Income Inequality Convergence Among EU Regions

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Abstract

Economic inequality has increased in many EU countries in the past few decades. Yet efforts to assess regional disparities across the EU mostly concentrate on convergence in average per capita incomes, offering little analysis of how regional income is distributed. Using new data from the Luxembourg Income Study (LIS) for 1989–2013, we test whether income inequality convergence has taken place among EU regions and assess which structural factors may affect the pace of this process. The analysis offers three findings. First, NUTS 2 regions are converging to a higher level of income inequality. Second, this process is significantly faster when regions share similar structural characteristics. Finally, there is evidence of a convergence-acceleration effect for regions receiving Cohesion Policy funds, suggesting therefore that these may be driving the convergence process.

Keywords: Inequality, income distribution, convergence, cohesion policy, European Union
JEL codes: O15, O52, D31, P48.

1. Introduction

Economic inequality has increased in many countries around the world in the past few decades (see, e.g., OECD 2011; Morelli et al. 2015), exacerbated by the effect of the recent recession (Heathcote et al. 2010), rising to the fore in the policy debate. In the European Union (EU), the share of the population 'at risk of poverty and social exclusion' peaked in 2014, rising by more than 5 million since the beginning of the financial crisis and so exceeding 122 million, which is roughly a quarter (24.4%) of the EU 28 population. Nearly 40% of total income goes on average to people in the highest income quintile and less than 10% to people in the first quintile.[1]

Rising inequality is a reason for concern because of its ethical considerations, as some literature on distributive justice has long argued (for example, Solimano 1998), and because it is now part of the development goals of the United Nations.[2] Should this not be enough, rising inequality is also a reason for concern because of its social consequences (Klasen 2008; Dabla Norris et al. 2015; Hirschmann 1973) and its economic effects (Ostry et al. 2014; Easterly, 2007; Thorbecke and Charumilind 2002),[3] implying that equity and efficiency are not separate or separable objectives and that there may be an efficiency gain from greater equality (Klasen 2008; Bourguignon et al. 2007). Recent contributions by Stiglitz (2012) and Piketty (2014) have emphasised the role of political economy explanations (through the perpetuation of rent-seeking activities) and the inherent features of capitalism (characterised by the tendency of returns on capital to exceed the rate of economic growth) as root causes of increasing inequalities. In empirical terms, according to Atkinson (2016), the change in the shape of the distribution driving the rise in inequality is the explosion of gains accruing to those at the very top of the income distribution, but the circumstances of those at the bottom have contributed too.

A crucial aspect to understanding this phenomenon is its subnational dimension, especially in the case of large areas of economic integration. In the EU, as also pointed out by Mahler (2002) and Barca (2009), regional analyses may provide interesting insights, uncovering significant within-country disparities; these have been documented in Förster et al. (2005) and Bonesmo Fredriksen (2012). In addition, motivations for this kind of exercise also exist on theoretical grounds, as people's wellbeing is determined by the 'place', with its social, economic and institutional conditions; therefore, a closer look may be more informative for the measurement of inequality. Furthermore, the regional aspect gained further importance with the integration process that brought part of the Eastern bloc countries into the EU, increasing the diversity of regional inequality patterns.

[1] For statistics on economic inequality in the EU, refer to: https://ec.europa.eu/eurostat/statistics.

[2] Goal 10 aims to reduce inequalities within and among countries.

[3] For example, increasing inequality may harm the process of economic growth by affecting human capital accumulation and heightening social conflict. However, there is no consensus on the effects of inequality on growth; see Forbes (2000). On this point, for European regions, see Panzera and Postiglione (2021) and Perugini and Martino (2008), among others.

Despite its relevance to social and economic outcomes, to the increase in inequality in the EU regions, and its importance at the subnational level, the debate presents two key limitations that motivate this study. Few studies have explored income inequality convergence, primarily focusing on cross-national analysis, with less attention paid to the regional dimension, especially within the EU.[4] Second, there has been a considerable effort to study regional convergence in per capita income levels (GDP) in the EU, almost implicitly considering such an outcome as expressing both economic performance and social progress. The existing literature on the effectiveness of the EU regional policy, also referred to as Cohesion Policy, seems to have conflated efficiency (economic growth convergence) and equity goals (disparities in income distribution), while the former does not necessarily imply the latter (for a comprehensive review, see Pieńkowski and Berkowitz, 2016).[5] In general, less attention has been paid to the redistributive aspects of economic integration. For example, it is not well understood whether or not the Cohesion Policy has contributed to reducing the inequalities between countries or regions in terms of GDP per capita, while failing to reduce inequalities in terms of income distribution within countries or regions.

This study contributes to filling this gap by offering a systematic investigation of income inequality in European regions. Using data from the Luxembourg Income Study (LIS) for 1989–2013, we construct a new dataset on regional income inequality. First, we show a significant variation in regional income inequality: citizens of the same EU country may live in very unequal or relatively equal regions. Then we test whether regions with higher inequality levels have experienced larger reductions in income concentration, as well as assessing which structural factors may affect the pace of convergence. Our findings reveal a process of regional convergence, where EU regions are converging to a higher level of inequality and so becoming 'equally more unequal'. Sharing the same structural characteristics, such as similar levels of governance quality, significantly accelerates this process. Finally, the evidence also suggests that the pace is significantly faster in regions receiving Cohesion Policy funds. Apart from adding to the debate on the process of integration and the socioeconomic disparities in the EU, this study also adds to the broader literature on convergence, traditionally interested in disparities in national incomes, but much less so in other development outcomes, such as poverty and inequality.[6]

The paper is structured as follows. The next section provides a brief review of the literature. Section 3 illustrates the data, providing an initial picture of how inequality distribution has changed over time at the regional level in the EU. Sections 4 to 6 present the results, while the last section concludes.

[4] A notable exception is Bouvet (2010).

[5] On the limits of GDP as an indicator of economic performance and social progress, see Stiglitz et al. (2009).

[6] Traditionally, empirical work in this area has been concerned with convergence in national income levels (Barro and Sala-i-Martin, 1991, 1992; Sala-i-Martin, 1996). However, recent convergence analysis has also extended to the evolution of other development outcomes between countries. For example, Deaton (2004) and Canning (2012) looked at the evolution of health, Noorbakhsh (2007), Prados de la Escosura (2015) and Ortega et al. (2016) extended the concept of convergence to human development, Caminada et al. (2010) and Rodriguez-Pose and Tselios (2015) focused on social welfare in the EU, while Savoia et al. (2023) tested for convergence in income inequality and poverty among Egyptian regions.

2. On inequality convergence

Should we expect inequality convergence? The literature indicates that convergence is a possibility, resulting from 'endogenous' and 'exogenous' mechanisms. Where endogenous mechanisms are concerned, inequality convergence may derive from standard growth theory. Assuming that countries or regions have the same structural characteristics, the neoclassical growth model may be consistent with convergence both in the average income level and in the entire distribution of income, where convergence of income distribution is a mechanism of falling (rising) inequality in economies of high (low) initial disparities (Bénabou, 1996). Exogenous mechanisms may be related to the redistributive consequences of major historical events or long-term changes in the global economy. For example, Ravallion (2003) argues that the institutional changes in the transition economies resulting from the end of the Cold War may have increased income inequality in such economies, such that they are closer to the levels of traditional market economies. Similarly, changes in the global division of labour and in the patterns in international trade may have resulted in falling labour shares in more advanced economies and increasing labour shares in less developed ones. In turn, these changes in the functional distribution of income may have resulted in personal income inequality convergence, where advanced economies have seen rising levels of (personal) income inequality and developing economies have experienced a decrease. However, Dao et al. (2017) found that such patterns may be subject to significant heterogeneity (as changes in labour share differ across groups of countries and when skilled and unskilled labour is considered).

Ultimately, in the absence of a consolidated theory predicting convergence (or divergence), whether we should see convergence in income distribution is an empirical matter. But the empirical literature on inequality convergence is rather scant. The first study to discuss and test for the existence of a negative relationship between the change in inequality measure and its initial value was Bénabou (1996), who found initial evidence of unconditional inequality convergence on a panel of countries from around the world between 1970 and 1990 using cross-national data. Ravallion (2003) provided the first systematic study. Revisiting Bénabou's findings with new data and correcting for measurement errors in the initial inequality measure, he found evidence of a rather slow convergence process across countries. Further evidence supporting the convergence hypothesis is provided in Bleaney and Nishiyama (2003), Alvaredo and Gasparini (2015) and Chambers and Dhongde (2016), suggesting that income distribution across countries is becoming 'equally unequal' (increasingly unequal, but similarly so in different countries). The cross-national evidence seems relatively robust across different dimensions – income inequality measure, dataset, panel structure and composition, and method of estimation – although the rate of convergence is sensitive to dataset choice (Lustig and Teles 2016). Another set of studies has focused on income inequality at subnational level within a federal state. Panizza (2001) and Lin and

Huang (2011) test for and find convergence between US states. Conversely, Ho (2015), re-examining this hypothesis in a long-run perspective, cast doubt on inequality convergence among US states.

