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ORIGINAL ARTICLE

Dynamics of inequality and growth in Europe: may spatial models solve the puzzle?

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Abstract
The link between income inequality and economic growth remains poorly understood. The global economic crisis challenged numerous growth studies by highlighting considerable degrees of spatial interdependence among economies. The existence of fewer restrictions on factor movements prompted spatial redistributions of income inequalities. Our paper attempts to reestimate such inequality impacts across the EU by allowing for these redistributions. We employ the spatial Durbin error specification, and unlike other studies, we make statistical inferences along the lines of a welfare-adjusted production function. Our results lend support to the presence of spillover effects emanating from income redistribution larger than those from unemployment, knowledge, or human capital.

Keywords Income inequality · Economic growth · Spatial Durbin error model · Spillover effect · Welfare regime

JEL Classification I24 · O40 · O52

1 Introduction

The panel data literature has extensively discussed the nonspatial relationship between inequality and growth (Banerjee and Duflo 2003; Sen 2009; Stiglitz 2012). In recent years, some evidence has shown that income inequalities are spatially autocorrelated and that failing to account for this autocorrelation may produce biased

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estimates (Bebonchu 2013; Ezcurra 2007). Yet still, scholarly work appears to pay little attention to the further exploration of the effects of this autocorrelation, particularly with respect to their role in explaining variance in growth rates across countries and time.

Spatial patterns in income inequality across the EU appear not to be a static phenomenon (Chambers and Dhongde 2016) even though they appear to align with relatively a static delineation of welfare regimes. As a result, as Esping-Andersen (1990) observed, welfare preferences are spatially clustered: the Scandinavian countries promote an equality of high standards, which results in a commitment to a heavy social service burden (a *sociodemocratic* welfare regime). Central and Western European countries tend to encourage family-based assistance dynamics and typically show moderate levels of inequality (a *conservative* welfare regime). The Anglo-Saxon countries encourage market solutions to social problems and promote an equality of minimal needs (a *liberal* welfare regime). This typology has often been expanded into a four- (or five-)case model: the *southern* welfare regime is viewed as a rudimentary conservative model marked by substantial failures in the social protection safety net (Ferrera 1996), while most Central and Eastern European countries are considered to employ *neoliberal* welfare regimes, as they engaged in liberal retrenchment and in the recalibration of their social protection systems when the Soviet Union collapsed (Bohle and Greskovits 2007).

While growth effects of welfare, unless extensive, appear to be benign, spatial redistributions of human capital appear to play quite a decisive role in inequality-led growth dynamics (Berg et al. 2018). Similarly, Rehme (2015) argues that any adverse redistribution effects on growth are offset by efficiency gains. Some recent evidence may suggest that the equalizing effect of human capital mobility is small (Bachmann et al. 2016). Yet the mounting evidence on the relevance of cross-border factor movements, particularly human and knowledge capital, for growth (Bachmann et al. 2016; Puskarova and Piribauer 2016) and the concentration of wealth (Roser and Crespo-Cuaresma 2016) as well as physical capital for local wages (Maczulskij 2013; Lamo et al. 2013) appears to further support the general notion of dynamic income inequality clustering.

In the light of the above findings, we suggest approaching the inequality-growth nexus with respect to spatial dependence in income inequality data and, unlike other studies, making statistical inferences within the welfare-adjusted production function. We employ a sample of 27 EU member states for 2005 through 2013. Our results indicate that cross-country inequalities might matter more than previously suggested (Bebonchu 2013). In addition, our model also highlights spillover effects emanating from human capital, unemployment, and debt, suggesting that the impact of inequality clustering on growth remains large even if the effects of skills and adverse workforce and capital conditions in a given neighborhood are controlled for.

The paper is structured as follows. In the following section, we outline the theoretical and empirical discourse on the direction of effects of inequality on growth. We then present the proposed model and describe our data sources and processing methods. In the fifth section, the paper presents the estimation results and in the sixth section, the robustness analysis. The seventh and final sections summarize the key findings of the paper.

2 Theoretical and empirical foundations

The last few years have witnessed a growing number of studies explaining the causal relationship between income inequality and economic growth (Rajan 2010; Kumhof et al. 2012; Stockhammer 2012). However, there is currently no consensus among scholars regarding the direction of this relationship. There are at least four perspectives on the issue. The first group of studies affirms a negative relationship between income inequality and economic growth. For example, Alesina and Rodrik (1994) argue that because the majority of voters vote for higher taxes and redistribution from owners of capital to those of labor, there is a trade-off between positive effects of higher distribution (more disposable income for workers) and negative effects of higher taxation, resulting in lower economic growth rates. The negative incline in the inequality-growth curve may also arise because poor individuals in countries with high levels of inequality and low levels of redistribution are not able to accumulate the human capital required to promote economic growth (Perotti 1993). The same conclusions are reached by Berg, Ostry, Tsangarides and Yakhshilikov (2018).

