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ORIGINAL PAPER

The Granger-causality between income and educational inequality: a spatial cross-regressive VAR framework

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Abstract This paper tests the causal processes between income and educational inequality within regions of the European Union, using a spatial cross-regressive VAR framework. The results show that there is a heterogeneous causality from income inequality to educational inequality and vice versa, and interregional income and educational externalities are relevant to this causality. This finding raises potentially interesting economic policy implications.

JEL Classification D31 · D62 · I24 · R12

1 Introduction

A number of theoretical mechanisms have been constructed in order to uncover the link between income inequality and educational inequality. They are focused on the ways in which income distribution affects educational distribution, and vice versa. On the one hand, higher educational inequality implies higher income inequality. A greater share of highly educated workers within a region may signal to employers that those with less education have less ability, leading to a greater income inequality between workers with high and low levels of education (Thorbecke and Charumilind 2002; Spence 1973). The most educated also have higher productivity, better job opportunities, higher levels of aspiration and are better informed about the labour market, and thus command higher earnings. On the other hand, higher income inequality implies higher educational inequality. A greater level of income inequality within a region increases the population excluded from educa-

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tional opportunities and the chances leading to higher educational inequalities. Moreover, in economies with credit market imperfections (Galor and Zeira 1993), the poor have curtailed access to human capital. In sufficiently wealthy economies, equality stimulates investment in human capital, which is greater if it is shared by a larger segment of society, and alleviates the adverse effects of credit market constraints on human capital accumulation as fewer people underinvest in education (Galor and Moav 2000, 2004). Therefore, low levels of income inequality offer a wide range of economic chances to both advanced and disadvantaged groups, allowing for a better allocation of resources and more efficiency in human capital investment (Rodríguez-Pose and Tselios 2010). There is also mounting empirical evidence to support the positive association between income and educational inequality (e.g. Tselios 2008; Rodríguez-Pose and Tselios 2009a; Becker and Chiswick 1966).

Despite this acknowledged positive association, there is no clear evidence on the direction in which this causal relationship runs. The present paper employs a spatial cross-regressive VAR framework with Granger-causality tests (a) to detect the direction of causality (unidirectional or bilateral) between income and educational inequality in the regions of the European Union (EU), (b) to see whether this relationship is present within all regions of Europe (homogeneity) or within specific regions (heterogeneity), and (c) to explore whether interregional income and educational externalities are relevant to this relationship. Although limited studies in the past have dealt with the Granger-causality in a panel context (i.e. Hurlin and Venet 2001; Hood et al. 2008; Erdil and Yetkiner 2009; Tselios 2011), these studies do not consider the importance of interregional interaction effects. The purpose of this paper is to reconsider the direction of causality between income and education with a special focus on the role of externalities. The introduction of spatial (interregional) externalities in the analysis is important, because regions interact through labour migration, capital mobility, technology transfers, forward and backward linkages and knowledge spillovers (Armstrong 2002; Pfaffermayr 2009). Regions are naturally open to a range of social, economic, political and cultural flows, and thus, substantial interaction exists between them (Magrini 2004). This highlights the need for an explicit treatment of spatial interaction effects in Granger-causality tests. Moreover, previous empirical studies of the spatial distribution of income and education in the European context underline the importance of spatial interactions and geographical location in regional economic performance (e.g. Rodríguez-Pose and Tselios 2009b, 2011; Tselios 2008). Economic activities are not randomly distributed in space, and welfare remains geographically clustered. Its clustering over space is held as evidence in favour of the importance of external effects from proximity. From a methodological point of view, this paper is an extension of the technique proposed by Hurlin and Venet (2001), adding spatial cross-regressive effects. Failing to acknowledge the presence of spatial externalities 'at least leads to biased inference, can be a cause of inconsistent estimation, and leads to an incorrect understanding of true causal processes' (Corrado and Fingleton 2012: 210). The proposed model is not a structural model (i.e. theory-driven approach)—which starts with a fully specified economic model, well grounded in theory, that specifies the forces driving the variation in the data and the error terms (Holmes 2010)—but it is a data-driven model.[1]

The next section outlines a procedure for evaluating the causal processes (homogeneous versus heterogeneous) between income and educational inequality within a panel data framework with interregional externalities. Section 3 describes the data and the variables used in the analysis, and Sect. 4 reports the empirical results of the Granger-causality between income and educational inequalities in the regions of the EU. The final section discusses conclusions, the limits of the results and the economic policy implications.

2 Granger-causality in a spatial cross-regressive VAR framework

I consider within-region (interpersonal) income and educational inequality variables, denoted $IncIneq$ and $EducIneq$, observed in T periods and in N regions. For each region $i \in [1, N]$ and $\forall t \in [1, T]$, $IncIneq_{i,t}$ denotes income inequality of region i at time t, and $EducIneq_{i,t}$ is a measure of educational inequality of region i at time t.

Interregional externalities are captured by a spatial weights matrix, which is a binary matrix with elements equal to 1 in the case of the k-nearest neighbouring regions, and 0 otherwise. Therefore, each region i is connected to a set of neighbouring regions by means of spatial patterns introduced exogenously in order to avoid identification problems (Ertur et al. 2006). The values in the cells of the matrix comprise an explicit hypothesis about the strength of interlocation connection (i.e. regions) (Corrado and Fingleton 2012). More specifically, the k-nearest neighbours is defined as follows

[1] A researcher taking the structural approach, through the use of theory, can obtain restrictions to help pin down parameters and, by estimating the structural parameters of a fully specified model, can simulate the impact of alternatives that have never actually occurred in the data (Holmes 2010). However, a cost of the structural approach is that the researcher must be explicit up-front about the underlying model and the underlying economics. This paper puts emphasis on the importance of interregional externalities which occur through many mechanisms. Therefore, adopting a data-driven model, I do not need to make explicit up-front the underlying mechanisms of interregional externalities. Structural econometric modellers must also add statistical structure in order to rationalise why economic theory does not perfectly explain data and must be able to argue that their model will be invariant to the contemplated change in economic environment (Reiss and Wolak 2007). A data-driven model does not face this problem, because a structural model is not based on an artificial economy. Moreover, I do not use a structural model because causal relations cannot be established a priori (Hume 1748). In the proposed model, I construct a spatial weights matrix (see Sect. 2) which captures externalities. Instead of constructing the spatial weights matrix, some researchers suggest directly entering variables that proxy externalities in the regression model (see Harris et al. 2011). Nevertheless, Corrado and Fingleton (2012) argue that such an approach itself requires strong identifying assumptions and therefore possesses no real advantage compared to employing a spatial weights matrix. Modelling spatial interaction in the economic context means in many cases modelling externalities which are difficult to pin down (Corrado and Fingleton 2012). Overall, the putative advantages do not always mean structural models should be favoured over non-structural models. Reiss and Wolak (2007) say that '[t]he advantages of structural models of course do not all come for free. All economic theories contain assumptions that are not easily relaxed. While theorists sometimes have the luxury of being able to explore stylized models with simplifying assumptions, structural econometric modelers have to worry that when they use stylized or simplifying assumptions they will be dismissed as arbitrary, or worse: insensitive top the way the world 'real works" (page 4290).