So far, we have discussed the international evidence, but what do we know about the European regions? While there has been considerable interest in studying per capita income convergence at a disaggregated level, the literature has produced little analysis of income inequality convergence. The process of European integration, through the Cohesion Policy, may have facilitated convergence in per capita regional income, but it is less clear whether growth in average regional incomes has resulted in higher or lower income concentration. This could be empirically important, especially in relation to the changes in the incomes of those at the bottom (for a related argument, see Goedemé and Collado 2016). Indeed, Förster et al. (2005), analysing the Eastern European countries at regional level with LIS data in the 1990s, found that the overall inequality was dominated by inequalities within regions rather than between them.[7] Empirical research on income inequality convergence at the regional level is limited. Tselios (2009) offers initial evidence of unconditional convergence among European regions, at NUTS 1 and NUTS 2 levels,[8] over the period 1995–2000. Ezcurra and Pascual (2005) provide descriptive evidence, in graphical form (based on density functions), for a panel of NUTS 1 regions over 1993–98.

Existing evidence suggests that some reduction in regional disparities may have occurred, but it is based on very short periods, on a limited sample of regions. This ultimately suggests that the question of whether income inequality within European regions has converged or not still awaits a systematic assessment. Therefore, this paper reinvestigates and extends the analysis of convergence in income distribution across European regions. We overcome data coverage and comparability issues using LIS data, and analyse convergence over longer periods, thereby reflecting the long-term nature of inequality dynamics. Next, we construct and use both aggregate measures of inequality (Gini index) and quintile shares of income, thus looking at the profile of the income distribution. Apart from testing the hypothesis of unconditional convergence, we also look at conditional inequality convergence, in order to assess the importance of initial regional conditions. Finally, we provide novel evidence by studying whether the pace of convergence is related to specific periods and whether less developed regions receiving EU Cohesion Policy funds have played a role in this process.

3. Data

[7] In general, as noted by Milanovic and Van der Weide (2014), the literature on the relationship between growth and income inequality also focuses exclusively on the effects on average incomes, suggesting that there has been little interest in the specific parts of the income distribution (the higher moments of the distribution).

[8] NUTS levels refer to the Eurostat territorial classification scheme.

This section introduces the dataset, describes the variables, and illustrates the procedure for generating the inequality measures at the NUTS 2 level.[9] It also provides descriptive evidence on income inequality.

The analysis of income distribution at regional level in the EU has been subject to limitations because of data availability and comparability. To improve on this, we opt for the LIS database, since it allows us to study a longer period and ensures clear comparability of inequality statistics.[10] For EU countries, Eurostat provides household income and poverty micro data in two different surveys: first, via the European Community Household Panel (ECHP); second, via the European Union Statistics on Income and Living Conditions (EU-SILC). Although these provide fair coverage when combined, ECHP and EU-SILC have different data collection methodologies (see Atkinson et al. 2010), and it is unclear whether and to what extent they produce comparable statistics.

Building on the LIS effort to bring together and harmonise ex-post income micro data, we therefore construct regional measures of inequality at the NUTS 2 level based on disposable household income. This is a harmonised variable including total monetary and non-monetary current income for the household, net of income taxes and social security contributions. Frequently, income micro data are not directly available at the NUTS 2 level in the LIS database. Therefore, where the availability of territorial disaggregation of data is not regular over time, we carefully aggregated households' incomes at NUTS 3 or LAUs (lower levels) to reconstruct the NUTS 2 regions and generate regional inequality measures. In this process, we consider for each country the administrative reforms that might have affected regional boundaries. Where there have been reforms producing major changes in territorial boundaries in some waves, we preferred to exclude either these regions (e.g. in Finland and Sweden) or the entire country (e.g. the Czech Republic) to avoid making incorrect imputations of households' residence. Appendix A reports further details on inequality measures and provides the list of countries (Table A1).

For all regions, we compute the following inequality measures: Gini index and quintile income shares. The analysis covers different periods and samples of NUTS 2 regions: 1990–2013 (sample A), 1995–2013 (sample B), 2000–13 (sample C), and 2004–13 (sample D), including, respectively, 53, 75, 98 and 103 observations.

Summary statistics for all measures of inequality show that there has been an overall increase in inequality, corresponding to a widening gap in the extreme parts of the entire distribution: on average, the poorest quintiles reduced their shares of total income, while the richest quintile gained (see Table A2 in Appendix B). Figure 1 presents the intra-country variations in income inequality at the NUTS 2 level over time. For each country and year, the box plots report five summary statistics dividing the

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[9] NUTS 2 refers to the level of the application of regional policies within the EU.

[10] LIS (https://www.lisdatacenter.org) collects social and economic data from national statistics institutes in developed and developing countries, and then conducts an ex-post harmonisation to make them comparable. Details of the LIS harmonisation rules are available at https://www.lisdatacenter.org/wp-content/uploads/files/data-lis-guide.pdf.

distribution of the regional Gini index for each country into four parts: the minimum value, lower quartile (25th percentile), median value (50th percentile), upper quartile (75th percentile), and the maximum value. We observe two facts. First, there is significant variation in regional income inequality. National trends hide significant subnational disparities: citizens of the same country may live in very unequal or relatively equal regions. Northern countries, however, have relatively low levels of variation. Second, although countries in the Mediterranean region exhibited the highest levels of within-country inequality, there has been a noticeable reduction in the disparity among regions in the most recent data wave (around 2013).[11]

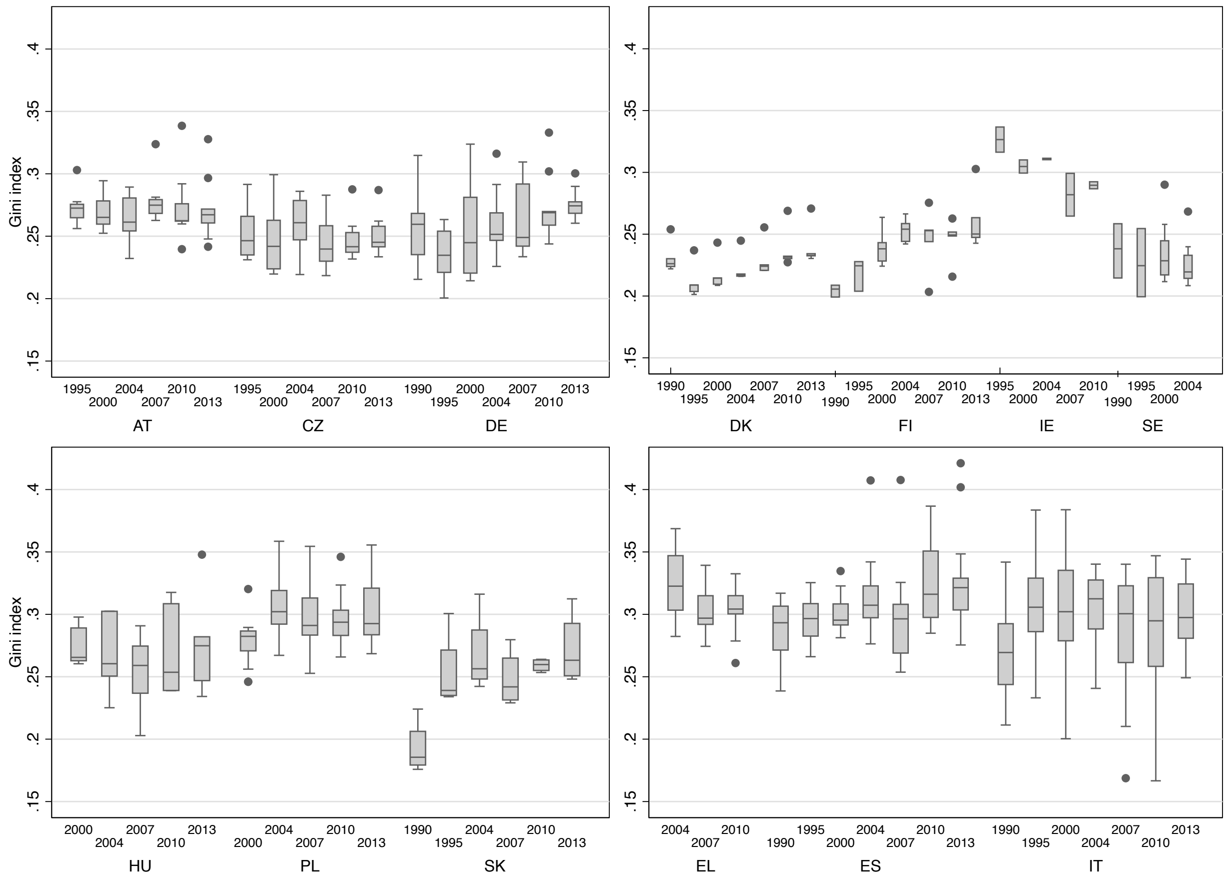

Figure 1: Within-country variation in income inequality, Gini index at the NUTS 2 level

Notes: Gini index calculated on equivalised disposable household income. Grey dots represent outside values. Luxembourg (LU), Estonia (EE) and Slovenia (SI) are considered single NUTS 2 regions and therefore excluded (see Table A1 in Appendix A for the number of regions across countries).