Li and Zou (1998) suggest a positive nexus between income inequality and economic growth. Their study assumes that government spending is allocated entirely to consumption, which leads to situations in which individuals vote for higher taxes to increase levels of government consumption. This, in turn, slows economic growth. Forbes (2000) reestimates Li and Zou's model on panel data and includes other factors such as gender, human capital, and market imperfections and reaches the same conclusion.

The third strand of studies proposes a nonlinear relationship between income inequality and economic growth. The famous inverted U-shaped Kuznets curve models that over the course of economic development, economic growth is first associated with increasing income inequality and, in later stages, decreasing inequality. Barro (1999) estimates this relationship with various controls—the investment ratio, government consumption, the rule of law index, the democracy index, the inflation rate, years of schooling, the total fertility rate, and terms of trade. He concludes that the effect of inequality on economic growth is negative for countries with GDP per capita levels below the threshold of 2.070 USD and positive for those with levels above this threshold. Banerjee and Duflo (2003) challenge Barro (1999) and argue that it is not the level of income inequality but the absolute change in income inequality that causes the nonlinear incline of the relationship.

The fourth strand of studies finds no link between income inequality and economic growth whatsoever. Castelló and Domenech (2002), for example, conclude that even though some results point to the negative slope of the relationship once human capital is taken into account, the sign of the relationship reverts to positive. Thus, it is human capital that precipitates all effects of income inequality on growth. In addition, the authors highlight that when introducing spatial dummies, the relationship becomes insignificant. Our paper follows up on this analytical framework and considers spatial dimensions of income inequality together with human capital effects on growth.

3 Model

Modeling income inequality within the growth accounting framework remains a challenge. This is even more the case when our attempt is to introduce spatial dependence in determinants, and the first attempts to estimate spatial autocorrelation in income inequalities did not provide adequate theoretical foundations for understanding inequality and growth. For example, Ezcurra (2007) estimates growth effects of spatial income inequalities using a spatial error model (SEM) and while controlling for initial per capita GDP, the sectoral composition of economic activity, population density, and market potential. Bebonchu (2013) employs a dynamic spatial Durbin model (SDM) with educational attainment applied as a single control.

Our empirical contribution lies in an attempt to estimate the response of aggregate output to inequality, both locally and within the neighborhood, within the welfare-adjusted production function. To do so, we follow the spirit of Cingano's (2014) extension to the Solow model and the earlier work of Persson and Tabellini (1994) and Alesina and Rodrik (1994). The extension relies on the production function that for the sample of countries $i=\{1, 2,\ldots, N\}$ and years $t=\{1, 2,\ldots, T\}$ takes the following form:

$$Y_{it} = AS_{it}^{1-\beta} L_{it}^{\beta} C_{it}^{1-\beta} \exp\left(\upsilon_{it}\right) \tag{1}$$

where Y_{it} denotes the aggregate product depending on capital C_{it}, L_{it} denotes labor, and S_{it} denotes the aggregate level of government spending on productive services. Standard error ε_{it} reflects random noise in the model and is in exponential form for practical reasons—so that taking logs makes Eq. (1) linear in parameters. Coefficients β and $(1-\beta)$ denote the output elasticities of labor and physical capital, respectively.

Following Alesina and Rodrik (1994), capital is to be interpreted in a broad sense as including physical human capital and all proprietary technology. In a similar vein, Puskarova and Piribauer (2016) suggest technological parameter A being subject to human and knowledge capital. Thus, we rewrite Eq. (2) accordingly:

$$Y_{it} = K_{it}^{\beta_K} H_{it}^{\beta_H} S_{it}^{1-\beta} L_{it}^{\beta} C_{it}^{1-} \exp\left(\upsilon_{it}\right) \tag{2}$$

where K_{it} and H_{it}, respectively, represent knowledge capital and human capital, and β_K and β_H are their partial elasticities, respectively.