$$\begin{cases} \omega_{ij}(k) = 0 & \text{if } i = j \\ \omega_{ij}(k) = 1 & \text{if } d_{ij} \leq d_i(k) \\ \omega_{ij}(k) = 0 & \text{if } d_{ij} > d_i(k) \end{cases}$$

where d_{ij} is the great circle distance between centroids of regions i and j and $d_i(k)$ is the kth-order smallest distance between regions i and j such that each region i has exactly k neighbours. Although the specification of the spatial weights matrix is a major point of contention in the literature and the choice of spatial weights can have a substantive impact on the results (Abreu et al. 2005), I use $k = 3, 5, 7$ and 9 to study the robustness of the results. The main reason is that due to the specific geographical configuration of the European regions and the number of total observations (94 regions), the islands of Sicily, Sardinia, Nisia Aigaiou and Crete, the Canaries, the Azores, Madeira and Ireland are connected to continental Europe (Tselios 2008). The spatial weights matrix is then row-standardised (W) so the elements in each row add up to 1. Therefore, $\omega_{ij}(k) = w_{ij}(k) \big/ \sum_j w_{ij}(k)$. It should be noted here that row-standardisation does not change the relative dependence among neighbours, but it does change the total impact of neighbours across regions as it implies a form of spatial smoothing (Anselin 1992). The spatial weights matrix should be row-standardised to yield a meaningful interpretation of the results (Anselin 1992). In this matrix, geographical proximity can play a part in the fostering, facilitating and nurturing of flows of regional wages, knowledge and ideas across European regions (Tselios 2008; McCann and Shefer 2005). $[W\ IncIneq_t]_i$ is the average income inequality of the neighbouring regions of region i at time t, and $[W\ EducIneq_t]_i$ is the average educational inequality of the neighbouring regions of region i at time t. These spatially lagged variables are a weighted average of the values in locations neighbouring each observation (Anselin 1992) and capture the importance of external economies that cross the weak, and sometimes artificial, regional boundaries (Vayá et al. 2004). Therefore, $[W\ IncIneq_t]_i$ captures interregional income externalities and $[W\ EducIneq_t]_i$ captures interregional educational externalities.

Given the standard Granger (1969) causality definition,[2] for each region $i \in [1, N]$, the variable $EducIneq_{i,t}$ is causing $IncIneq_{i,t}$ if we are better able to predict $IncIneq_{i,t}$ using all available information than if the information apart from $EducIneq_{i,t}$ had been used. However, this definition does not consider the interregional educational interactions and thus the information taken from $[W\ EducIneq_t]_i$. The methodology proposed in this paper is an extension of the technique proposed by Hurlin and Venet (2001), which allows us to test whether the causal processes between income and education within a panel data framework are homogeneous or heterogeneous and whether interregional externalities are relevant to these processes.

But, what is the 'correct' econometric specification which explores the causality between income and educational inequality by considering the potential influence of externalities? Devising a reasonable empirical strategy for answering this question is far from straightforward. In spatial econometrics, the 'classical' specification search approach is a sequential procedure that typically includes the following steps: (1)

2 Granger-causality is a statistical concept of causality that is based on prediction and its mathematical formulation is based on linear regression modelling of stochastic processes (Granger 1969).

estimate the initial model (i.e. a model without spatially lagged variables that has a well-behaved disturbance term), (2) test for a spatial autoregressive process and (3) if the null hypothesis of no spatial correlation is rejected, apply a remedial procedure (Florax et al. 2003: 558). For example, if the Moran's I test (Cliff and Ord 1981) adapted to estimated residuals of a spatial econometric specification fails to reject the hypothesis of spatial dependence, there are either potential misspecifications in the form of spatial autocorrelation and heterogeneity, or potential interregional spillovers (Moreno et al. 2005; Tselios 2011). This points towards the use of different modelling strategies (Anselin and Rey 1991; Florax et al. 2003). However, this paper does not follow this approach because the econometric specifications include lagged dependent variables in order to explore causality effects. These dynamic models do not allow us to test whether the Moran's I test adapted to estimated residuals rejects the null hypothesis of spatial dependence or not. Although the proposed method does not allow us to test for spatial error (nuisance spatial dependence) or spatial lagged dependent variables (Anselin 1988, 2000; Anselin and Bera 1998), the present paper is a first attempt to introduce the spatial dimension in the Granger-causality tests for panel data using a spatial cross-regressive model which is a substantive spatial dependence. This paper, however, does not aim to show which econometric specification is the most appropriate (or 'correct') per se, but to show whether interregional externalities are relevant to the Granger-causality between income and educational inequalities. In other words, it aims to explore the reverse causality between income and education, paying particular attention to the role played by the spatial location of the various regions.

I consider a time-stationary spatial cross-regressive VAR representation, adapted to a panel data context. For each of the regions i and $\forall t \in [1, T]$:

$$
\begin{aligned}
IncIneq_{i,t} = {} & \sum_{k=1}^{p} \gamma^{(k)} IncIneq_{i,t-k} + \sum_{k=0}^{p} \beta_i^{(k)} EducIneq_{i,t-k} \\
& + \sum_{k=0}^{p} \xi_i^{(k)} \left[W\, EducIneq_{t-k}\right]_i + \delta z_{i,t} + \upsilon_{i,t}
\end{aligned}
$$

where p indicates the number of time periods and $k \in [1, p]$ indicates the lag periods. $\gamma^{(k)}$ are the autoregressive coefficients which are identical for all regions, and $\beta_i^{(k)}$ and $\xi_i^{(k)}$ are the regression coefficient slopes which are assumed to be constant $\forall k \in [1, p]$. If $\xi_i^{(k)}$ is statistically significant, it means that the average educational inequality level of the neighbouring regions of region i has an impact on the income inequality of region i. Several economic factors, such as labour and capital mobility and technology and knowledge diffusion among others, may be particularly important because they directly affect regional interactions (Le Gallo et al. 2003). $z_{i,t}$ is a vector of control time-variant variables and δ is a vector of coefficients $\upsilon_{i,t} = \alpha_i + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ are $i.i.d.$ $\left(0, \sigma_\varepsilon^2\right)$ and α_i represents the fixed effects.