4. Inequality Convergence Tests

Following Ravallion (2003), let I_{it} denote the observed Gini index, or other measures of inequality, in a region i at time $t = 0$ and $t = T$, i.e., in the first and last year of the period considered, respectively. We

[11] It is worth noting that the exceptional outside values for Spain (ES) in 2013 (with a Gini index of 0.42 and 0.40) refer, respectively, to the autonomous regions of Ceuta and Melilla, Spanish enclaves in North Africa.

regress the observed changes over time in a measure of inequality on the initial values across regions, estimating:

$$I_{iT} - I_{i0} = \alpha + \beta I_{i0} + \varepsilon_i \quad (i = 1, \dots, N) \quad (1)$$

where α and β are parameters to be estimated. A significant negative (positive) estimate of β implies that there is convergence (divergence).[12]

Are more unequal European regions narrowing (or broadening) their gap in income concentration with less unequal regions? Unconditional convergence results for Gini index and quintile shares indicate that within-region inequality has been converging, regardless of initial regional conditions, i.e., no matter why EU regions are equal or unequal. In particular, the convergence simulation reveals that inequality levels are converging, but to higher levels of inequality (see Appendix C for estimates and point estimation).

5. Conditional convergence

The first set of regressions revealed that inequality convergence at regional level occurred regardless of the initial conditions, although at a relatively slow pace, and to a higher level of inequality. To what extent do the structural characteristics of the regions matter in this process? Is the 'speed' of the convergence significantly faster if they share the same initial conditions? To find out, we introduce in the baseline specification a set of variables to account for potential drivers of income inequality and so test for conditional convergence. We estimate:

$$I_{iT} - I_{i0} = \alpha + \beta I_{i0} + \gamma \mathbf{X}_{i0} + \varepsilon_i \quad (i = 1, \dots, N) \quad (2)$$

The set of initial conditions, the vector $\mathbf{X}_{i0}$, includes country dummies and the following variables: (i) the level of economic development (GDP per capita), as different initial regional economic performances might have a different effect on inequality, following the Kuznets hypothesis of an inverted U-shaped relationship (Kuznets 1955); (ii) the labour income share (captured by the compensation of employees/GDP); and (iii) a measure of the capital share (reflected by the Gross Fixed Capital Formation – GFCF), as the global division of labour and international trade patterns may have resulted in falling labour shares in more advanced economies and increasing labour shares in less developed ones, changing the functional distribution of income (Dao et al. 2017). In some specifications, for the 2000–13 period only, we were also able to control for socioeconomic variables

[12] This corresponds to the concept of beta-convergence associated with the idea of convergence in country income levels, as developed by Barro and Sala-i-Martin (1991, 1992), where there is absolute beta-convergence if poor economies tend to grow faster than rich ones (Sala-i-Martin 1996). Others have emphasised a different statistical notion of convergence (Quah 1993): sigma-convergence, which looks at whether the cross-sectional dispersion across countries is decreasing, and for which beta-convergence is a necessary, but not sufficient, condition (see Sala-i-Martin 1996). We do not pursue this approach here because it would not allow us to focus on whether initial conditions matter for inequality convergence and for estimating its speed, while both are interesting aspects of the process of inequality dynamics we would like to document.

including: (iv) measures of human capital and technological innovation, as there is growing evidence that technological innovation leads to higher levels of inequality through the job polarisation mechanism, with high demand for both highly skilled (well-paid) and low-skilled (low-paid) jobs, to the detriment of middle-income jobs (Acemoglu 2002; Autor and Dorn 2013; see also Goos et al. 2014 for evidence on Europe); (v) population density, to account for population dynamics and changes in household structure, as the trend toward smaller households (e.g. in OECD countries) is likely to increase income inequality because smaller households are less able to benefit from savings through pooling resources and sharing expenditures (OECD 2011; Furceri and Ostry 2019); and (vi) an indicator expressing the quality of institutions, since low levels of corruption and better institutions are supposed to provide economic opportunities to a large part of the population (Acemoglu 2008).[13]

Ordinary least square (OLS) results confirm that inequality has been converging in all our periods of investigation, with the coefficients of initial values negative and statistically significant for all inequality measures.[14] One should also note that the magnitude of the estimated coefficients for the initial values of the Gini index and the top–bottom quintiles is substantially larger compared to unconditional regression in absolute terms (Table 1). This suggests that *all other initial conditions being equal*, regional disparities reduce faster.

Looking at the control variables entering OLS regressions, initial regional conditions seem to contribute significantly to explaining the variation of inequality and quintile shares of income. For the period 1990–2013, we find some evidence supporting the Kuznets hypothesis, with the level of income inequality following an inverted U-shaped curve along with the economic development (and a corresponding significant effect operating in the same direction for the top–bottom quintile shares of income). With respect to the functional distribution of income, a variation of capital share is significantly associated with an increase in income inequality and a widening gap between the top and bottom of the income distribution, while there is no clear evidence on the role of labour share. We check the robustness of the results by repeating the analysis on different periods, including different samples of regions, by dropping influential observations and by testing for cross-sectional and temporal dependence. The coefficients remain essentially unvaried in terms of sign and significance, while the speed of the convergence reduced or remained stable depending on the sample composition.

[13] See Table A3 in Appendix B for summary statistics of inequality measures and control variables for all available years.

[14] However, as an exception, for Quintile 4 we observe a weak significance of its initial level in both unconditional and conditional OLS estimates for the sample 1990-2013 (see Table 1 and Table A4 in the appendix). This is something worth investigating further. Indeed, we employed Fixed Effects (FE) and Iteratively Reweighted Least Squares (IRLS) estimators, controlling for unobserved time-invariant factors at the regional level and time effects, while down-weighting potential outliers in the sample. We found that coefficients are indeed significant and that the model has a better fit. For brevity, the corresponding tables of estimates are excluded but available upon request.

Table 1: Conditional convergence in inequality, OLS 1990–2013

	Change in Gini, 1990–2013	Changes in quintile shares, 1990–2013				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value 1990	-0.821***	-1.086***	-0.644***	-0.837***	-0.469*	-0.730***
	(0.114)	(0.246)	(0.105)	(0.169)	(0.273)	(0.138)
GDP per capita (ln)	0.471***	-18.906**	-18.682***	-8.235	-4.127	45.178***
	(0.142)	(7.074)	(6.293)	(5.552)	(6.603)	(12.973)
GDP per capita squared (ln)	-0.025***	1.041**	1.004***	0.457	0.242	-2.493***
	(0.008)	(0.397)	(0.347)	(0.305)	(0.363)	(0.712)
GFCF (ln)	0.012***	-0.563**	-0.400***	-0.205	-0.201	1.363***
	(0.003)	(0.242)	(0.142)	(0.153)	(0.223)	(0.355)
Labour Income Share	0.220**	-8.372**	2.868	-7.836*	-9.424*	23.265**
	(0.082)	(3.831)	(4.301)	(4.530)	(5.144)	(8.919)
Constant	-2.016***	97.339***	92.765***	54.596**	32.233	-183.366***
	(0.632)	(31.960)	(27.390)	(24.156)	(31.051)	(57.164)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	62.55***	24.34***	20.58***	11.33***	5.10***	11.72***
Adj. R-Sq.	0.721	0.605	0.648	0.588	0.050	0.592
Obs.	50	50	50	50	50	50
RMSE	0.018	0.941	0.654	0.641	1.046	1.727

Notes: Influential observations: Hamburg (DE60) and Åland (FI20). Berlin (DE30) is excluded from the sample as control variables are unavailable for 1990. Control variables expressed in billions of euros and deflated to 2005 constant price euros using sectoral price deflators obtained from AMECO. Significance levels: 10% (*), 5% (**) and 1% (***). Heteroscedasticity robust standard errors are in parentheses.

We repeat the analysis also for 2000–13 with a larger sample and different model specifications. In this case, we can add further variables to control for the level of tertiary education (expressed as the percentage of the population 25-64 years old with a tertiary qualification), technology (given by the number of patent applications to the European Patent Office per million inhabitants), population density (expressed as the population average per square kilometre), and the quality of regional institutions (given by the European Quality of Government Index, EQI).[15] OLS estimates for 2000–13 generally confirm previous results. However, in this case, the effect of economic development is first to reduce and then exacerbate the level of economic inequality, narrowing and then widening the gap at the extremes of the income distribution. This pattern is consistent across all samples when employing panel estimation, as illustrated in the following section. More interestingly, these estimates add evidence on the role of institutional structural factors in this process. The EQI coefficient in Panel A of Table 2, negative and significant, indicates that improving the quality of regional institutions will result in a decrease in economic inequality. In addition, when looking at the extremes of the income distribution, the inverse sign of the coefficients for the lowest and the highest quintile confirms the potential 'redistributive' effect of better regional governance. These results are generally also confirmed in Panel B, where further controls allow the sharing of the same level of regional education and technology, and the same population density.

[15] EQI is a composite indicator (Charron et al. 2014) capturing EU citizens' perceptions and experiences with corruption (corruption pillar), and the extent to which they rate their public services as impartial (impartial pillar) and of good quality (quality pillar) across EU countries. We use data from the first round as a proxy for the initial EQI values.