Alesina and Rodrik (1994) allow for redistributive effects of capital tax and conclude that under majority voting rule, the rate of growth is subject to varying individual labor/capital shares, and thus $S_{it} \approx G_{it}$. The appeal of our model is twofold. First, the model attributes the role of debt for government spending. Alesina and Rodrik (1994) assume public budgets constantly to balance out. However, the vast majority of governments use foreign borrowings to capitalize their redistribution systems: $S_{it} \approx D_{it}$. This is often the case in an economic recession when unemployment grows and for tax collection contracts. Second, our model assumes a role of unemployment in long-term growth. Labor is supplied inelastically; however, the economy's aggregate workforce varies by various structural, random, and cyclical factors that push part of the labor out of the market. Thus, labor endowment in our model is indirectly proportional to unemployment rates: L_{it} = f (U_{it}). Moreover, unlike other cash transfers (old age pensions and childcare support), unemployment benefits are endogenous, so they generate additional income that might affect an individual's decision regarding whether to spend on education (Dissou et al. 2016). Taking this into account, we rewrite Eq. (2) as follows:

$$Y_{it} = K_{it}^{\beta_K} H_{it}^{\beta_H} G_{it}^{\beta_G} D_{it}^{\beta_D} U_{it}^{\beta_U} C_{it}^{1-} \exp\left(\upsilon_{it}\right) \tag{3}$$

where β_G, β_D, and β_U denote partial elasticities of aggregate output on income inequality, debt, and unemployment, respectively.

To compare, Cingano (2014) uses the Solow model and shows that output growth is a function of the initial level of production and of the ultimate determinants of a steady state. This implies that each growth determinant has an impact on each subsequent pattern of growth. Cingano's baseline model takes income inequality, physical capital, and human capital as ultimate determinants yet notes that scholarly work must test a broader set of controls of long-term growth such as social capital, trade openness, or institution quality.

Applying logs in Eq. (3) yields the following form of the production function:

$$\ln Y_{it} = \beta_H \ln H_{it} + \beta_K \ln K_{it} + \beta_U \ln U_{it} + \beta_D \ln D_{it} + \beta_G \ln G_{it} + (1-\beta) \ln C_{it} + \varepsilon_{it} \tag{4}$$

In accordance with the findings of Ezcurra (2007), we expect our model to include a spatially autocorrelated fraction within the error term rather than time autocorrelation being included in the dependent variable (Cingano 2014). In accordance with the spatial perspective, the spillovers from region i to region j are subject to a concept of closeness (neighborhood). The neighborhood of regions i and j is captured in an N times N nonnegative spatial weight matrix W. Specifically, $\mathrm{W}_{ij} > 0$, if regions i and j are assumed to be neighbors. Moreover, $\mathrm{W}_{ii} = 0$ since no region is assumed to be a neighbor to itself. The spatially autocorrelated standard error takes the following form:

$$\varepsilon_{it} = \varepsilon_{it} + \lambda \sum_{j \neq i}^{N} W_{ij} \varepsilon_{jt} \tag{5}$$

By substituting ε_{it}, we obtain our baseline model that fits the properties of an SEM:

$$\begin{aligned} \ln Y_{it} = {} & \beta_H \ln H_{it} + \beta_K \ln K_{it} + \beta_U \ln U_{it} + \beta_D \ln D_{it} \\ & + \beta_G \ln G_{it} + (1-\beta) \ln C_{it} \\ & + \varepsilon_{it} + \lambda \sum_{j \neq i}^{N} W_{ij} \varepsilon_{jt} \end{aligned} \tag{6}$$

Moreover, we assume that each of the growth determinants affects not only local production (*direct effects*) but also production in the neighborhood (*indirect* spillover *effects*). We may define spillover effects unfolded by each variable in a similar way as the spatial autocorrelated error included in Eq. (7). The estimated elasticities relating to the spatially autocorrelated fraction of the variables are denoted with superscript *E,* and the new model specification we arrive at is known in the literature as a spatial Durbin error model (SDEM):

$$
\begin{aligned}
\ln Y_{it} =& \beta_H \ln H_{it} + \beta_K \ln K_{it} + \beta_U \ln U_{it} + \beta_D \ln D_{it} + \beta_G \ln G_{it} + (1-\beta)\ln C_{it} \\
&+ \beta_H^E \left[\sum_{j\neq i}^{N} W_{ij} \ln H_{jt}\right] + \beta_K^E \left[\sum_{j\neq i}^{N} W_{ij} \ln K_{jt}\right] \\
&+ \beta_U^E \left[\sum_{j\neq i}^{N} W_{ij} \ln U_{jt}\right] + \beta_D^E \left[\sum_{j\neq i}^{N} W_{ij} \ln D_{jt}\right] \\
&+ (1-\beta)^E \left[\sum_{j\neq i}^{N} W_{ij} \ln C_{jt}\right] + \varepsilon_{it} + \lambda \sum_{j\neq i}^{N} W_{ij}\varepsilon_{jt}
\end{aligned} \tag{7}
$$

For simplicity, we collapse this model in our estimations where appropriate.