Given the heterogeneity of the data-generating process, I then test the following three hypotheses.

1. *Non-causality* hypothesis (H_1): $\forall i \in [1, N]$, $EducIneq_{i,t-k}$ and $\left[W\,EducIneq_{t-k}\right]_i$ do not cause $IncIneq_{i,t}$. For all regions, educational inequality of region i and (average) educational inequality of its neighbouring regions do not cause income inequality of region i. I assess the non-causality hypothesis by constructing a test statistic (F_1),[3] comparing the sum of squared residuals from a set of restricted models (RSS_2) to the sum of squared residuals produced by a set of unrestricted models (RSS_1). The unrestricted model includes lags of income inequality ($IncIneq_{i,t-k}$), lagged values of educational inequality ($EducIneq_{i,t-k}$), spatial and temporal lags of educational inequality ($[W\,EducIneq_{t-k}]_i$), and the fixed effects themselves (α_i) to predict current values of income inequality ($IncIneq_{i,t-k}$). Lagged values of income inequality coefficients are constrained to be equal ($\gamma_{i,t-1} = \gamma_{i,t-k}$) for all the models presented. In the unrestricted model, the regression slope coefficients are set to be equal ($\beta_{i,t-1} = \beta_{i,t-k}$ and $\xi_{i,t-1} = \xi_{i,t-k}$), while in the restricted model, they are constrained to 0 ($\beta_{i,t-1} = 0$ and $\xi_{i,t-1} = 0$), leaving only the fixed effects and the various lags of the income inequality variable 0 to predict current values of income inequality (Hurlin and Venet 2001). The F_1 test statistic is

$$F_1 = \frac{(RSS_2 - RSS_1)\big/(Np)}{RSS_1\big/[NT - N\,(1 + p) - p]}$$

Interpretation of the statistic relies on the F-distribution with Np, $NT - N(1+p) - p\,df$. An insignificant statistic for this test indicates that the educational inequality of a particular region and educational inequality of its neighbouring regions do not cause income inequality of this region in any cross section, and thus, the testing process ends here. However, a significant test statistic indicates that for at least one (and possibly all) of the regions, there exists a causal relationship, and therefore, I proceed to test for homogeneous causality.

2. *Homogeneous causality* hypothesis (H_2): $\forall i \in [1, N]$, $EducIneq_{i,t-k}$ and $\left[W\,EducIneq_{t-k}\right]_i$ cause $IncIneq_{i,t}$. For all regions, educational inequality of region i and educational inequality of its neighbouring regions cause income inequality of region i. In order to test this hypothesis, I calculate a test statistic (F_2) comparing the sum of squared residuals from the unrestricted model (RSS_1) to the sum of squared residuals (RSS_3) from a restricted model in which the slope terms are constrained to be equal for each cross section in the sample ($\beta_{t-1} = \beta_{t-k}$ and $\xi_{t-1} = \xi_{t-k}$). The F_2 test statistic is

$$F_2 = \frac{(RSS_3 - RSS_1)\big/(Np)}{RSS_1\big/\,[NT - N\,(1 + p) - p]}$$

Acceptance of this hypothesis indicates that a common causal process is manifest for all cross sections in the sample, and the testing process ends here, while a

[3] The F tests tend to be the most conservative of a set of analogous tests, such as the likelihood ratio and Wald tests, and are the least sensitive to small sample deviations from normally distributed disturbances (Greene 2003; Hood et al. 2008).

rejection indicates that for at least one or more regions, educational inequality of a particular region and educational inequality of its neighbouring regions do not cause the income inequality of this region.

3. *Heterogeneous causality* hypothesis (H_3): $\exists i \in [1, N]$, $EducIneq_{i,t-k}$ and $\left[W\, EducIneq_{t-k}\right]_i$ cause $IncIneq_{i,t}$. There is at least one region where educational inequality of region i and educational inequality of its neighbouring regions cause income inequality of region i. For each region i, this hypothesis is tested using a test statistic (F_3) which compares the unrestricted sum of squared residuals estimated (RSS_1) in addition to the sum of squared residuals ($RSS_{2,i}$) from a model in which the slope coefficient for the cross section in question is constrained to 0 or excluded from the model equation ($\beta_{i,t-k} = 0$ and $\xi_{i,t-k} = 0$). The F_3 test statistic is

$$F_3 = \frac{\left(RSS_{2,i} - RSS_1\right) / (Np)}{RSS_1 / [NT - N(1+p) - p]}$$

The next step of analysis is to examine whether the variables $IncIneq_{i,t-k}$and $\left[W\, IncIneq_{t-k}\right]_i$ cause $EducIneq_{i,t}$. For each of the regions i and $\forall t \in [1, T]$:

$$\begin{aligned} EducIneq_{i,t} &= \sum_{k=1}^{p} \gamma^{(k)} EducIneq_{i,t-k} + \sum_{k=0}^{p} \beta_i^{(k)} IncIneq_{i,t-k} \\ &\quad + \sum_{k=0}^{p} \xi_i^{(k)} \left[W\, IncIneq_{t-k}\right]_i + \delta z_{i,t} + \upsilon_{i,t} \end{aligned}$$

I test the following three hypotheses.

1. *Non-causality* hypothesis (H_1): $\forall i \in [1, N]$, $IncIneq_{i,t-k}$ and $\left[W\, IncIneq_{t-k}\right]_i$ do not cause $EducIneq_{i,t}$. For all regions, income inequality of region i and (average) income inequality of its neighbouring regions do not cause educational inequality of region i.
2. *Homogeneous causality* hypothesis (H_2): $\forall i \in [1, N]$, $IncIneq_{i,t-k}$ and $\left[W\, IncIneq_{t-k}\right]_i$ cause $EducIneq_{i,t}$. For all regions, income inequality of region i and income inequality of its neighbouring regions cause educational inequality of region i.
3. *Heterogeneous causality* hypothesis (H_3): $\exists i \in [1, N]$, $IncIneq_{i,t-k}$ and $\left[W\, IncIneq_{t-k}\right]_i$ cause $EducIneq_{i,t}$. There is at least one region where income inequality of region i and income inequality of its neighbouring regions cause income inequality of region i.

Based on the above hypotheses, there are the following four scenarios.

(a) Independence: there is not any linear association between income inequality and educational inequality.
(b) Unidirectional causality from educational inequality to income inequality.
(c) Unidirectional causality from income inequality to educational inequality.
(d) Bilateral or feedback causality.