Table 2: Conditional convergence in inequality, OLS 2000–13

PANEL A	Change in Gini, 2000–13	Changes in quintile shares, 2000–13				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value 2000	-0.796***	-0.710***	-0.688***	-0.550**	-1.069***	-0.784***
	(0.102)	(0.120)	(0.247)	(0.213)	(0.122)	(0.157)
GDP per capita (ln)	-0.441*	16.206**	5.099	8.699	18.247**	-46.697**
	(0.237)	(6.691)	(9.220)	(6.828)	(7.831)	(20.981)
GDP per capita squared (ln)	0.024*	-0.841**	-0.269	-0.443	-0.988**	2.450**
	(0.012)	(0.346)	(0.481)	(0.352)	(0.411)	(1.057)
GFCF (ln)	0.001	-0.090	-0.059	-0.222	0.067	0.507*
	(0.004)	(0.168)	(0.181)	(0.147)	(0.136)	(0.284)
Labour Income Share	0.091**	-4.191***	-1.150	-2.051	-1.781	7.190*
	(0.039)	(1.406)	(1.936)	(1.551)	(1.925)	(3.704)
EQI	-0.016***	0.836***	-0.057	0.567*	0.491	-2.116***
	(0.005)	(0.300)	(0.255)	(0.306)	(0.314)	(0.656)
Constant	2.196*	-69.674**	-13.598	-31.584	-56.378	244.676**
	(1.156)	(31.937)	(45.129)	(34.113)	(36.409)	(103.958)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	2.9e+09***	51.11***	11.48***	1.74***	29.92***	6.36***
Adj. R-Sq.	0.574	0.399	0.238	0.382	0.470	0.517
Obs.	90	90	90	90	90	90
RMSE	0.019	0.760	0.802	0.814	0.954	1.868

PANEL B	Change in Gini, 2000–13	Changes in quintile shares, 2000–13				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value 2000	-0.792***	-0.691***	-0.654***	-0.598***	-1.143***	-0.806***
	(0.109)	(0.136)	(0.222)	(0.206)	(0.118)	(0.170)
GDP per capita (ln)	-0.467*	17.188**	6.847	7.032	19.352**	-47.501**
	(0.236)	(7.339)	(8.309)	(7.623)	(8.491)	(21.985)
GDP per capita squared (ln)	0.025**	-0.902**	-0.360	-0.357	-1.080**	2.525**
	(0.012)	(0.386)	(0.443)	(0.397)	(0.452)	(1.120)
GFCF (ln)	0.002	-0.112	-0.054	-0.266*	-0.027	0.644*
	(0.004)	(0.164)	(0.174)	(0.145)	(0.151)	(0.326)
Labour Income Share	0.093**	-4.430***	-0.712	-2.078	-2.932	7.680*
	(0.042)	(1.591)	(2.090)	(1.662)	(2.105)	(3.856)
Tech. innovation (ln)	-0.002	-0.021	0.032	0.157*	0.229	-0.403
	(0.003)	(0.100)	(0.098)	(0.092)	(0.145)	(0.291)
Tertiary education (ln)	0.003	0.308	-0.913	0.124	0.902	-0.113
	(0.012)	(0.517)	(0.637)	(0.624)	(0.622)	(1.155)
Population density (ln)	-0.001	0.061	0.141	-0.142	-0.040	0.067
	(0.004)	(0.126)	(0.146)	(0.149)	(0.140)	(0.357)
EQI	-0.016**	0.888***	-0.054	0.396	0.377	-1.879***
	(0.006)	(0.292)	(0.292)	(0.306)	(0.339)	(0.665)
Constant	2.283**	-73.939**	-19.757	-23.900	-58.792	247.144**
	(1.140)	(34.689)	(40.492)	(37.247)	(38.920)	(106.499)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	9.37***	31.74***	11.88***	1.57***	19.78***	4.93***
Adj. R-Sq.	0.560	0.380	0.247	0.378	0.486	0.510
Obs.	90	90	90	90	90	90
RMSE	0.020	0.772	0.797	0.817	0.940	1.881

Notes: Panels include 11 countries (AT, CZ, DE, DK, EE, ES, FI, IT, LU, PL, SI). When accounting for the quality of institutions, the sample size is reduced to 90 observations due to the unavailability of EQI data for Hungary. Control variables are expressed in billions of euros and deflated to 2005 constant price euros using sectoral price deflators obtained from AMECO. Significance levels: 10% (*), 5% (**) and 1% (***). Heteroscedasticity robust standard errors are in parentheses.

5.1 Panel regressions

In this section, we exploit both the cross-sectional and time dimensions of our data by re-examining conditional convergence with panel methods. We compute changes for each inequality measure based on the 'first' and 'last' year values in each available wave in the LIS dataset and test for convergence in the two main sample periods: 1990-2013 and 2000-2013.[16] We estimate the following dynamic panel

[16] The available waves in the LIS dataset include the following years: 1990, 1995, 2000, 2004, 2007, 2010 and 2013. Table A1 in Appendix A reports the list of countries and further details.

model with country and time dummies, clustering the standard errors at the regional level to account for serial correlation and heteroskedasticity of unknown form:

$$\Delta I_{it} = \alpha + \beta_1 I_{it-1} + \gamma \mathbf{X}_{it-1} + \mu_i + \delta_t + \varepsilon_{it} \quad \text{with } i = 1, \dots, N \text{ and } t = 1, \dots, T \qquad (3)$$

We first re-examine the OLS cross-section results using Pooled OLS estimation, then we employ the Fixed-Effects (FE) and the Generalized Method of Moments (GMM) estimators since they allow us to control for time-invariant regional characteristics, eliminating a potential source of omitted variable bias and cross-sectional dependence.

In line with our expectations, Pooled OLS estimates support the hypothesis of inequality convergence, with Gini index and quintile coefficients statistically significant in both the sample periods and the magnitude of the coefficients generally lower compared to cross-section results (Tables 3-4). Regarding the control variables, the evidence confirms a U-shaped evolution in income inequality as regions become more developed. Corresponding significant evidence is found in the same direction for the top–bottom quintile shares of income. Although the U-shaped relationship is strongly confirmed, it is worth noting that estimates are sensible to the regions included in the sample. This is not surprising, as the empirical evidence on the inequality–growth relationship seems to depend on identification strategy, data and countries involved. According to Milanovic (2016), the current upswing in inequality can be viewed as a second Kuznets curve driven by technological progress, globalisation, inter-sectoral reallocation of labour and policy, suggesting the possibility of Kuznets waves. We are probably just drawing part of it in line with previous findings on EU regions from Castells-Quintana et al. (2015).[17]

Table 3: Conditional convergence in inequality, Pooled OLS 1990–2013

	Changes in Gini, 1990–2013	Changes in quintile share, 1990–2013				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value	-0.555***	-0.622***	-0.653***	-0.654***	-0.841***	-0.584***
	(0.064)	(0.058)	(0.060)	(0.058)	(0.115)	(0.073)
GDP per capita (ln)	-0.269**	9.234***	4.761	4.506	2.633	-19.180*
	(0.108)	(3.204)	(3.777)	(3.737)	(3.004)	(10.579)
GDP per capita squared (ln)	0.013**	-0.428**	-0.213	-0.202	-0.130	0.885
	(0.005)	(0.162)	(0.192)	(0.189)	(0.150)	(0.531)
GFCF (ln)	0.006***	-0.237***	-0.210***	-0.104	-0.106*	0.602***
	(0.002)	(0.080)	(0.067)	(0.064)	(0.059)	(0.128)
Labour Income Share	-0.003	-1.162	1.325	0.382	0.021	-0.629
	(0.030)	(1.291)	(0.932)	(1.281)	(1.694)	(2.415)
Constant	1.564***	-42.754**	-17.405	-13.367	5.927	123.943**
	(0.535)	(15.970)	(18.721)	(18.281)	(14.502)	(52.919)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	11.86***	13.61***	8.10***	5.83***	3.63***	7.31***
Adj. R-Sq.	0.372	0.396	0.358	0.313	0.355	0.344
Obs.	293	293	293	293	293	293
Regions	50	50	50	50	50	50
RMSE	0.022	0.828	0.716	0.748	0.920	1.928

Notes: Influential observations: Hamburg (DE60), Åland (FI20) and Bratislava (SK01). Control variables expressed in billions of euros and deflated to 2005 constant price euros using sectoral price deflators obtained from AMECO. Significance levels: 10% (*), 5% (**) and 1% (***). Clustered standard errors at regional level are in parentheses.

[17] For a historical analysis of Kuznets's hypothesis, see Moran (2005).

Regarding the functional distribution of income, results are in line with previous evidence: variations in capital share are significantly associated with changes in overall inequality and top-bottom income shares, while no evidence is found for labour share in these specifications.

It is worth noting that, with panel estimates, technology, level of education and population dynamics have a statistically significant effect on the Gini index and shape part of the quintile distribution. Estimation results indicate that an increase in technological innovation significantly benefits the bottom and middle quintiles, while being detrimental to upper income populations, thereby contributing to reduce overall inequality. Improvements in educational attainment seem to have a weak effect on middle-upper income shares. Finally, demographic variations significantly contribute to explaining inequality distribution among regions. In this setting, we cannot re-estimate the impact of the quality of regional institutions (EQI) as available data do not allow us to perform panel regressions.