We expect human and knowledge capital (either local or externalized) to positively affect aggregate production $-\beta_H > 0$, $\beta_K > 0$, $\beta_H^E > 0$, $\beta_K^E > 0$. Unemployment is assumed to work counterproductively in the model $\beta_U < 0$, while rising unemployment in the neighborhood may emerge for local production as insignificant or even positive because job scarcity tends to drive labor out of the country to work and contribute to production elsewhere. The link between indebtedness and production conventionally takes the form of a U curve—in its left section, rising public debt helps local production grow until the marginal effect reaches zero. After this point, costs of public debt exceed the benefits of additional public spending. Thus, in our paper, we can assume that rising debt helps the local economy exit the crisis and, thus, that $\beta_D > 0$ (Salotti and Trecroci 2012). Nevertheless, the spillover effects of debt might be small or insignificant. For the expected sign of the relationship between inequality and production, we expect locally increasing inequality to hamper growth $\beta_G < 0$, which, however, may pose an advantage to neighbors in terms of attracting labor and benefits $\beta_G^E > 0$.

4 Data

To measure income inequality, we employ the Gini coefficient of equivalized disposable income. The Gini coefficient ranges from zero (all people have the same level of income) to 100 (one person receives all of the income). The Gini coefficient is sometimes criticized as being too sensitive to changes occurring around the center of the income distribution. This sensitivity is attributable to the Gini coefficient reflecting a ranking of the population, as ranking is most likely to change the densest part of the distribution, which is likely to be around the center.

As a proxy for knowledge capital, we use the number of patent applications to the European Patent Office (EPO) per million inhabitants. The data are again derived from Eurostat. Several concerns have been articulated in the literature regarding qualifying patent applications as a reliable proxy for knowledge capital (Puskarova and Piribauer 2016). Many patent applications are merely for upgrades of already existing patents. Furthermore, costs required to register a patent may prevent some innovators from doing so. Moreover, a vast portion of knowledge is never codified (e.g., Griliches 1990). Despite these concerns, no better proxy has been deployed to date.

Human capital remains a challenging concept to measure. It conventionally refers to intangible assets in the form of skills, experience, and education uniquely contained in a human being. Several studies have employed educational attainment or years of schooling as appropriate measures of human capital, though these studies report rather ambiguous findings in this regard (Arcand and d'Hombres 2007). Other studies have attempted to improve the explanatory power of human capital for growth by employing indexes such as the Global Human Capital Index. Those indexes, however, are biased by the subjectivity of the observer. The present study follows the approach used by Barro and Lee (2010) and employs their dataset on country-level years of schooling as a measure of human capital.

Regarding public debt, we use data from Eurostat, which defines public debt (according to the Maastricht Treaty) as consolidated general government gross debt, at nominal (face) value, outstanding at the end of the year. The general government sector comprises all debt registered for the central government, state government, local government, and social security funds. Unlike the debt level as defined in national financial statistics, the Maastricht debt level also includes "imputed" borrowing. Examples include government-initiated transactions that are attributable to the general government sector but are financed via public enterprises instead of the core budget and capital expenditures by public–private partnerships, provided that certain project risks are borne by the government.

As for unemployment, we measure the number of unemployed persons as a percentage of the labor force (total number of people employed and unemployed) based on the International Labour Office's (ILO) definition. Unemployed persons include persons aged 15–64 who are without work during the reference week, are available to start work within the next two weeks, and have been actively seeking work for the past four weeks or have already found a job to start within the next three months.

Table 1 lists all of the variables used in this paper and their sources and a description of the dataset used as represented by respective means and standard deviations.

The neighborhood of each pair of EU countries is represented in our model by spatial weight matrix W. We determine each element of the W matrix as a weighted inverse distance $1/r^p$ where r stands for the distance between two particular capitals of EU states and where $p=2$ because we assume exponential distance decay effects in our estimations. We use a sample of EU-27 countries and take the distances between them as the shortest travel distance between their capitals[1] because we assume that the capitals are the economic centroids. To avoid overestimation problems (Elhorst 2012), the matrix is row standardized.

[1] Retrieved from http://distancecalculator.globefeed.com/world_distance_calculator.asp.