3 Data and variables

The data used in this paper to test whether there is a homogeneous or heterogeneous Granger-causality between income and educational inequality are drawn from the European Community Household Panel (ECHP) data survey.[4] This is Europe's first cross-national longitudinal household survey.[5] In this survey, more than 100,000 individuals were interviewed at approximately one-year intervals about their socio-economic status, and information was collected about their income, educational attainment, living places (location of household), etc. Since it is necessary to use a sample of regions for which I have details of the dispersion of income and education for each year of the study period, I create a balanced data set which includes information about the period 1995–2000 and 94 NUTS I or NUTS II regions belonging to 12 countries.[6] However, for inferences about regional indicators from micro-data, there is always a trade-off between the appropriate level of territorial disaggregation to be adopted and the reduction of the sample size, which affects the reliability of the estimates (Longford et al. 2010; Jesuit et al. 2003). The various countries considered in this study are the following: Austria, Belgium, Germany, Denmark, Spain, France, Greece, Ireland, Italy, Luxembourg, Portugal and the UK. Due to the short time-series period, the Granger-causality tests are implemented with annual lags ($p = 1$). However, generally speaking, the direction of causality may depend critically on the number of lagged terms included (Gujarati 2003).

(1) Income inequality ($IncIneq_{i,t}$) is measured using the microeconomic variable 'total net personal income (detailed, NC, total year prior to the survey)'. The main sources of personal income are wages and salaries, income from self-employment or farming, pensions, unemployment and redundancy benefits, any other social benefits or grants and private income (Rodríguez-Pose and Tselios 2009b). For a region i with population M of individuals $\kappa \in \{1, 2, \ldots, M\}$, income inequality is calculated by the Theil entropy index of inequality (Theil 1967), which is

[4] For a review of the ECHP survey see Peracchi (2002).

[5] The successor to the ECHP came in the form of the EU Statistics on Income and Living Conditions (EU-SILC) which was launched in 2003 (Atkinson and Marlier 2010). The EU-SILC differs markedly from its predecessor in two important ways: (a) while the ECHP has the advantage of being input-harmonised, that is of being based on standardised questionnaires common across all of the countries where it was implemented, the EU-SILC is output-harmonised, that is, instead of being based on harmonised questionnaires, the procedure involves the specification of a set of social and economic indicators which should be provided by the new data set, but it is up to each member state to decide how these are to be collected; (b) whereas the ECHP is a panel survey, in which the same individuals were interviewed year after year, the EU-SILC takes the form of a rotating panel, where the individuals are interviewed usually for a maximum of four years, and the sample is regularly refreshed with new members (Iacovou et al. 2012). According to Longford et al. (2010), the EU-SILC 'provides reliable statistics at national level but sample sizes do not allow reliable estimates at subnational level, despite a rising demand from policy-makers and local authorities' (page 1). Finally, although the EU-SILC survey domains over the enlarged EU, micro-data that would enable us to identify regions and compare them are available only for a few countries (Longford et al. 2010). For example, no location is indicated in the data for the UK, and it is collapsed to only six categories in Germany (Longford et al. 2010).

[6] Nomenclature of Territorial Units for Statistics (NUTS) provides a single uniform breakdown of territorial units where each member state is subdivided into three administrative units (NUTS I, II and III).

defined as $IncIneq = \sum_{\kappa} y_{\kappa} \log(y_{\kappa} / p_{\kappa})$, where y_{κ} is the income share, which is individual κ's total income as a proportion of the total income for the entire regional population M, and p_{κ} denotes population share. This index is income and population size invariant and varies from 0 for perfect equality to $\log(1/p_{\kappa})$ for perfect inequality. Income data refer not only to each individual in the household, but also to each normally working (15+ hours per week) individual using the variable 'Main activity status—self defined', which is also extracted from the ECHP data. The letter index controls for unemployment, inactivity and household size (Rodríguez-Pose and Tselios 2009b). For both indices, wages are the main source of personal income as they constitute 45 per cent of the personal income of the whole of the population and 78 per cent of the personal income of normally working people (Rodríguez-Pose and Tselios 2009a,b). Therefore, I measure income inequality not only for the whole of the population, but also for normally working people (Rodríguez-Pose and Tselios 2009a; Tselios 2008, 2011).

(2) Educational inequality ($EducIneq_{i,t}$) is proxied using the microeconomic variable 'highest level of general or higher education completed'. For a region i with population M of individuals $\kappa \in \{1, 2, \ldots, M\}$, this is defined by the Theil entropy index as $EducIneq = \sum_{\kappa} \tau_{\kappa} \log(\tau_{\kappa} / \tau_{\kappa})$, where τ_{κ} is the human capital share, which is individual κ's highest educational level completed as a proportion of the total human capital for the entire regional population M, and p_{κ} denotes population share.[7] Information on education includes three educational categories which are mutually exclusive and allow for international comparison as they are defined by the International Standard Classification of Education (ISCE): (a) less than second stage of secondary level education completed, (b) second stage of secondary level education completed, and (c) recognised third level completed. However, this proxy for educational attainment is not problem-free as it measures the input of formal education without considering the output of knowledge, skills and competences embodied in individuals (Sianesi and Reenen 2003). Moreover, countries have different requirements for completing any given formal

[7] The procedure proposed to measure educational inequality is better than just using the variance for two main reasons. (a) It allows us to compare educational inequality with income inequality, as they use the same disproportionality functions and thus the same indices (i.e. Theil index of income and Theil index of education, or Gini coefficient on income and Gini coefficient on education). More specifically, in the literature on inequality, it is conceptualised as the average disproportionality. Inequality concerns a 'disproportionate share', which means a share that is bigger or smaller than the average share of all basic units. The challenge for the inequality literature is to comprehend how to aggregate those basic unit disproportionalities to obtain a measure of overall inequality. As each region has a different distribution of income (resp. education), an index of income (resp. education) inequality that is comparable across regions has to be compiled. The index should be fundamentally based on the principle that income (resp. education) inequality increases as the income (resp. education) ratios deviate from 1.0. Hence, the task in hand is to devise summary measures of income (resp. education) inequality that distinguish more inequality from less inequality (Firebaugh 2003). Conceptualising inequality as the average disproportionality across all basic units implies that the degree of income (resp. education) inequality depends on the average distance of the income (resp. education) ratios r_i from 1.0. Income (resp. education) inequality is unaffected by proportional increases or decreases. Inequality indices I are expressed in a common form $I = \frac{1}{N} \sum_{i=1}^{N} f(r_i)$, where f denotes the disproportionality or distance function which captures the mathematical functions for determining deviations of income (resp. education) ratios from 1.0. (b) This procedure was initially used by Thomas et al. (2001) and, more recently, by Tselios (2008) and Rodríguez-Pose and Tselios (2009a).