The results remain robust when testing for cross-sectional dependence and when estimating panel-corrected standard errors regressions, as illustrated in Tables A5–A6 in Appendix D.[18]

Table 4: Conditional convergence in inequality, Pooled OLS 2000–13

PANEL A	Changes in Gini, 2000–2013	Changes in quintile share, 2000–2013				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value	-0.473***	-0.477***	-0.706***	-0.681***	-0.828***	-0.469***
	(0.046)	(0.054)	(0.093)	(0.137)	(0.083)	(0.061)
GDP per capita (ln)	-0.196**	6.687**	4.618	2.094	4.277	-17.048**
	(0.084)	(2.571)	(3.456)	(3.103)	(2.724)	(7.133)
GDP per capita squared (ln)	0.010**	-0.321**	-0.227	-0.098	-0.231	0.846**
	(0.004)	(0.130)	(0.176)	(0.164)	(0.147)	(0.359)
GFCF (ln)	0.004***	-0.199**	-0.250***	-0.170*	-0.143	0.614***
	(0.002)	(0.082)	(0.064)	(0.095)	(0.127)	(0.190)
Labour Income Share	0.023	-1.626	1.651	-0.828	0.189	0.774
	(0.031)	(1.251)	(1.105)	(1.029)	(1.718)	(2.924)
Constant	1.081**	-29.250**	-13.907	1.462	-0.574	101.494***
	(0.427)	(12.607)	(16.937)	(15.530)	(11.898)	(36.525)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	7.47***	6.49***	5.08***	2.68***	4.09***	4.21***
Adj. R-Sq.	0.296	0.257	0.340	0.312	0.383	0.266
Obs.	392	392	392	392	392	392
Regions	98	98	98	98	98	98
RMSE	0.021	0.775	0.791	0.863	0.906	1.890

[18] We employ Pesaran's test statistic under the null hypothesis of no cross-section dependence (Pesaran 2004). The test does not reject the null hypothesis in each sample period.

Table 4: (continued)

PANEL B inf. obs	Changes in Gini, 2000–2013	Changes in quintile share, 2000–2013				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value	-0.529***	-0.578***	-0.650***	-0.633***	-0.909***	-0.558***
	(0.052)	(0.048)	(0.071)	(0.057)	(0.100)	(0.075)
GDP per capita (ln)	-0.209***	6.665**	4.837*	3.728	3.247	-17.855**
	(0.075)	(2.597)	(2.654)	(2.383)	(2.593)	(7.140)
GDP per capita squared (ln)	0.010***	-0.310**	-0.227	-0.212*	-0.169	0.886**
	(0.004)	(0.134)	(0.137)	(0.121)	(0.137)	(0.358)
GFCF (ln)	0.005***	-0.228***	-0.188**	-0.030	-0.213*	0.603***
	(0.002)	(0.082)	(0.078)	(0.064)	(0.112)	(0.151)
Labour Income Share	-0.027	0.166	2.891***	-1.312	1.667	-3.303
	(0.025)	(1.331)	(1.006)	(1.032)	(1.683)	(2.109)
Tech. innovation (ln)	-0.004**	0.140***	0.065	0.143***	-0.051	-0.281**
	(0.001)	(0.050)	(0.063)	(0.045)	(0.069)	(0.124)
Tertiary education (ln)	-0.001	-0.184	-0.129	0.451*	0.510*	-0.505
	(0.007)	(0.272)	(0.275)	(0.244)	(0.274)	(0.583)
Population density (ln)	0.003**	-0.131**	-0.101*	-0.078	-0.059	0.318**
	(0.001)	(0.060)	(0.057)	(0.053)	(0.076)	(0.141)
Constant	1.223***	-30.477**	-17.836	-6.024	3.510	113.914***
	(0.369)	(12.508)	(12.900)	(11.599)	(11.442)	(35.910)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	8.90***	7.30***	6.55***	4.85***	3.17***	5.24***
Adj. R-Sq.	0.324	0.304	0.328	0.311	0.414	0.315
Obs.	380	380	380	380	380	380
Regions	95	95	95	95	95	95
RMSE	0.019	0.736	0.670	0.670	0.801	1.701

Notes: Influential observations: Åland (FI20), Valle d'Aosta (ITC2), and Mazowieckie (PL12). Control variables are expressed in billions of euros and deflated to 2005 constant price euros using sectoral price deflators obtained from AMECO. Significance levels: 10% (*), 5% (**) and 1% (***). Clustered standard errors at regional level are in parentheses.

5.2 Dynamic panel GMM regressions

Panel convergence regressions are a reparameterization of a dynamic panel specification equivalent to an AR(1) model. In this case, assuming T is short enough, FE estimates are upward-biased and Pooled OLS estimates are biased toward zero (see Quah 2003; Barro 2012). GMM cures this by using suitable lagged variables as Instrumental Variables, so providing unbiased FE estimates. Hence, below we estimate the dynamic panel convergence regressions by GMM. We also provide Pooled OLS and FE estimates: they are useful reference points for the unbiased GMM estimates, which should fall within the range of the upward-biased FE and the downward-biased OLS estimate. For this purpose, we employ the GMM difference estimator (Arellano and Bond, 1991) instrumenting differences with levels, where the lagged values of the inequality measure are GMM instruments for the initial value and time dummies are standard instruments.

Table 5 below presents GMM-IV two-step estimates for the Gini index in the 1990-2013 and 2000-2013 periods, also reporting Pooled OLS and Fixed Effects estimates for comparison. Given the short time dimension of our panel, we can only use up to the second lag of the Gini as an instrument; therefore, to reduce their number, we impose limits on the lags used as instruments. The dynamic GMM results generally confirm evidence of income inequality convergence. It is worth noting that the GMM-IV estimated coefficient is below the upward-biased FE estimate and above the down-ward biased OLS estimate. The Sargan test of over-identifying restrictions fails to reject the null hypothesis of valid instruments, thereby offering support for the validity of the instruments and the assumption of no serial correlation (lagged values of the Gini index are not correlated with the error term). In addition, the table presents estimates for the full sample, that is, when using all the available observations. Results are also confirmed in this case and are robust to reducing instruments counts.

Finally, we also conduct convergence tests for the quintile shares of income, reported in Table 6, and find general confirmation of our results. However, we observe that the estimate of the lagged dependent variable's coefficient for the fourth quintiles appears to be more sensitive to the choice of lag length. This confirms the importance of further investigating influential observations.

Table 5: Convergence in inequality: Gini index (OLS, FE and Two-Step Difference GMM)

	Sample 1990-2013			Sample 2000-2013			Full-sample 1990-2013		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Gini initial value	-0.517***	-0.903***	-0.645***	-0.439***	-0.996***	-0.611***	-0.418***	-0.927***	-0.638***
	(0.053)	(0.060)	(0.194)	(0.056)	(0.058)	(0.128)	(0.045)	(0.045)	(0.099)
constant	0.148***	0.254***		0.123***	0.282***		0.118***	0.255***	
	(0.014)	(0.016)		(0.015)	(0.016)		(0.012)	(0.012)	
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	No	No	Yes	No	No	Yes	No	No
Obs	310	310	253	392	392	294	581	581	450
Groups	53	53	53	98	98	98	127	127	122
No. of instruments			10			6			14
AR1 (p-value)			0.002			0.000			0.000
AR2 (p-value)			0.226			0.601			0.875
Sargan (p-value)			0.653			0.101			0.350
Hansen-J (p-value)			0.587			0.236			0.210

Notes: Full sample 1990-2013 includes all available observations in our panel dataset. Significance levels: 10% (*), 5% (**) and 1% (***). Robust standard errors are in parentheses.

Table 6: Convergence in inequality: Quintile shares of income (Two-Step Difference GMM)

	Changes in quintile shares, 1990–2013				
	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Q1 initial value	-0.646***				
	(0.184)				
Q2 initial value		-0.700***			
		(0.163)			
Q3 initial value			-0.818***		
			(0.139)		
Q4 initial value				-0.491***	
				(0.115)	
Q5 initial value					-0.503***
					(0.133)
Time dummies	Yes	Yes	Yes	Yes	Yes
Obs	253	253	253	253	253
Groups	53	53	53	53	53
No. of instruments	7	7	7	7	7
AR1 (p-value)	0.000	0.003	0.055	0.022	0.000
AR2 (p-value)	0.163	0.167	0.101	0.156	0.461
Sargan (p-value)	0.788	0.270	0.673	0.034	0.452
Hansen-J (p-value)	0.714	0.073	0.633	0.081	0.210

Table 6: (continued)

	Changes in quintile shares, 2000–2013				
	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Q1 initial value	-0.940*** (0.156)				
Q2 initial value		-0.674*** (0.197)			
Q3 initial value			-0.964*** (0.115)		
Q4 initial value				-0.713*** (0.248)	
Q5 initial value					-0.559*** (0.188)
Time dummies	Yes	Yes	Yes	Yes	Yes
Obs	294	294	294	294	294
Groups	98	98	98	98	98
No. of instruments	5	5	5	5	5
AR1 (p-value)	0.001	0.002	0.055	0.094	0.001
AR2 (p-value)	0.795	0.990	0.444	0.147	0.570
Sargan (p-value)	0.715	0.047	0.557	0.000	0.477
Hansen-J (p-value)	0.790	0.278	0.740	0.111	0.494

Notes: Significance levels: 10% (*), 5% (**) and 1% (***). Robust standard errors are in parentheses.

To conclude, we acknowledge the importance of implementing GMM estimation in this context. However, this does not come without costs when T is short, as it necessarily implies a significant loss in degrees of freedom in our case (i.e., a loss of at least two waves of observations when employing a single lag, out of 5 available waves in the longest period). In the sub-period 2000-2013, where T=5, further improvements might have come at the cost of losing an additional period, reducing drastically the sample size. In short, we face a trade-off between potential efficiency gains from using deeper lags and sample size loss. A valid and relatively popular alternative to the GMM approach is the use of the bias-corrected Least Squares Dummy Variable estimator (Bruno 2005), which does not require sacrificing valuable degrees of freedom. We have also implemented this alternative. The results, omitted for brevity, are in line with the FE estimates generated by GMM-IV procedures.