Table 1 Descriptive and summary statistics, sample means and standard deviations

Variable	Proxy	Source	Nobs	Min	Max	Mean	Standard deviation
D	Gross government debt (% GDP)	Eurostat online databases	243	3.7	175.1	56.55	33.00
G	Gini coefficient of equivalized disposable income*	EU statistics on income and living conditions	243	22.7	38.9	29.6	3.96
H	Years of schooling	Eurostat online databases	243	7.2	13.1	10.67	1.11
I	Investments (bln. EUR)	Cambridge econometrics	243	0.80	433.88	27.24	0.01
C	Physical capital stock (tn. EUR)**	Cambridge econometrics	243	1.80	2.36	2.06	1.05
K	Patent applications to the European Patent Office	Eurostat online databases	243	1.15	49,240	688.07	9.02
S	Income quintile share ratio	EU statistics on income and living conditions	243	3.2	7.8	4.77	1.11
T	Share of population aged 25–64 with tertiary education attainment—ISCED 5–6 (%)	Eurostat online databases	243	9.1	36.3	22.49	7.02
U	Unemployment (%)	Eurostat online databases	243	3.1	27.5	8.72	4.14
Y	Gross domestic product (EUR, const. 2000 prices, % growth)	Eurostat online databases	243	− 17.7	11	1.49	4.11

*Total income of a household, after tax and other deductions, that is available for spending or saving, divided by the number of household members converted into equalized adults (weighting each by age)

**Calculated from yearly I using perpetual inventory calculation $C_{it+1} = C_{it}\,(1 - r) + I_{it+1}$, $r = 0.12$

Table 2 Estimation results: OLS versus SEM, MLE

OLS, No spatial effects			SEM with RE		SEM with spatial FE and RE	
β_G—income inequality	3.951855	(0.000000)	− 0.924235	(0.000018)	− 0.838124	(0.000039)
β_U—unemployment	0.530679	(0.037967)	− 0.102985	(0.000000)	− 0.128205	(0.000000)
β_D—debt	− 0.044558	(0.072863)	0.027599	(0.023063)	0.053948	(0.000049)
β_K—knowledge capital	0.037550	(0.006833)	0.156703	(0.000000)	0.154696	(0.000000)
β_H—human capital	0.177712	(0.000000)	− 0.729603	(0.000000)	− 0.626446	(0.000000)
$(1-\beta)$—physical capital	− 0.521341	(0.000000)	1.039150	(0.000000)	0.779521	(0.000001)
τ	0.260612	(0.146224)				
σ^2	0.0164		0.0068		0.0058	
pseudo R^2	0.8404		0.9053		0.9132	
adj. pseudo R^2	0.8363		0.9033		0.9114	
log likelihood	158.0573		263.3569		284.3498	
LM test—Wy	0.3136	(0.575)	4.9474	(0.026)	6.5751	(0.010)
robust LM test—Wy	62.9435	(0.000)	1.3040	(0.253)	2.7660	(0.096)
LM test—$W\varepsilon$	83.8532	(0.000)	6.7375	(0.009)	5.6658	(0.017)
robust LM test—$W\varepsilon$	146.4831	(0.000)	3.0942	(0.079)	1.8567	(0.173)

p values are shown in parentheses; FE denotes fixed effects; RE denotes random effects; SEM stands for the spatial error model; pseudo R^2 represents the goodness of fit of the model; adjusted (adj.) pseudo R^2 represents the goodness of fit without FE; the LM test is the Lagrange multiplier test; σ denotes the standard error; τ denotes the weight attached to the cross-sectional component of the data with $0 \le \tau^2 = \sigma^2$, and when $\tau^2 = \sigma^2$, the estimation with RE reduces to the estimation with FE

5 Model estimation

To test the model, we organize our dataset into a panel of $N=27$ EU member states and $T=9$ years spanning 2005 through 2013. We employ the MATLAB code for estimation of spatial panel data models developed by Paul Elhorst.[2] The code is based on maximum likelihood estimation (MLE), and goodness-of-fit measures—the so-called pseudo R^2 and adjusted pseudo R^2—are calculated using the approach developed by Lee and Yu (2010). The results of the estimations are summarized in Table 2.

Table 2 yields following findings:

1. Based on the Lagrange Multiplier (LM) test, we can reject the null hypothesis that the autocorrelation in the dependent variable (as implied by Cingano's 2014 model) could explain the dataset better than the spatial autocorrelation in the error term. This validates our selection of the spatial model specification.
2. Income inequality appears to have a significant impact on output growth. However, the direction of the relation changes once spatial effects are controlled for.

[2] Retrieved from https://spatial-panels.com/software/ and http://www.regroningen.nl/elhorst/software.shtml