educational level, and thus when comparing educational attainment across European countries, there is no consistent definition of what a particular level means in terms of knowledge, competences and skills (Centre for Educational Research and Innovation and Organisation for Economic Co-operation and Development 1998; Rodríguez-Pose and Tselios 2011). The education systems of each country vary in terms of resources, duration and the preparation of students (Rodríguez-Pose and Tselios 2011; Rodríguez-Pose and Vilalta-Bufí 2005; Sianesi and Reenen 2003). Finally, international comparison needs some caution due to differences in the level of government that takes decisions about education. Whether the regional educational system is organised by regional governments or whether it is a part of nationally-organised system depends on the level of decentralisation. For instance, Rodríguez-Pose and Tselios (2011) show that the disparities in educational attainment in the EU are higher at a national than a subnational level, but within the UK and Germany, there are striking regional disparities. ‘Whereas in the German case the 16 *Länder* have power over a devolved education system, which could explain subnational disparities in educational attainment, this is not the case among English regions, but could influence differences in attainment in Scotland’ (Rodríguez-Pose and Tselios 2011: 6). Despite these problems, many studies use the ISCE for international comparison.

Both income and educational inequality are measured using the Theil entropy index. This index satisfies all the criteria of inequality indices: income scale invariant, population size invariant, additively decomposable, consistent with the welfare principles (i.e. income transfers have a greater effect among the poor than among the rich). Rodríguez-Pose and Tselios (2009b, 2011) have decomposed the European income and educational inequality of the Theil index into three components: country–region–individual. More specifically, the overall income and educational inequality in Europe are decomposed into the within-region inequality (i.e. interpersonal inequality), between-region but within-country inequality and between-country inequality. They show that the within-region component, which is used in this paper, accounted for the largest proportion of all European income and educational inequality. From a policy point of view, this is very important, as it begs the question of why regional disparities (i.e. interregional inequalities) have attracted so much attention and become a focal point of EU policy, when the dimension of within-region income and educational inequalities are greater than of between-region and between-country inequalities. To check the robustness of the results, both income and educational inequality are calculated using not only the Theil index, but also the Gini index and the squared coefficient of variation. Although the Gini index is the most popular measure of inequality, it has some limitations as it is not consistent with the welfare principle and it is not additively decomposable. However, the Gini index provides non-redundant information about inequality as it is relatively more sensitive to changes around the median of the income distribution and less sensitive to transfers among the very poor or the very rich (Rodríguez-Pose and Tselios 2009b).

Table 1 Non-causality hypothesis

Non-causality hypothesis (H_1)	F_1
Direction: from educational inequality to income inequality	
$\forall i \in [1, N]$, $EducIneq_{i,t-1}$ does not cause $IncIneq_{i,t}$	2.2163***
$\forall i \in [1, N]$, $EducIneq_{i,t-1}$ and $\left[W\ EducIneq_{t-1}\right]_i$ do not cause $IncIneq_{i,t}$	5.6928***
Direction: from income inequality to educational inequality	
$\forall i \in [1, N]$, $IncIneq_{i,t-1}$ does not cause $EducIneq_{i,t}$	1.3493***
$\forall i \in [1, N]$, $IncIneq_{i,t-1}$ and $\left[W\ IncIneq_{t-1}\right]_i$ do not cause $EducIneq_{i,t}$	3.6198***

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

4 Empirical results

I calculate the Granger-causality tests in a VAR model with and without spatial cross-regressive effects in order to assess the role of interregional income and educational externalities.

(1) Testing the *non-causality* hypothesis (H_1): The F_1 test statistics are presented in Table 1. These are statistically significant, allowing us to reject H_1, both with and without spatial cross-regressive effects, and for both directions. Hence, for at least one region (and possibly all), there is statistical evidence that (a) educational inequality (and the educational inequality of the neighbouring regions) Granger causes income inequality, and (b) income inequality (and the income inequality of the neighbouring regions) Granger causes educational inequality. In other words, there is a linear association between income inequality and educational inequality. Therefore, not only may a greater share of highly educated workers within a region (and its neighbouring regions) signal to employers that those with less education have less ability, leading to a greater income inequality between workers with high and low levels of education (causality from educational inequality to income inequality), but also a greater level of income inequality within a region (and its neighbouring regions) may increase the population excluded from educational opportunities and chances and may lead to higher educational inequalities (causality from income inequality to educational inequality). The next step is to examine whether this causal relationship is homogeneous.

(2) Testing the *homogeneous causality* hypothesis (H_2): Failure to reject H_2 (insignificant test statistic) indicates that the causal process is homogeneous for all 94 regions, while rejecting H_2 would indicate that for at least one or more regions (a) educational inequality (and the educational inequality of the neighbouring regions) does not Granger cause income inequality, or (b) income inequality (and the income inequality of the neighbouring regions) does not Granger cause educational inequality. The F_2 test statistics are presented in Table 2. These statistics reject H_2, concluding that the causal processes are heterogeneous or do not exist across all the regions in the sample. This shows that the association between income inequality and educational inequality differs across European regions. This is hardly surprising because the economic geography of Europe is charac-

Table 2 Homogeneous causality hypothesis

Homogeneous causality hypothesis (H_2)	F_2
Direction: from educational inequality to income inequality	
$\forall i \in [1, N]$, $EducIneq_{i,t-1}$ causes $IncIneq_{i,t}$	2.2220***
$\forall i \in [1, N]$, $EducIneq_{i,t-1}$ and $\left[W\, EducIneq_{t-1}\right]_i$ cause $IncIneq_{i,t}$	5.6856***
Direction: from income inequality to educational inequality	
$\forall i \in [1, N]$, $IncIneq_{i,t-1}$ causes $EducIneq_{i,t}$	1.3592***
$\forall i \in [1, N]$, $IncIneq_{i,t-1}$ and $\left[W\, IncIneq_{t-1}\right]_i$ cause $EducIneq_{i,t}$	3.5542***

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

terised by wide disparities in the levels of a number of socio-economic characteristics (e.g. disparities in productivity, economic development, public expenditure, transport infrastructure), in institutions (e.g. language and cultural differences) and in physical endowments (e.g. differences in climate, fertility) that shape income and educational distribution differently across space. This test also highlights the important roles played by regional heterogeneity in accounting for differences in the degree of income and educational inequality levels and their relationship across the European regions.

