.29	18.33***
EG	37.48***	36.78***
INEQ	1.33	3.09***
R&D	21.33***	31.90***
EDU	38.22***	36.07***

Note: *** statistically significant at *P*=0.01.

Table III: Results of Blomquist and Westerlund slope homogeneity test

test	old EU countries	new EU countries
Δ_{adj}	7.66***	10.51***
Δ	10.06***	13.81***

Note: *** statistically significant at *P*=0.01.

Table IV: Results of CIPS panel unit root test

	CIPS (without trend)		CIPS (with trend)	
old EU coutries	level	Δ	level	Δ
POV	0.22	-12.19***	-1.41	-10.78***
EG	-1.41*	-7.72***	-2.90	-5.69***
INEQ	-0.98	-9.01***	0.65	-7.18***
R&D	-1.38*	-7.08***	0.54	-6.23***
EDU	-0.19	-7.95***	0.23	-7.17***
new EU countries	level	Δ	level	Δ
POV	-4.25***	-8.85***	-2.42**	-6.82***
EG	-1.02	-3.94***	-0.66	-2.51**
INEQ	-3.25***	-10.98***	-3.49***	-9.03***
R&D	-2.49**	-7.74***	-2.68***	-5.78***
EDU	-2.37**	-7.28***	-0.48	-5.93***

Note: * statistically significant at *P*=0.10, ** at *P*=0.05 and *** at *P*=0.01.

Table V: Results of combined Johansen–Fisher panel cointegration test

	old EU countries		new EU countries	
no. of CEs	trace stat.	max. eigenvalue stat.	trace stat.	max. eigenvalue stat.
none	20.79	20.79	18.02	18.02
at most 1	19.41	282.8***	13.86	69.12***
at most 2	13.86	106.0***	5.545	171.3***
at most 3	5.545	2903.***	1.386	222.4***
at most 4	92.10***	276.3***	239.5***	239.5***
at most 5	395.1***	276.3***	244.9***	208.3***

Note: *** statistically significant at *P*=0.01, CE denotes cointegrated vector.

Table VI: Results of panel FMOLS model

	dependent var.				
	old EU countries				
indep. var.	POVR	EG	INEQ	R&D	EDU
POVR		-0.003**	0.010	0.038	-0.212*
EG	-8.360***		-0.742*	6.959***	-9.662
INEQ	0.463*	-0.012		-1.082***	-1.898**
R&D	0.164	0.004*	-0.092***		0.051
EDU	-0.098*	-0.002*	-0.020***	0.045	
R^2	0.902	0.997	0.941	0.979	0.972
Adj. R^2	0.887	0.997	0.932	0.976	0.957
	new EU countries				
indep. var.	POVR	EG	INEQ	R&D	EDU
POVR		-0.004***	0.003	0.012	0.022
EG	-27.62***		1.674***	3.064***	-23.06***
INEQ	1.331***	0.021***		-0.083	-2.955***
R&D	0.966**	0.024***	-0.047		0.757
EDU	0.107	-0.004**	0.001	-0.031*	
R^2	0.830	0.992	0.887	0.969	0.975
Adj. R^2	0.793	0.990	0.870	0.964	0.968

Note: * statistically significant at P=0.10, ** at P=0.05, and *** at P=0.01.

Table VII: Results of panel VECM Granger causality test (χ^2 statistics)

	independent variables					
	old EU countries					
dep. var.	Δ POVR	Δ EG	Δ INEQ	Δ R&D	Δ EDU	ECT
Δ POVR		6.694	16.845*	10.032	14.448	-0.004**
Δ EG	14.463		9.742	15.766*	9.117	-0.000
Δ INEQ	15.081	26.820***		28.475***	8.398	-0.016**
Δ R&D	9.427	23.176**	7.150		10.387	-0.015**
Δ EDU	4.649	7.181	6.306	24.212***		-0.037**
	new EU countries					
dep. var.	Δ POVR	Δ EG	Δ INEQ	Δ R&D	Δ EDU	ECT
Δ POVR		9.315	7.317	18.996*	7.191	-0.014**
Δ EG	20.911**		7.886	5.716	7.443	-0.0001***
Δ INEQ	18.583*	14.629		24.054**	18.512*	-0.015***
Δ R&D	8.697	23.755**	14.645		13.082	-0.021**
Δ EDU	11.968	15.913	21.349**	24.103**		-0.147**

Note: * statistically significant at P=0.10, ** at P=0.05 and *** at P=0.01 using the Wald test.