Table 3 Estimation results: SDEM without FE, MLE

	Baseline model		Welfare regime model		Physical capital model	
λ–$W\varepsilon$	0.391995	(0.000001)	0.392969	(0.000001)	0.434990	(0.000000)
β_G—Income Inequality	− 0.114092	(0.576574)	− 0.293408	(0.154269)	− 0.266997	(0.180595)
β_U—Unemployment	− 0.109917	(0.000000)	− 0.085316	(0.000013)	− 0.080253	(0.000150)
β_D—Debt	0.079692	(0.000000)	0.055455	(0.000002)	0.040590	(0.000679)
β_K—Knowledge capital	0.165500	(0.000000)	0.137494	(0.000000)	0.162593	(0.000000)
β_H—Human capital	0.629744	(0.000000)	− 0.483914	(0.000000)	− 0.572904	(0.000000)
(1-β)—Physical capital					0.917187	(0.000000)
γ—Welfare Regime			− 0.035398	(0.000001)		
$\beta_G{}^E$–Wg	2.791813	(0.000000)	2.817687	(0.000000)	2.765718	(0.000000)
$\beta_U{}^E$–Wu	0.133133	(0.000874)	0.098039	(0.041865)	0.114132	(0.055512)
$\beta_D{}^E$–Wd	− 0.012730	(0.498699)	0.027205	(0.174879)	0.033771	(0.108453)
$\beta_K{}^E$–Wk	0.019806	(0.057796)	0.035027	(0.144589)	0.021148	(0.050763)
$\beta_H{}^E$–Wh	0.634863	(0.000000)	0.583131	(0.000029)	0.558196	(0.000001)
$(1-\beta)^E$–Wc					− 0.615983	(0.084887)
γ^E–Wr			0.027126	(0.136778)		
σ^2	0.0101		0.0095		0.0090	
pseudo R^2	0.8829		0.8913		0.8936	
adj. pseudo R^2	0.8832		0.8916		0.8940	
logL	209.11627		217.74662		223.64289	
Wald test (for Wy)	264.9129	(0.000000)	288.3422	(0.000000)	299.4580	(0.000000)
LR test (for Wy)	178.2321	(0.000000)	183.0031	(0.000000)	189.2209	(0.000000)
Wald test (for $W\varepsilon$)	72.9282	(0.000000)	74.3455	(0.000000)	74.9943	(0.000000)
LR test (for $W\varepsilon$)	174.1529	(0.000000)	186.8744	(0.000000)	190.4981	(0.000000)

p values are shown in brackets; FE denotes fixed effects; Wy, Wg, Wu, Wd, Wk, Wh, Wc, Wr, $W\varepsilon$ = spatial autocorrelation in dependent variable GDP; G (income inequality index); U (unemployment); D (public debt); K (knowledge capital); H (human capital measured as years of schooling); C (physical capital stock); R (welfare regime dummy); ε (residuals); pseudo R^2 represents the goodness of fit of the model; the adjusted (adj.) pseudo R^2 represents the goodness of fit without FE; the LM test is the Lagrange multiplier test; σ denotes the standard error

Estimating the SEM turns positive effects of income inequality on growth negative.

3. The estimated effects of other growth determinants appear statistically significant and relatively large. As expected, output growth appears to follow the dynamics of unemployment and physical capital while following those of knowledge capital and debt less.

Table 2 implies that accounting for spatial effects changes the direction of the estimated partial elasticities of several growth determinants. It appears that spatial effects might play a significant role in explaining the variation in aggregate output and that neglecting spatial dependence among the countries might result in severe omitted variable bias (see also LeSage and Pace 2009). For example, negative debt effects returned by ordinary least squares (OLS) turn positive once the SEM is employed. In addition, via OLS, inequality effects are found to be positive, while the SEM returns them negative. This result challenges some earlier empirical work (Li and Zou 1998; Forbes 2000). Table 3 displays the estimations of our model. In the baseline specification, we relax on physical capital effects. We also reproduce the estimations with a welfare regime dummy to control for interactions between welfare and income inequality.

In all three specifications, the likelihood ratio and Wald test point to the significance of the spatial autocorrelation in the residuals: the estimated test values for W_{ε} are lower than those for W_{y}. The estimated parameters of the model suggest strong elasticity in the aggregate output on income inequality in the neighboring countries, but insignificant local income inequality effects on growth. The results also show positive spillover effects emerging from human capital and unemployment and less so from knowledge capital. Physical capital and debt appear to matter only for local growth and not for neighborhood growth.

It is worth noting that in conventional (nonspatial) linear models, parameter estimates have a straightforward interpretation. LeSage and Pace (2009), however, show that the interpretation of the parameter estimates of spatial autoregressive models might lead to erroneous conclusions due to the nonlinear nature of models involving a spatial lag in the dependent variable or standard error. Moreover, spatial autoregressive models typically exhibit nonzero cross-partial derivatives. The nonlinear nature of spatial autoregressive model specifications implies that changes in a country's human capital not only affect aggregate output in the same country (direct effects) but also the output growth in neighboring countries (indirect or spillover effects). Due to nonnegative spillover effects, spatial autoregressive models involve dealing with N^2 partial derivatives for a particular explanatory variable. To manage this overwhelming amount of information, LeSage and Pace (2009) suggest reporting a summary metric for indirect (spillover) effects measured by the average of either the row or column sums of the off-diagonal elements of the matrix. A summary metric for direct impacts is represented by the average of diagonal elements of the matrix. In compliance with this approach, Table 4 reports average direct and indirect (spillover) impact estimates.