(3) Testing *heterogeneous causality* hypothesis (H_3): Hypothesis H_3 determines which regions in the sample contribute to the causal findings, leading from educational inequality to income inequality and/or vice versa. The results of the tests for H_3 are presented in Table 3 and show the following.

(a) Independence: The relationships '$EducIneq_{t-1}$ does not cause $IncIneq_t$' and '$IncIneq_{t-1}$ does not cause $EducIneq_t$' appear to hold for 39 regions. However, the relationships '$EducIneq_{t-1}$ and $\left[W\, EducIneq_{t-1}\right]$ do not cause $IncIneq_t$' and '$IncIneq_{t-1}$ and $\left[W\, IncIneq_{t-1}\right]$ do not cause $EducIneq_t$' appear to hold for fewer regions (21), because the income inequality of the neighbouring regions (and/or the educational inequality of the neighbouring regions) contributes to causality. In other words, interregional income and educational externalities are important for causality. This may show that geographical proximity can play a key role in the fostering, facilitating and nurturing of flows of regional wages, knowledge and ideas across European regions, leading to interdependences among regions. For example, the educational inequality of the neighbouring regions $\left[W\, EducIneq_{t-1}\right]$ of Ostösterreich (AT1) contributes to the causal finding, leading from educational inequality to income inequality. If we do not take into account this impact (VAR without spatial cross-regressive effects), the educational inequality of Ostösterreich in Austria does not cause income inequality of this region. This shows the importance of interaction effects for the income–education relationship in the region of Ostösterreich.

(b) Unidirectional causality from educational inequality to income inequality: The relationships '$EducIneq_{t-1}$ causes $IncIneq_t$' and '$IncIneq_{t-1}$ does not cause $EducIneq_t$' appear to hold for 32 regions. However, the relationships

Table 3 Heterogeneous causality hypothesis

Homogeneous causality hypothesis (H_2): for region i		F_2			
		Direction: from educational inequality to income inequality		Direction: from income inequality to educational inequality	
		$EducIneq_{t-1}$ does not cause $IncIneq_t$	$EducIneq_{t-1}$ and $\left[W\ EducIneq_{t-1}\right]$ do not cause $IncIneq_t$	$IncIneq_{t-1}$ does not cause $EducIneq_t$	$IncIneq_{t-1}$ and $\left[W\ IncIneq_{t-1}\right]$ do not cause $EducIneq_t$
AT1	Ostösterreich	0.3506	4.5773***	0.0176	0.0328
AT2	Südösterreich	0.4327	0.7389	0.0000	0.0004
AT3	Westösterreich	0.0440	0.0728	0.0050	0.0773
BE1	Région Bruxelles-capitale/Brussels hoofdstad gewest	4.1882***	8.9764***	0.0027	0.0140
BE2	Vlaams Gewest	8.4839***	38.8284***	0.0004	0.0001
BE3	Région Wallonne	0.0419	2.4403***	0.0131	0.0990
DE1	Baden-Württemberg	0.0001	0.0115	0.0021	0.1847
DE2	Bayern	0.0015	0.3786	0.1502	0.3258
DE3	Berlin	6.5794***	10.9590***	0.0065	0.0599
DE4	Brandenburg	0.0063	0.0095	0.0112	0.0025
DE5	Bremen	2.4229***	12.1756***	0.6465	1.3770**
DE6	Hamburg	2.1869***	3.4525***	0.6373	0.8296
DE7	Hessen	0.1081	0.3376	0.1575	0.6093
DE8	Mecklenburg-Vorpommern	0.3119	0.5468	0.0354	0.1322
DE9	Niedersachsen	0.0667	0.1120	0.1016	0.2177

Table 3 continued

Homogeneous causality hypothesis (H_2): for region i		F_2			
		Direction: from educational inequality to income inequality		Direction: from income inequality to educational inequality	
		$EducIneq_{t-1}$ does not cause $IncIneq_t$	$EducIneq_{t-1}$ and $[W\ EducIneq_{t-1}]$ do not cause $IncIneq_t$	$IncIneq_{t-1}$ does not cause $EducIneq_t$	$IncIneq_{t-1}$ and $[W\ IncIneq_{t-1}]$ do not cause $EducIneq_t$
DEA	Nordrhein-Westfalen	0.6178	1.0856	0.0378	0.5555
DED	Sachsen	0.0042	0.0280	0.0095	0.0351
DEE	Sachsen-Anhalt	0.1485	0.2787	0.0038	0.0557
DEF	Schleswig-Holstein	0.0456	0.5066	0.0253	0.0370
DEG	Thüringen	0.1519	0.2905	0.0334	0.0969
DEX	Rheinland-Pfalz+Saarland	0.0233	0.0500	0.0891	0.4225
DK	Denmark	0.0020	0.0122	0.0795	0.1534
ES1	Noroeste	6.0045***	9.5466***	0.9208	1.1788
ES2	Noreste	5.5488***	8.8901***	0.3733	0.6137
ES3	Comunidad de Madrid	5.2642***	16.6400***	0.1780	0.2715
ES4	Centro (ES)	3.9074***	6.0561***	0.3144	0.2354
ES5	Este	0.4722	1.3872**	0.2752	0.4434
ES6	Sur	10.8538***	19.9085***	0.2064	0.1391
ES7	Canarias (ES)	2.5907***	17.4486***	0.4853	0.5851
FR1	Île de France	3.0012***	5.3890***	0.9895	2.7357***
FR2	Bassin Parisien	0.5271	0.9173	7.8261***	11.8920***
FR3	Nord–Pas-de-Calais	0.5263	0.9524	6.6089***	14.0453***
FR4	Est	0.2931	0.4697	8.2242***	14.8090***
FR5	Ouest	0.1605	0.2704	3.6876***	8.4056***