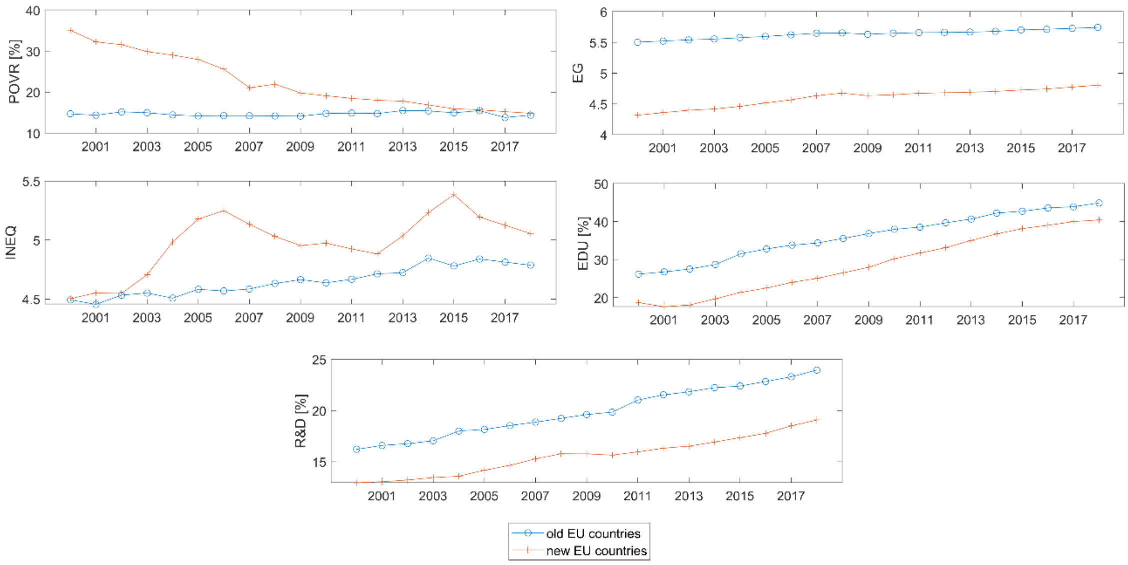

Fig. I: Yearly averages of variables in the model

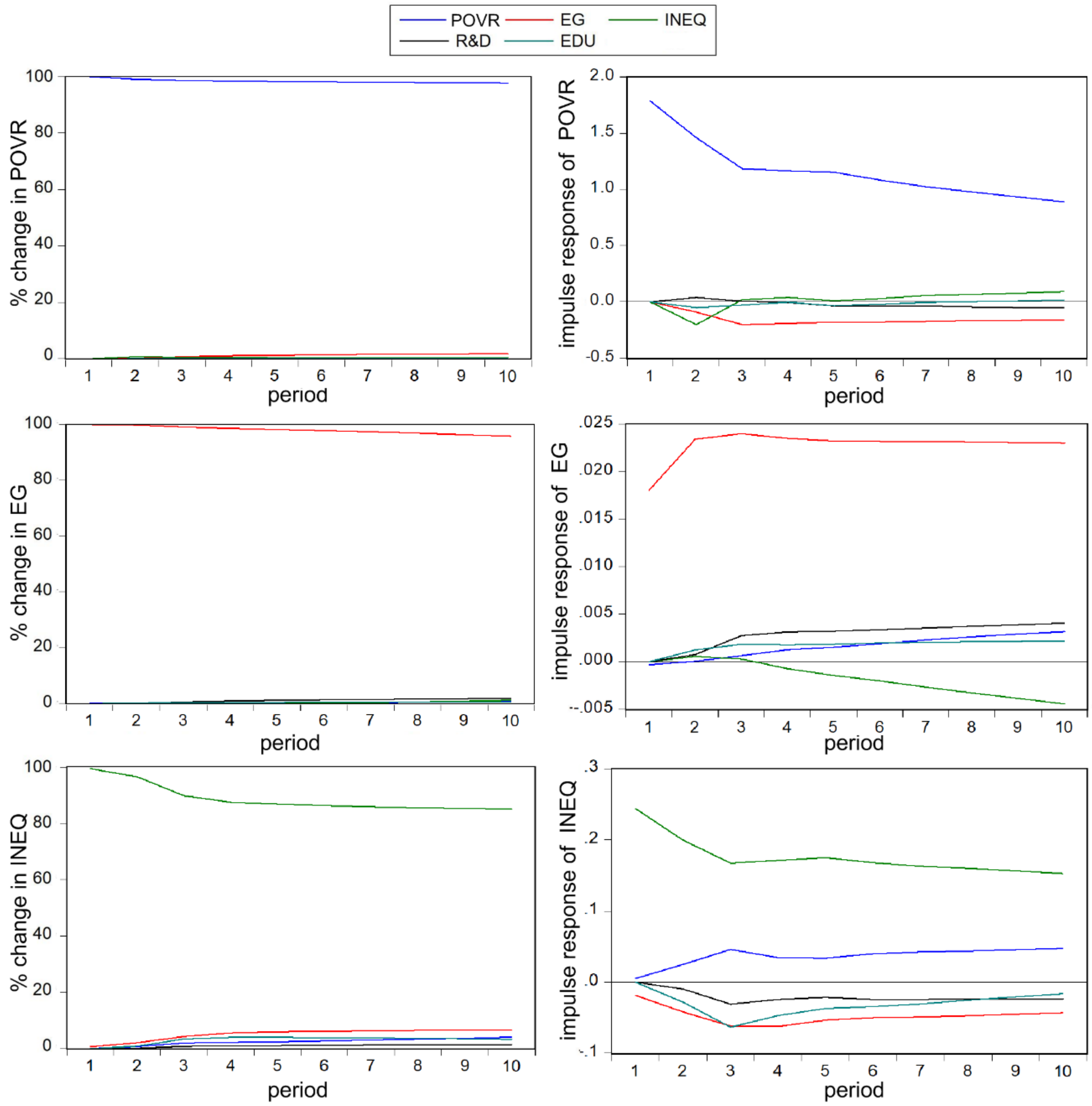

Fig. II: Results of variance decomposition for old EU countries

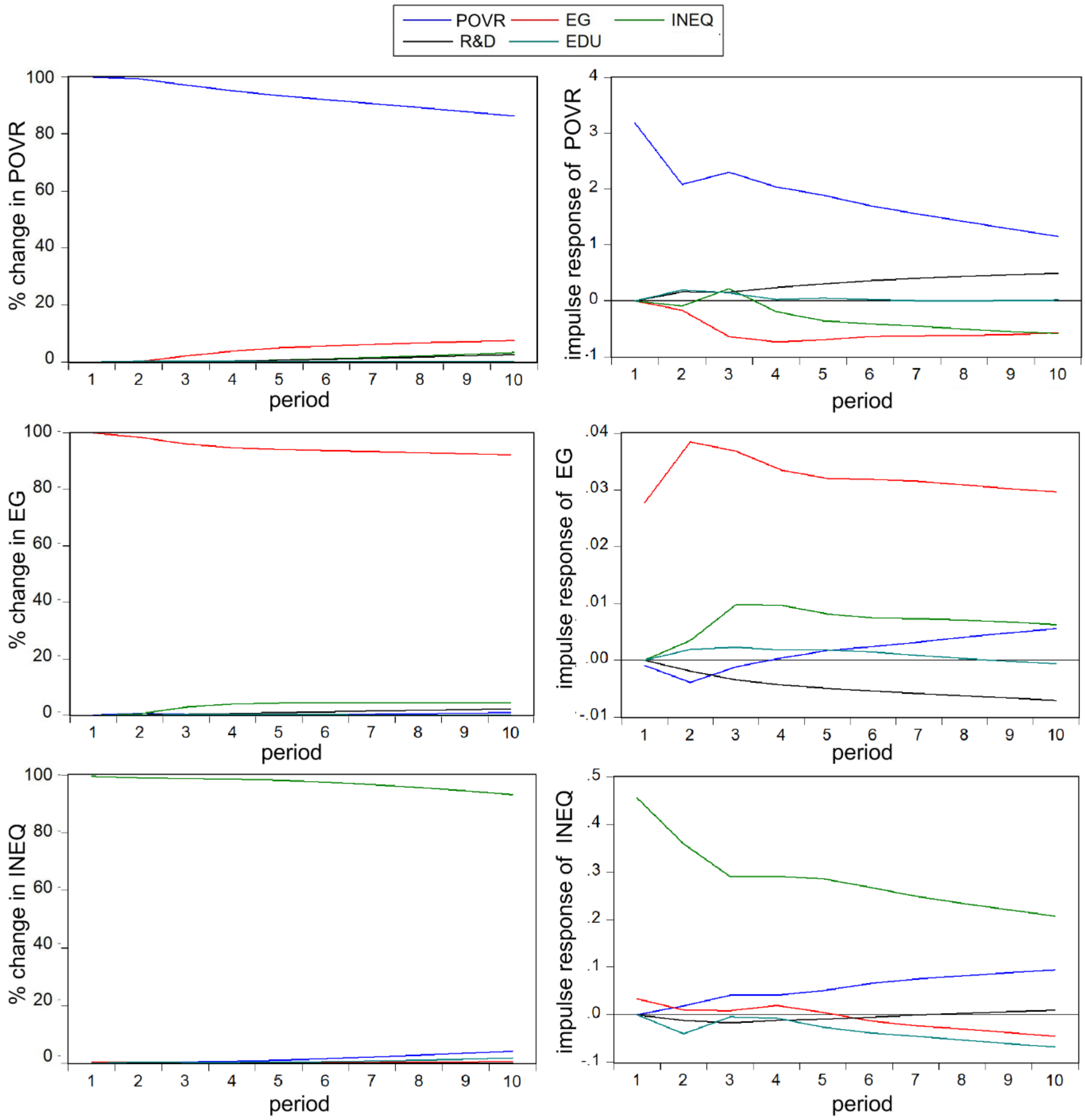

Fig. III: Results of variance decomposition for new EU countries

Appendix A: Results of panel DOLS model

	old EU countries				
	dependent var.				
indep. var.	POVR	EG	INEQ	R&D	EDU
POVR		-0.002	0.040	0.017	-0.271*
EG	-8.439**		-2.226*	3.683	-13.063
INEQ	-1.107	-0.015		-1.090***	-2.376*
R&D	0.074	0.007*	-0.253***		0.102
EDU	-0.055	-0.002	-0.027**	0.050	
R^2	0.934	0.998	0.997	0.985	0.973
Adj. R^2	0.899	0.997	0.969	0.977	0.954
	new EU countries				
indep. var.	POVR	EG	INEQ	R&D	EDU
POVR		-0.003**	-0.018	-0.003	-0.044
EG	-24.06***		1.435	5.003***	-8.642**
INEQ	-1.185*	0.029**		-0.151	0.183
R&D	0.166	0.025***	-0.053		-0.204
EDU	-0.063	-0.007**	-0.015	-0.034	