The estimates align with the mainstream evidence showing that income inequality hampers growth. However, the estimates further suggest that income inequality across European countries is spatially autocorrelated and that output growth is strongly elastic to this autocorrelation. Even though our results struggle to determine what drives this strong responsiveness, the underlying model implies that the process involves utility-maximizing individuals trying to adjust their capital/labor endowments, which may mean that relatively high skilled yet capital scarce individuals respond to rising income equality at proximity and move for work. The low estimated coefficient for the welfare regime effect shows that this effect might be attributable to within-regime rather than cross-regime mobilities. For example, the fall in income inequality among researchers in the Czech Republic and Austria has prompted Slovak researchers to move and join research teams under the proximal welfare regime in the Czech Republic rather than to that in Austria.

Table 4 Direct and indirect effects estimation, SDEM minus FE, MLE

	Baseline model		Welfare regime model		Physical capital model	
Direct effects						
Income inequality *G*	– 0.286428	(0.178992)	– 0.336601	(0.092214)	– 0.273211	(0.000000)
Unemployment *U*	– 0.112321	(0.000007)	– 0.087182	(0.000000)	– 0.092033	(0.082195)
Debt *D*	0.077712	(0.000000)	0.054077	(0.000000)	0.056390	(0.000050)
Knowledge capital *K*	0.163432	(0.000000)	0.135776	(0.000000)	0.156309	(0.000021)
Human capital *H*	0.684930	(0.000000)	0.526320	(0.000000)	0.616704	(0.000000)
Physical capital *C*					0.977231	(0.000000)
Welfare regime *R*			– 0.041003	(0.000000)		
Indirect effects						
Income inequality	3.040513	(0.000000)	3.068692	(0.000000)	3.043569	(0.000000)
Unemployment	0.168808	(0.003705)	0.124310	(0.023705)	0.152588	(0.038993)
Debt	– 0.011854	(0.573008)	0.025333	(0.092876)	0.035761	(0.092703)
Knowledge capital	0.017993	(0.139797)	0.031821	(0.224355)	0.028904	(0.089363)
Human capital	0.628788	(0.000004)	0.577551	(0.000011)	0.594277	(0.000000)
Physical capital					– 0.694333	(0.063807)
Welfare regime			0.038742	(0.285322)		

p values are shown in parentheses

The results appear to also hold when controlling for human capital, knowledge capital, and unemployment. As expected, local unemployment has adverse effects on growth and yet induces fishing out effects, leading to positive cross-border growth dynamics. Human capital appears to prompt output growth both locally and across borders. Spillover effects resulting from knowledge capital appear, on the other hand, to be insignificant or negligible. The role of knowledge capital for growth remains within-country borders. Physical capital appears to be a major driver of local growth, yet our empirical analysis also detects positive effects from investments in the neighborhood.

The observed absence of knowledge capital spillover significance may relate to several aspects of our research design. First, patent applications are a weak proxy for knowledge capital, and the effects of nonpatentable knowledge might be quite sizeable (Griliches 1990). Moreover, some patents involve mere upgrades of existing ones and per se their growth effects are less significant than those of patents of a more revolutionary nature. Third, royalty payments hamper the diffusion of patented knowledge.

6 Robustness checks

We subjected our results to various robustness checks. First, we examined alternative measures of income inequality. For this purpose, we employed the upper-lower-quintile ratio of income distribution. We also reproduced the model estimations for

Table 5 Estimation results: SDM/SDEM without FE, MLE

	SDEM with S		SDEM with W for $k=5$		SDM	
λ–$W\varepsilon$	0.382975	(0.000002)	0.327992	(0.000127)		
β_G—income inequality	− 0.139396	(0.001135)	− 0.107007	(0.621727)	− 0.375958	(0.100290)
β_U—unemployment	− 0.097469	(0.000001)	− 0.101189	(0.000000)	− 0.108023	(0.000000)
β_D—Debt	0.077645	(0.000000)	0.071682	(0.000000)	0.069672	(0.000000)
β_K—knowledge capital	0.156828	(0.000000)	0.167418	(0.000000)	0.165961	(0.000000)
β_H—human capital	0.693342	(0.000000)	0.605575	(0.000000)	0.677024	(0.000000)
${\beta_G}^E$–Wg	2.948660	(0.000000)	2.786533	(0.000000)	2.061391	(0.000000)
${\beta_U}^E$–Wu	0.150004	(0.000136)	0.108675	(0.021875)	0.134327	(0.000229)
${\beta_D}^E$–Wd	− 0.017535	(0.340686)	0.004426	(0.819152)	− 0.024392	(0.143776)
${\beta_K}^E$–Wk	0.026585	(0.008547)	0.011738	(0.275631)	0.055662	(0.000541)
${\beta_H}^E$–Wh	0.638008	(0.000000)	0.617624	(0.000000)	0.659518	(0.000000)
ρ–Wy					0.378696	(0.000001)
σ^2	0.0097		0.0107		0.0102	
pseudo R^2	0.8876		0.8824		0.8979	
adj. pseudo R^2	0.8878		0.8826		0.8882	
logL	214.02758		203.77546		208.44681	