Table 3 continued

Homogeneous causality hypothesis (H_2): for region i		F_2			
		Direction: from educational inequality to income inequality		Direction: from income inequality to educational inequality	
		$EducIneq_{t-1}$ does not cause $IncIneq_t$	$EducIneq_{t-1}$ and $[W\ EducIneq_{t-1}]$ do not cause $IncIneq_t$	$IncIneq_{t-1}$ does not cause $EducIneq_t$	$IncIneq_{t-1}$ and $[W\ IncIneq_{t-1}]$ do not cause $EducIneq_t$
FR6	Sud-Ouest	0.3347	0.7609	4.9630***	9.8580***
FR7	Centre-Est	0.0479	0.1032	0.0131	7.1264***
FR8	Méditerranée	0.1040	0.1714	1.8389***	4.5939***
GR1	Voreia Ellada	4.4101***	7.4532***	0.1464	0.3696
GR2	Kentriki Ellada	3.6833***	5.8786***	0.1491	0.6159
GR3	Attiki	1.0548	5.3280***	0.0020	0.2935
GR4	Nisia Aigaiou, Kriti	0.0002	0.9857	0.3743	0.2899
IE	Ireland	2.3226***	4.2571***	0.0269	0.2412
IT1	Nord Ovest	2.0354***	3.8336***	0.3759	0.8146
IT2	Lombardia	0.1900	0.5781	0.1548	0.1623
IT3	Nord Est	0.7746	1.4007***	0.0604	0.0753
IT4	Emilia-Romagna	1.4829***	2.3389***	0.0340	0.2916
IT5	Centro (I)	1.2978***	2.0697***	0.1987	0.2139
IT6	Lazio	1.3198***	2.3800***	0.2801	0.2480
IT7	Abruzzo-Molise	1.8437***	4.7059***	0.1357	0.1413
IT8	Campania	2.9949***	4.6893***	0.2188	0.2355
IT9	Sud	1.9200***	2.9684***	0.3464	0.2314
ITA	Sicilia	1.2651***	2.3417***	1.4017**	6.2232***

Table 3 continued

Homogeneous causality hypothesis (H_2): for region i		F_2			
		Direction: from educational inequality to income inequality		Direction: from income inequality to educational inequality	
		$EducIneq_{t-1}$ does not cause $IncIneq_t$	$EducIneq_{t-1}$ and $[W\ EducIneq_{t-1}]$ do not cause $IncIneq_t$	$IncIneq_{t-1}$ does not cause $EducIneq_t$	$IncIneq_{t-1}$ and $[W\ IncIneq_{t-1}]$ do not cause $EducIneq_t$
ITB	Sardegna	3.5097***	5.6905***	0.3808	0.4643
LU	Luxembourg	0.4137	0.7005	0.1210	0.3939
PT11	Norte	1.0359	2.7444***	0.0493	4.5934***
PT12	Centro (PT)	3.2049***	6.4334***	3.8619***	6.1287***
PT13	Lisboa e Vale do Tejo	1.0285	1.9208***	0.8256	3.7371***
PT14	Alentejo	1.7738***	4.0635***	1.2560*	1.5999
PT15	Algarve	2.3926***	5.4557***	1.6278***	2.4015***
PT2	Açores (PT)	3.6738***	6.0147***	1.0044	4.8844***
PT3	Madeira (PT)	1.1888***	2.5485***	5.2903***	15.4477***
UK11	Cleveland, Durham	0.5145	1.6475***	0.0713	1.4959***
UK12	Cumbria	0.4022	1.2760***	0.0007	0.0110
UK13	Northumberland, Tyne and Wear	0.2502	0.4793	1.3941***	6.5678***
UK21	Humberside	1.0569	1.9078***	2.2601***	6.1980***
UK22	North Yorkshire	1.7185***	2.5078***	0.0428	0.5305
UK23	South Yorkshire	0.1537	1.4514***	2.1948***	3.7613***
UK24	West Yorkshire	0.0377	1.7589***	1.7796***	3.7513***
UK31	Derbyshire, Nottinghamshire	0.0198	0.1243	0.5108	1.6137***
UK32	Leicestershire, Northamptonshire	22.6141***	36.4524***	0.0001	0.0220
UK33	Lincolnshire	0.9496	4.1490***	1.8245***	4.3556***

Table 3 continued

Homogeneous causality hypothesis (H_2): for region i		F_2			
		Direction: from educational inequality to income inequality		Direction: from income inequality to educational inequality	
		$EducIneq_{t-1}$ does not cause $IncIneq_t$	$EducIneq_{t-1}$ and $[W\ EducIneq_{t-1}]$ do not cause $IncIneq_t$	$IncIneq_{t-1}$ does not cause $EducIneq_t$	$IncIneq_{t-1}$ and $[W\ IncIneq_{t-1}]$ do not cause $EducIneq_t$
UK40	East Anglia	0.5440	0.8691	0.5145	7.6550***
UK51	Bedfordshire, Hertfordshire	5.4692***	15.6634***	0.0141	0.4238
UK52	Berkshire, Buckinghamshire, Oxfordshire	0.2371	0.3242	1.4233***	2.7849***
UK53	Surrey, East-West Sussex	0.6226	1.0611	1.9180***	6.2823***
UK54	Essex	2.4147***	4.4758***	0.3304	2.4591***
UK55	Greater London	3.6627***	5.4179***	0.3548	1.8722***
UK56	Hampshire, Isle of Wight	0.6146	0.9669	0.0044	2.9083***
UK57	Kent	0.7534	10.8359***	0.8568	2.7957***
UK61	Avon, Gloucestershire, Wiltshire	0.0300	0.0848	2.7338***	4.7358***
UK62	Cornwall, Devon	0.7697	1.5813***	2.4217***	11.5048***
UK63	Dorset, Somerset	4.5335***	7.6055***	1.8909***	7.3848***
UK71	Hereford and Worcester, Warwickshire	0.0536	0.1265	0.3185	2.9788***
UK72	Shropshire, Staffordshire	0.1209	0.4796	0.9424	3.2729***
UK73	West Midlands (County)	0.2171	0.3268	0.4483	0.9996
UK81	Cheshire	0.5458	1.1473***	0.1109	1.0924
UK82	Greater Manchester	1.0926	1.7783***	2.7651***	5.6810***
UK83	Lancashire	2.3333***	4.4442***	0.0291	0.1127
UK84	Merseyside	2.8491***	8.0961***	3.1621***	8.8642***
UK91	Clwyd, Dyfed, Gwynedd, Powys	13.1704***	23.0297***	0.0421	1.0236

Table 3 continued

Homogeneous causality hypothesis (H_2): for region i		F_2			
		Direction: from educational inequality to income inequality		Direction: from income inequality to educational inequality	
		$EducIneq_{t-1}$ does not cause $IncIneq_t$	$EducIneq_{t-1}$ and $[W\ EducIneq_{t-1}]$ do not cause $IncIneq_t$	$IncIneq_{t-1}$ does not cause $EducIneq_t$	$IncIneq_{t-1}$ and $[W\ IncIneq_{t-1}]$ do not cause $EducIneq_t$
UK92	Gwent, Mid-South-West Glamorgan	4.3541***	14.5388***	0.0319	0.3862
UKA1	Borders-Central-Fife-Lothian-Tayside	0.0864	0.1473	0.2043	1.0274
UKA2	Dumfries and Galloway, Strathclyde	0.4000	0.6275	0.2424	0.5670
UKA4	Grampian	0.9921	1.3985***	0.2359	1.1072

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

'$EducIneq_{t-1}$ and $\left[W\ EducIneq_{t-1}\right]$ cause $IncIneq_t$' and '$IncIneq_{t-1}$ and $\left[W\ IncIneq_{t-1}\right]$ do not cause $EducIneq_t$' are true for 36 regions.