6. EU Cohesion Policy and the convergence process

The purpose of this section is to provide initial evidence on the role played by European regional policy, focusing on two aspects: (i) whether the convergence process changed over time as a result of the transition from one 'programming period' to the next during 1989–2013; and (ii) whether the speed of convergence is different in less developed regions financed by Cohesion Policy funds.[19] We begin by estimating convergence tests for the four programming periods (PP):

$$\Delta I_{it} = \alpha + \beta_1 I_{i0} + \beta_2 PP_t + \sum_{t=1}^{4} \beta_t \, PP_t * I_{i0} + \varepsilon_{it}$$

$$\text{with } i = 1, \dots, N \text{ and } t = 1, \dots, 4 \qquad (4)$$

[19] Following the 1988 reform of the EU Structural Funds, the four programming periods of the Cohesion Policy were 1989–93, 1994–99, 2000–06 and 2007–13. See http://ec.europa.eu/regional_policy/. Supported regions, defined as 'Objective 1' (later as 'Convergence Objective'), were identified from official EU documents.

where ΔI_{it} captures the variation of the inequality for each region in each PP, that is, $(I_{iT} - I_{i0})$, β_1 is the coefficient of the initial level of inequality of each PP, that is, (I_{i0}), β_2 captures the common shocks with time dummies PP_t for each programming period, while β_t represents the four coefficients of the interaction terms between the time dummies and the initial value of income inequality (therefore, the sum refers to the period dummy, where dummy PP1 is the benchmark).

With equation (5) we investigate whether the speed of convergence is different for less developed regions financed by the Cohesion Policy (CP) funds:

$$\Delta I_{it} = \alpha + \beta_1 I_{i0} + \beta_2 CPfunds_t + \sum_{CPfunds=1}^{4} \beta_t \, CPfunds_t * \beta_1 I_{i0} + \gamma_t + \varepsilon_{it}$$

$$\text{with } i = 1, \dots, N \text{ and } t = 1, \dots, T \qquad (5)$$

where $CPfunds_t$ represents the dummy 'support' for each episode over 1989–13: it identifies whether a region has received CP funds in a given PP, β_t represent the four coefficients of the interaction terms between these dummies and the initial value of inequality of the relative period and γ_t captures common shocks (time dummies).

Table 7 presents pooled OLS and FE estimates for the Gini coefficient in the four episodes of the Policy, with different samples of regions and model specifications. Here, following equation (4), we look at how the speed of convergence also depends on the period. The first set of regressions (Panel A) indicates an acceleration effect over the periods following 1989–93. Due to their high collinearity with the initial value of Gini, the coefficients of the pooled OLS specification with interaction terms appear to be statistically insignificant (the Variance Inflation Factor is above 150). However, they become significant both when testing the nonlinear restrictions that each PP has no effect on the speed of convergence and when running FE regressions.[20] Hence, pooled OLS and FE estimates confirm evidence of convergence in income inequality, suggesting that it may have been faster in more recent episodes.

The second set of regressions (Panel B) confirms this by estimating the speed for each PP in cross-section regressions. Results for the first period seem to reveal that no convergence occurred during 1989–93, given that the coefficient is not statistically significant. A possible explanation for this result can be attributed to the limited number of observations. However, estimates for the remaining three intervals show that there has been a significant acceleration over time. Also in this case, we test our hypotheses repeating the regressions for the quintile income shares. The results show the same pattern for each quintile, suggesting that moving from one period to the next has affected the speed of

[20] Performing linear restriction tests, we assess the magnitude and significance of the convergence speed for each episode, that is: $\beta_1+\beta_2=0$, $\beta_1+\beta_3=0$ and $\beta_1+\beta_4=0$. The results reveal that the coefficients become significant and in line with the other estimates. The second linear restriction tests whether the three interaction terms in the programming periods are identical. In Pooled OLS the test fails to reject the null hypothesis $H_0=\beta_2=\beta_3=\beta_4$, suggesting that the speed is different across periods, while rejecting the null hypothesis in FE estimates, thus providing inconclusive evidence on whether the change in convergence speed is the same across periods.

convergence in all parts of the distribution. In particular, this effect is significantly larger in the third and fourth periods for the bottom part of the distribution (FE specifications).[21]

Table 7: Speed of convergence in different programming periods, Gini index 1989–2013

	PANEL A Change in Gini over all PPs						PANEL B Change in Gini in each PP			
							PP1 1989–93	PP2 1994–99	PP3 2000–06	PP4 2007–13
	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Gini initial value	-0.301***	-1.128***	-0.294***	-1.135***	-0.234	-0.913***	-0.234	-0.261***	-0.307***	-0.333***
	(0.054)	(0.075)	(0.050)	(0.072)	(0.173)	(0.151)	(0.174)	(0.066)	(0.053)	(0.093)
Dummy PP2			-0.015**	0.002	-0.008	0.033				
			(0.006)	(0.004)	(0.044)	(0.034)				
Dummy PP3			-0.019***	-0.000	0.001	0.075**				
			(0.005)	(0.004)	(0.048)	(0.036)				
Dummy PP4			-0.005	0.008**	0.022	0.129***				
			(0.006)	(0.004)	(0.051)	(0.037)				
Gini 1994 * dummy PP2					-0.027	-0.119				
					(0.159)	(0.123)				
Gini 2000 * dummy PP3					-0.073	-0.277**				
					(0.173)	(0.129)				
Gini 2007 * dummy PP4					-0.099	-0.441***				
					(0.185)	(0.131)				
Constant	0.090***	0.317***	0.099***	0.316***	0.083*	0.256***	0.083*	0.074***	0.084***	0.105***
	(0.015)	(0.020)	(0.015)	(0.019)	(0.048)	(0.042)	(0.048)	(0.018)	(0.014)	(0.026)
F-stat	30.85***	228.74	13.06***	67.16***	9.23***	56.76***	1.80	15.52***	32.86***	12.89***
Adj. R-Sq.	0.149	0.603	0.204	0.618	0.199	0.648	0.023	0.170	0.195	0.173
Obs.	336	336	336	336	336	336	49	75	108	104
Regions	114	114	114	114	114	114	49	75	108	104
RMSE	0.027	0.017	0.026	0.016	0.026	0.016	0.034	0.024	0.023	0.026
$\beta_1 + \beta_2 = 0$					-0.261***	-1.032***				
$\beta_1 + \beta_3 = 0$					-0.306***	-1.189***				
$\beta_1 + \beta_4 = 0$					-0.332***	-1.354***				
$\beta_2 = \beta_3 = \beta_4$ (p-value)					0.768	0.001				

Notes: Panel A includes 15 countries (AT, CZ, DE, DK, EE, ES, FI, HU, IE, IT, LU, PL, SE, SI, SK). Panel B includes 6 countries in 1989–93 (DE, DK, ES, FI, IT, LU), 10 countries in 1994–99 (AT, CZ, DE, DK, ES, FI, IE, IT, LU, SE), 14 countries in 2000–06 (AT, CZ, DE, DK, EE, ES, FI, HU, IE, IT, LU, PL, SE, SI) and 13 countries in 2007–2013 (AT, CZ, DE, DK, EE, ES, FI, HU, IT, LU, PL, SI, SK). Significance levels: 10% (*), 5% (**) and 1% (***). Clustered standard errors at regional level are in parentheses.

In Table 8, we test whether less developed regions financed by CP funds have converged at a different speed. To this end, following equation (5), we identify such regions with a dummy in each Policy episode (1 if it receives funds and 0 otherwise), using as a reference category all regions not financed. Then we interact them with the initial level of inequality, assuming, therefore, that the effect of the initial level of inequality on its subsequent change (in each of the four episodes) also depends on having received CP funds. Referring to the full sample spanning the period 1989–2013, we find evidence of a convergence-acceleration effect for supported regions in all PPs (except for 1994–99). Indeed, looking at the coefficient of the interaction terms, the estimated difference in the speed of convergence between regions receiving CP funds and regions not financed seems substantial. Repeating the test for quintile income shares generally confirms the evidence.[22]

[21] For brevity, the corresponding tables of estimates for quintile income shares are excluded but available upon request.

[22] For brevity, the corresponding tables of estimates for quintile income shares are excluded but available upon request.