S—ratio of upper and lower quintiles of income; p values are shown in brackets; FE denotes fixed effects; Wy, Wg, Wu, Wd, Wk, Wh, Wε = spatial autocorrelation in dependent variable GDP; G (income inequality index); U (unemployment); D (public debt); K (knowledge capital); H (human capital); ε (residuals); pseudo R^2 represents the goodness of fit of the model; the adjusted (adj.) pseudo R^2 represents the goodness of fit without FE; the LM test is the Lagrange multiplier test; σ denotes the standard error

an alternative specification of spatial weight matrix W, namely based on the five nearest neighbors. The results are shown in Table 5.

Finally, we checked the robustness of the results for an alternative specification of the model, namely the SDM, with spatial autocorrelation in the dependent variable. Furthermore, we tested the model for the significance of spatial and time-fixed effects, yet the results remain unchanged. Since the disparity between the pseudo R^2 and adjusted pseudo R^2 is small in all of our estimations, we may relax on the inclusion of two-way fixed effects.

Table 6 demonstrates the robustness of the model estimations to alternative proxies of human capital, income inequality, and physical capital. In terms of human capital, we employed the share of the working age population with a tertiary education (in the EU, tertiary education is coded as ISCED 5–6). For physical capital, we included investment flows in Euros published in the Cambridge Econometrics database. The estimated elasticities are again similar as shown in Table 6.

Table 6 Estimation of direct and indirect effects in the SDEM

	$G=S$		$H=T$		$C=I$	
Direct effects						
Income inequality G	− 0.081175	(0.114154)	0.333775	(0.182910)	− 0.198561	(0.449720)
Unemployment U	− 0.083918	(0.000263)	− 0.138612	(0.000002)	− 0.057221	(0.009718)
Physical capital C/ Debt D	0.066740	(0.000015)	0.090432	(0.000000)	0.005844	(0.343981)
Knowledge capital K	0.155934	(0.000000)	0.149496	(0.000000)	0.175229	(0.000000)
Human capital H	0.701543	(0.000000)	0.076031	(0.012636)	0.700131	(0.003558)
Indirect effects						
Income inequality G	3.043833	(0.000000)	1.932214	(0.000000)	2.994547	(0.000000)
Unemployment U	0.173460	(0.000702)	0.146616	(0.003770)	0.085976	(0.086881)
Physical capital C/ Debt D	− 0.011141	(0.555775)	0.004461	(0.815706)	0.047122	(0.009752)
Knowledge capital K	0.021993	(0.037613)	0.007484	(0.512496)	0.002123	(0.847876)
Human capital H	0.558298	(0.000004)	0.120346	(0.162195)	0.659693	(0.000002)

S—ratio of upper and lower quintiles of income; *p* values are shown in brackets; FE denotes fixed effects; *T* stands for the share of the tertiary educated population; *I* represents investment flows in EUR derived from the Cambridge Econometrics database

7 Concluding remarks

Using the welfare-adjusted production function, this paper estimates the marginal effects of income inequality on output growth in European countries. Since the literature fails to speak univocally on the issue, the study explores some recent evidence of strong spatial autocorrelation in income inequality and of other growth determinants and employs an SDEM for 2005 to 2013 to explicitly account for spatial dependence in the examined dataset. The results lend support to the presence of adverse effects of income inequality on local growth and yet suggest strong effects of growth elasticity on cross-border income inequality. It appears that declining income inequality at proximity prompts the cross-border mobility of skilled populations and leads to output yields. Similar yet lesser effects can be achieved for contracting unemployment or physical capital in the neighborhood.

Our results might contribute to the current debate on the impacts of European cohesion policy. Since local within-country income inequalities hamper growth, cohesion represents a necessary tool for balancing past of growth across Europe. By failing to do so, concentration patterns may strengthen and rule out already lagging countries with what may feed populism and critically affect public backlash against integration (Rodriguez-Pose 2018).

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