R^2	0.951	0.995	0.931	0.976	0.985
Adj. R^2	0.924	0.992	0.894	0.964	0.977

Note: * statistically significant at P=0.10, ** at P=0.05, and *** at P=0.01.

Appendix B: Results of panel FMOLS model for inequality measured by Gini coefficient

	dependent var.				
	old EU countries				
indep. var.	POVR	EG	Gini coef.	R&D	EDU
POVR		-0.003**	-0.001	0.038	-0.166**
EG	-8.999***		-0.026	7.597***	43.941***
Gini coef.	10.417*	-0.213		-13.864***	-7.442
R&D	0.201*	0.007***	-0.003***		1.280***
EDU	-0.115***	-0.002*	-0.001*	0.058**	
R^2	0.869	0.997	0.873	0.978	0.963
Adj. R^2	0.847	0.997	0.855	0.974	0.949
	new EU countries				
indep. var.	POVR	EG	Gini coef.	R&D	EDU
POVR		-0.005***	0.001	0.018**	0.104
EG	-29.93***		0.004	4.096***	-21.44***
Gini coef.	21.64	0.165		1.064	-51.22***
R&D	0.407	0.024***	-3.7E-05		0.384
EDU	-0.027	-0.004**	0.001	-0.032**	
R^2	0.885	0.991	0.885	0.967	0.978
Adj. R^2	0.867	0.990	0.867	0.962	0.973