Table 8: Speed of convergence in regions receiving CP funds, Gini index 1989–2013

	(1) Four PPs	(2) Four PPs	(3) Four PPs	(4) Four PPs
	Pooled OLS	FE	Pooled OLS	FE
Gini initial value	-0.322***	-1.115***	-0.317***	-1.021***
	(0.049)	(0.073)	(0.075)	(0.087)
Dummy CP1	0.036***	0.017*	0.214**	0.139**
	(0.010)	(0.009)	(0.084)	(0.069)
Dummy CP2	0.005	0.003	0.010	0.008
	(0.006)	(0.006)	(0.037)	(0.037)
Dummy CP3	0.002	-0.004	-0.002	0.095***
	(0.005)	(0.006)	(0.027)	(0.028)
Dummy CP4	0.000	0.004	-0.029	0.140***
	(0.005)	(0.006)	(0.026)	(0.034)
Dummy CP1 * Gini 1989			-0.624**	-0.462**
			(0.289)	(0.226)
Dummy CP2 * Gini 1994			-0.020	-0.042
			(0.128)	(0.124)
Dummy CP3 * Gini 2000			0.015	-0.363***
			(0.098)	(0.098)
Dummy CP4 * Gini 2007			0.107	-0.497***
			(0.093)	(0.120)
Constant	0.094***	0.304***	0.092***	0.281***
	(0.014)	(0.021)	(0.020)	(0.025)
Time dummies	Yes	Yes	Yes	Yes
F-stat	8.89***	52.44***	9.43***	49.05***
Adj. R-Sq.	0.247	0.627	0.260	0.657
Obs.	336	336	336	336
Regions	114	114	114	114
RMSE	0.026	0.016	0.025	0.015
$\beta_1 + \beta_2 = 0$			-0.940***	-1.482***
$\beta_1 + \beta_3 = 0$			-0.336***	-1.063***
$\beta_1 + \beta_4 = 0$			-0.302***	-1.383***
$\beta_1 + \beta_5 = 0$			-0.209***	-1.517***
$\beta_2 = \beta_3 = \beta_4 = \beta_5$ (p-value)			0.058	0.004

Notes: The sample includes 15 countries (AT, CZ, DE, DK, EE, ES, FI, HU, IE, IT, LU, PL, SE, SI, SK). Significance levels: 10% (*), 5% (**) and 1% (***). Clustered standard errors at regional level are in parentheses.

To conclude, this initial exploration suggests that convergence in income inequality may have been faster in more recent episodes, with less developed EU regions possibly driving the process. However, it is worth noting that the interpretation of this result as a causal effect of the Policy would require further analysis beyond the scope of this study. For example, one should consider that the effect of an increase in development spending on income inequality may materialise with delay. This could arguably contribute to explaining the convergence acceleration observed during the policy episodes. In our case, a lead-lag effect may depend on the direct or indirect nature of the policy measure in place, such as the introduction of progressive taxation and cash-transfers, or the implementation of education and labour market integration measures. However, other concurring factors may affect the magnitude of the redistributive impact of these measures. The effect of taxes and transfers, for example, may depend also on the size, mix and progressivity of each component (Joumard et al. 2013), while economic and social factors at play in the specific country impinge on the effectiveness and magnitude of the redistributive impact of other policy measures. Among these, the literature indicates that the policy treatment has significantly higher growth impact in regions with good human capital and quality of government (Becker et al. 2013; Rodríguez-Pose and Garcilazo, 2015), and the presence of territorial capital in the regions complements the policy action enhancing its impact (Fratesi and Perucca, 2014). Finally, there is also evidence suggesting that the existence of the optimal threshold in terms of funds intensity (Becker et al. 2012; Cerqua and Pellegrini, 2017). This evidence calls for new research elaborating further on the nature of the relationship and investigating in detail the Cohesion Policy mechanisms and the socio-economic environment of the regions in a counterfactual setting.

7. Conclusions

While convergence in income per capita in the EU has traditionally received much scrutiny, convergence in other equally important development outcomes is not well understood. This paper has contributed to filling this gap by asking whether EU regions are becoming more (or less) similar with respect to their income distribution. We tested for unconditional and conditional income inequality convergence, providing new stylised facts.

Both cross-section and panel estimates support the idea of inequality convergence among EU regions. Our findings indicate that inequality among NUTS 2 regions is converging, but to a higher level, so that they have tended to become *equally more unequal*. This process is significantly faster when regions share the same structural features, such as the same level of economic development, the same functional distribution of income and the same level of education and technology. In addition, our results suggest that sharing the same quality of regional institutions may also accelerate the process. Evidence is robust to different checks, including alternative samples and periods, inequality measures, influential observations, and cross-sectional and temporal dependence.

Furthermore, we investigated whether the pace of the convergence changed over time and if less developed regions financed by the Cohesion Policy funds played a significant role in this process. Panel estimates indicate that the second, third and fourth programming periods are driving the convergence effect, where the transition from one programming period to another suggests that the Cohesion Policy may have contributed to accelerating the process of (unconditional) convergence. The estimates found no effect for the first period, perhaps because of the sample composition and the limited number of observations. Finally, the evidence also indicates a significant convergence-acceleration effect for regions receiving Cohesion Policy funds, suggesting that these may therefore be driving the catch-up process.

Our findings have two types of implications. The first is that, as NUTS 2 regions seem to be converging to higher levels of income inequality, the planning of future EU policies ought not to ignore distributive consequences and should perhaps put increasing effort into pursuing growth with equity. The second relates to future research. Our findings call for more analysis, looking at the effects of specific interventions and channels through which the allocation of EU funds may affect the inequality convergence process we have documented in this paper. This means shifting the focus from the macro level to sectoral and micro-level analysis.

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Appendix

Appendix A - Data

In this paper, we use the variable *region_c* from the LIS database to carefully aggregate income microdata, with the aim of constructing regional measures of inequality at the NUTS 2 level.[23] These measures are based on the disposable household income (*dhi*).[24] Throughout this process, we take into consideration the administrative reforms that might have affected regional boundaries in each country using the Eurostat NUTS 2010 classification as a common reference.

To ensure the creation of a fully comparable income variable across countries, we first apply a top-bottom procedure to delete extreme values in incomes, and then we equivalise the variable using the LIS equivalence scale (i.e., the square root of the number of household members). For the purpose of bottom-coding, we set all values less than zero to zero, and for top-coding, we set all values exceeding ten times the median value to ten times the median value, which equally served as a benchmark applied to the LIS Key Figures (Gottschalk & Smeeding, 1997; Smeeding, 1997). We choose to use inflated weights instead of normalized weights because our analysis is limited to EU countries, and there are no significant discrepancies among the countries involved.[25]

Finally, since we are interested in using an equivalised income variable, we apply the household weight multiplied by the number of household members to weight by person (*hpopwgt*nhhmem*).

To test for inequality convergence, we compute delta variables for each inequality measure based on the "first" and "last" values, following the time spans under consideration. When data are not available precisely for the corresponding first-last year of interest, we replace the nearest value of the related LIS wave, if available.

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23 Income inequality data supporting the findings of this study are available from the Luxembourg Income Study (LIS). Restrictions apply to the availability of microdata and elaborations used under license for this study.

24 As for the representativeness of data when disaggregated at the NUTS 2 level, LIS includes in the datasets the same weights provided by the national statistical office in charge of conducting the surveys. The samples are proportionally distributed on the regional level between urban and rural areas to make them representative even for small regions. Table A7 in the supplementary material reports the number of households for each wave in LIS.

25 For example, normalized weights are suggested in the case of country comparison when the USA and Switzerland are involved in the analysis.

Table A1: Number of observations (NUTS 2 regions) across countries for each wave of the LIS database

		Wave III	Wave IV	Wave V	Wave VI	Wave VII	Wave VIII	Wave IX
		1990	1995	2000	2004	2007	2010	2013
Austria	AT	-	9	9	9	9	9	9
Czech Republic	CZ	-	8	8	8	8	8	8
Germany	DE	5	9	9	9	9	9	9
Denmark	DK	5	5	5	5	5	5	5
Estonia	EE	-	-	1	1	1	1	1
Greece	EL	-	-	-	13	13	13	-
Spain	ES	17	17	17	18	19	19	19
Finland	FI	3	3	5	5	5	5	5
Hungary	HU	-	-	7	7	7	7	7
Ireland	IE	-	2	2	2	2	2	-
Italy	IT	18	18	19	19	19	19	19
Luxembourg	LU	1	1	1	1	1	1	1
Poland	PL	-	-	16	16	16	16	16
Sweden	SE	3	3	8	8	-	-	-
Slovenia	SI	-	1	1	1	1	1	1
Slovak Republic	SK	4	4	-	4	4	4	4

Notes: Slovenia (SI) is treated as a single NUTS2 region in the framework of the EU Cohesion Policy and therefore aggregated in the analysis. Data for inequality measures have been interpolated for the wave V in Austria (AT) and for the waves IV and V in Spain (ES). *Source*: Luxembourg Income Study (LIS).