(c) Unidirectional causality from income inequality to educational inequality: The relationships '$EducIneq_{t-1}$ does not cause $IncIneq_t$' and '$IncIneq_{t-1}$ causes $EducIneq_t$' appear to hold for 16 regions. The relationships '$EducIneq_{t-1}$ and $\left[W\ EducIneq_{t-1}\right]$ do not cause $IncIneq_t$' and '$IncIneq_{t-1}$ and $\left[W\ IncIneq_{t-1}\right]$ cause $EducIneq_t$' hold for the same number of regions (16).

(d) Bilateral causality: The relationships '$EducIneq_{t-1}$ causes $IncIneq_t$' and '$IncIneq_{t-1}$ causes $EducIneq_t$' exist for 6 regions only, while the relationships '$EducIneq_{t-1}$ and $\left[W\ EducIneq_{t-1}\right]$ cause $IncIneq_t$' and '$IncIneq_{t-1}$ and $\left[W\ IncIneq_{t-1}\right]$ cause $EducIneq_t$' appear to hold for 21 regions. The latter relationships hold for more regions since interregional externalities matter for causality.

The above results show that there is a heterogeneous causality from income inequality to educational inequality and vice versa, and interregional income and educational externalities are related to this causality. Hence, the reverse causality between income and educational inequality is heterogeneous and is shaped by the spatial location of the various regions through geographical externalities.

These results are robust in terms of the definition of income inequality (i.e. income inequality for the whole of the population and income inequality for normally working people), to the measurement of income and educational inequality (i.e. Theil index, Gini index and the squared coefficient of variation), to the value of k (with $k = 3, 5, 7$ and 9) of the spatial weights matrix and to the inclusion of control variables such as unemployment, labour market participation and sectoral composition.[8] Unemployment and labour market participation variables are extracted from the ECHP data survey and are measured by the percentage of unemployed respondents and by the percentage of normally working respondents, respectively. The sectoral composition variables are extracted from the Eurostat database: 'agriculture' is the share of added value of agriculture, hunting, forestry and fishing in total added value; 'industry' is the share of added value of mining and quarrying, manufacturing, electricity, gas and water supply and construction in total added value; and 'services' is the share of added value of services (excluding extra-territorial organizations and bodies) in total added value. The robustness of the results to the inclusion of the above control variables may be a signal that there is no spatial dependence in the regression residuals, because spatial dependence in the regression residuals is usually an indication that additional variables should be included in the regression model (Anselin 2000, 1988). Moreover, by adding a set of control variables able to capture the main structural and economic features of the European regions, some important sources of regional heterogeneity are taken into account (Sterlacchini 2008). Finally, by introducing spatially lagged independent variables in the analysis, the effects of the interactions between neighbouring regions on the residuals is minimised (Rodríguez-Pose and Crescenzi 2008).

[8] These results can be provided upon request.

5 Conclusions and economic policy implications

This paper has used a spatial cross-regressive VAR framework to test the Granger-causality between income inequality and educational inequality within regions of the EU. Using a balanced regional data set constructed from the ECHP data survey for 94 NUTS I or NUTS II regions belonging to 12 countries from 1995 to 2000, the Granger-causality tests show that there is a heterogeneous causality from income inequality to educational inequality, and vice versa, and interregional income and educational externalities are important in this causality. This confirms that the income–education relationship varies across space, reflecting a general instability in the European labour market across regions, and the influence of a number of factors—such as trade between regions, interregional migration, knowledge diffusion, forward and backward linkages, and more generally interregional spillovers—that lead to geographically dependent regions. This phenomenon could be associated with the existence of income and education externalities that cross regional borders. However, there are spatial limits to the spread of externalities. Location and proximity clearly matter in exploiting the causality between income and education. If we ignore the influence of spatial location on the income–education relationship, we produce biased results and hence misleading conclusions.

A limitation of this method is that although we can detect the direction of causality, we cannot ascertain the fundamental reason behind it. Nevertheless, this method allows us to see the importance of interaction effects for particular regions in the EU. However, the fact that we have only a few time periods available calls for some cautions.

Overall, the causes and consequences of inequalities and thus the policy concerns may differ across space. Space plays an important role in the functioning and performance of economies in general and Europe's in particular. Understanding how inequalities originate and evolve over time and across space is an important step towards identifying not only the appropriate income and educational policy response, but also the effects of inequalities on the economic performance of regions. European regional policy should seek a synergy in the achievement of both equity and efficiency, but it may involve trade-offs in the extent to which the two goals can be attained. High levels of inequality in educational attainment are associated with higher income inequality, which may be interpreted as a sign of the responsiveness of the EU labour market to differences in qualifications and skills (Rodríguez-Pose and Tselios 2009a). Thus, the goal of equitable educational distribution is likely to lower income inequality. Policies that improve access to education provide a higher quality of education and, generally, increase educational attainment are likely to alleviate inequalities not only in education, but also in income. However, this might not be relevant for all regions, due to a heterogeneous causality from educational inequality to income inequality, and vice versa. This study also shows that interregional income and educational externalities are relevant to this causality. Hence, European regional policies should take into account the fact that income and educational externalities spill over the barriers of regional economies. For instance, a decrease in income inequality within a region might well be caused by a policy (e.g. tax policy) which lowered inequality within neighbouring regions. Generally, common regional activities in neighbouring regions (e.g. public infrastructure) and common policies across neighbouring regions (e.g. structural funds) affect many regions through spillover effects. Therefore, interregional linkages, geographical location and proximity are important for the income and educational inequalities of regions (Rodríguez-Pose and Tselios 2009b, 2011), but the spatial effects differ across space. Finally, inequalities are important in accounting for the economic performance of regions. Rodríguez-Pose and Tselios (2010) show, for example, that given existing levels of inequality in the EU, an increase in a region's income and educational inequality has a significant positive association with subsequent economic growth. This implies that regional policies involve a trade-off, by either advancing growth efficiency to the detriment of educational and income equity or by advancing equity to the detriment of efficiency. However, this study stresses the significance of a combined regional economic policy perspective that considers labour market and educational policies, and all these policies should emphasise the role of space.

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