Note: * statistically significant at P=0.10, ** at P=0.05, and *** at P=0.01.

Appendix C: Results of panel FMOLS using original data with missing values

	dependent var.				
	old EU countries				
indep. var.	POVR	EG	Gini coef.	R&D	EDU
POVR		-0.002***	0.001**	-0.003	-0.050
EG	-28.08***		-0.108***	4.856	-18.63***
Gini coef.	52.17**	-0.672***		-88.78***	-22.34
R&D	0.234	0.001	-0.002***		0.688***
EDU	-0.001	-0.002***	-1.9E-05	0.109***	
R^2	0.918	0.999	0.966	0.986	0.982
Adj. R^2	0.893	0.999	0.959	0.980	0.977
	new EU countries				
indep. var.	POVR	EG	Gini coef.	R&D	EDU
POVR		0.001	0.001***	0.018**	-0.074
EG	-22.13		-0.053*	5.647***	-8.019**
Gini coef.	67.26	-0.378*		9.725**	-12.51
R&D	2.008	0.023***	0.003**		-0.206
EDU	-0.447	-0.007***	0.001	-0.067**	
R^2	0.805	0.993	0.946	0.985	0.985
Adj. R^2	0.739	0.991	0.936	0.979	0.976

Note: * statistically significant at P=0.10, ** at P=0.05, and *** at P=0.01.