Appendix B - Descriptive statistics

Table A2: Income inequality across EU regions: summary statistics in four samples

	SAMPLE A (Obs. 53)		SAMPLE B (Obs. 75)		SAMPLE C (Obs. 98)		SAMPLE D (Obs. 103)	
Year	1990	2013	1995	2013	2000	2013	2004	2013
GINI INDEX								
mean	0.26	0.29	0.27	0.28	0.28	0.29	0.28	0.29
cv	0.15	0.11	0.15	0.11	0.14	0.11	0.13	0.12
sd	0.04	0.03	0.04	0.03	0.04	0.03	0.04	0.03
max	0.34	0.35	0.38	0.35	0.38	0.36	0.41	0.42
min	0.18	0.23	0.20	0.23	0.20	0.23	0.22	0.23
QUINTILE 1								
mean	9.52	7.78	8.88	8.23	8.84	8.22	8.69	8.22
cv	0.14	0.19	0.17	0.18	0.15	0.17	0.15	0.17
sd	1.30	1.48	1.48	1.48	1.36	1.42	1.34	1.42
max	12.53	10.32	12.56	10.42	12.13	10.54	12.07	10.54
min	7.44	3.97	5.42	3.97	4.89	3.97	4.14	3.97
QUINTILE 2								
mean	14.19	13.63	13.97	13.82	13.83	13.67	13.76	13.67
cv	0.08	0.08	0.08	0.07	0.07	0.07	0.08	0.07
sd	1.20	1.04	1.10	0.96	0.92	0.99	1.07	1.01
max	17.00	17.55	16.02	17.55	15.65	17.55	18.41	17.55
min	11.52	12.18	10.77	12.18	11.59	11.41	10.58	11.11
QUINTILE 3								
mean	17.96	18.01	18.12	17.99	17.94	17.98	17.69	17.94
cv	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06
sd	0.93	0.90	0.82	0.81	0.97	1.03	0.98	1.10
max	19.56	21.03	20.27	21.03	22.78	24.12	19.31	24.12
min	16.07	15.18	16.19	15.18	14.46	15.18	13.91	13.55
QUINTILE 4								
mean	23.01	23.33	23.06	23.21	22.73	23.15	22.86	23.13
cv	0.03	0.05	0.03	0.05	0.04	0.05	0.04	0.04
sd	0.76	1.25	0.71	1.14	0.92	1.04	0.96	1.03
max	25.12	28.30	24.73	28.30	24.99	28.30	27.02	28.30
min	20.25	19.16	20.33	19.16	18.33	19.16	20.49	19.16
QUINTILE 5								
mean	35.31	37.26	35.98	36.74	36.66	36.98	36.99	37.05
cv	0.09	0.07	0.08	0.07	0.08	0.07	0.08	0.08
sd	3.00	2.59	2.99	2.51	2.89	2.66	2.85	2.84
max	41.03	43.14	45.09	43.14	45.21	43.33	44.89	47.99
min	29.98	31.89	30.74	31.89	30.86	30.83	30.00	30.83

Notes: Gini index and percentage shares of income accruing to each quintile in initial and final year periods. Countries involved in sample A: DE, DK, ES, FI, IT, LU, SK; sample B: AT, CZ, DE, DK, ES, FI, IT, LU, SI, SK; sample C: AT, CZ, DE, DK, EE, ES, FI, HU, IT, LU, PL, SI, sample D: AT, CZ, DE, DK, EE, ES, FI, HU, IT, LU, PL, SI, SK.
Source: Luxembourg Income Study (LIS) http://www.lisdatacenter.org. Authors' calculations.

Table A3: Income inequality measures and control variables: source and summary statistics (1990-2013)

VARIABLES	SOURCE	OBS	MEAN	STD. DEV.	MIN	MAX
Gini index	LIS	712	.279	.039	.167	.421
Quintile 1 (% share of income)	LIS	712	8.692	1.409	3.966	13.429
Quintile 2	LIS	712	13.828	1.105	10.106	18.405
Quintile 3	LIS	712	17.91	.991	13.549	24.116
Quintile 4	LIS	712	22.978	.941	18.328	28.298
Quintile 5	LIS	712	36.592	3.019	22.181	47.99
Gdp	Cambridge Econometrics	4217	36.861	42.254	.629	328.979
Gdp per capita	Cambridge Econometrics	4217	19964.01	10509.29	2629.38	69157.47
Gross Fixed Capital Formation	Cambridge Econometrics	4217	7.873	8.704	.076	65.548
Compensation of employees	Cambridge Econometrics	4217	16.959	19.928	.362	145.804
Labour income share (Compensation of employees/Gdp)	Cambridge Econometrics	4217	.442	.097	.184	.936
EQI index	QoG	309	.168	.933	-2.284	2.781
Technology (patent applications per million inhabitants)	Eurostat database	2174	102.74	135.15	.066	711.99
Education tertiary (% pop. 25/64)	Eurostat database	2359	21.71	8.212	6.5	50.2
Population density (pop. avg per square km)	Eurostat database	3096	284.39	687.63	3.3	6478.5
Population (thousands)	Eurostat database	4217	1779.08	1502.60	24.29	9975.47

Notes: Summary statistics for all available years. Control variables from Cambridge Econometrics are expressed in billions of euro and deflated to 2005 constant price euros using sectoral price deflators obtained from AMECO. Source: Luxembourg Income Study (LIS) database; Cambridge Econometrics (2016); Quality of Government (QoG) Institute (2013); Eurostat database (2016).

Appendix C - Unconditional convergence and point estimation

The first panel in Table A4 reports the convergence test over the period 1990-2013 for the Gini index and quintile shares. The coefficients of the initial values are negative and statistically significant for all measures (except for the fourth quintile). Results indicate that within-region income inequality has been converging since the initial year 1990, regardless of regional initial conditions, i.e., no matter why EU regions are equal or unequal.

To give an appreciation of the "speed" of convergence, consider the Gini index in 1990 in the Spanish region of La Rioja (scoring 0.310) and the Finnish region of Helsinki-Uusimaa (scoring 0.208). The two regions are positioned very close to the regression line, but nearly at opposite extremes. According to our OLS estimates, the expected change in inequality will be $0.180+(-0.572 \times 0.310)=0.002$ in the former case and $0.180+(-0.572 \times 0.208)=0.061$ in the latter. Such trends imply that, after 23 years, the two regions are predicted to reach an inequality level of $0.310+0.002=0.313$ in La Rioja, and $0.208+0.061=0.269$ in Helsinki-Uusimaa. At this pace, it would take approximately 39 years before Helsinki-Uusimaa catches up with La Rioja. This is indicative of a significant process of unconditional convergence, where inequality levels are converging, but to a higher level. Such trend implies also that EU regions are converging to an average Gini index level of $|0.180/-0.572|=0.314$. Instead, looking at the distribution in quintile shares in 1990, the top quintile is converging to an average income share of 38.70 while the bottom quintile to a share of 6.41.

We repeat the analysis on different periods, including larger sample of regions, and detect the effect of influential observations by re-estimating the regressions using Iteratively Reweighted Least Squares (IRLS).[26] Table A4 reports additional estimates allowing to check if the "speed" of convergence changes during recent periods or if the tests include a larger sample of regions. OLS results are constant over the four periods examined and repeating convergence simulations lead to similar conclusions. The results are generally insensitive to checks for influential observations. IRLS regressions, down-weighting potential outliers in the sample, largely confirm previous findings, returning a significant coefficient also for the fourth quintile in 1990-2013 (driven by the German region of Bremen), while when looking at convergence of the Lorenz Curve, the trends imply that the three middle quintiles are converging to similar shares to the year 1990.[27]

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[26] The estimated speed may also be biased in case the initial value of the inequality is measured with error: under (over) estimating the initial value would return to over (under) estimation of the convergence (divergence) trend. In cross-country datasets, this may be a major issue. Indeed, Ravallion (2003) corrects for measurement errors by instrumenting the current initial level of inequality measure with the one in the previous year. However, this should not be an issue in this case, as the LIS database ensures comparability across regions.

[27] IRLS results available upon request.

Table A4: Unconditional convergence in inequality: OLS

	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
SAMPLE A - 1990-2013 (Obs 53)						
Initial value 1990	-0.572***	-0.561***	-0.622***	-0.841***	-0.443	-0.576***
	(0.094)	(0.131)	(0.125)	(0.191)	(0.313)	(0.100)
Constant	0.180***	3.598***	8.264***	15.154***	10.512	22.301***
	(0.025)	-1.293	-1.827	-3.517	-7.187	-3.503
SAMPLE B - 1995-2013 (Obs 75)						
Initial value 1995	-0.442***	-0.421***	-0.499***	-0.964***	-0.952***	-0.501***
	(0.063)	(0.117)	(0.068)	(0.165)	(0.224)	(0.082)
Constant	0.133***	3.091***	6.817***	17.336***	22.112***	18.801***
	(0.017)	(1.075)	(0.964)	(2.962)	(5.174)	(2.851)
SAMPLE C - 2000-2013 (Obs 98)						
Initial value 2000	-0.461***	-0.221***	-0.432***	-0.536***	-0.861***	-0.509***
	(0.080)	(0.069)	(0.078)	(0.173)	(0.165)	(0.129)
Constant	0.137***	1.338**	5.823***	9.653***	19.998***	18.971***
	(0.022)	(0.608)	(1.086)	(3.095)	(3.776)	(4.629)
SAMPLE D - 2004-2013 (Obs 103)						
Initial value 2004	-0.331***	-0.196***	-0.491***	-0.787***	-0.758***	-0.418***
	(0.076)	(0.073)	(0.140)	(0.219)	(0.123)	(0.099)
Constant	0.097***	1.235*	6.664***	14.173***	17.582***	15.529***
	(0.021)	(0.643)	(1.905)	(3.913)	(2.831)	(3.583)

Notes: changes in each measure of inequality are regressed against the respective initial values in four periods. Significance levels: 10% (*), 5% (**) and 1% (***). Heteroskedasticity robust standard errors are in parentheses.

Appendix D

Table A5: Panel Corrected Standard Errors 1990-2013

	Change in Gini, 1990-2013	Changes in quintile shares, 1990-2013				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value	-0.585***	-0.613***	-0.607***	-0.641***	-0.940***	-0.637***
	(0.141)	(0.152)	(0.142)	(0.158)	(0.215)	(0.127)
GDP per capita (ln)	-0.247**	9.088***	3.906	2.668	7.116	-17.051*
	(0.100)	(2.887)	(2.680)	(3.188)	(7.640)	(9.827)
GDP per capita squared (ln)	0.012**	-0.416***	-0.160	-0.115	-0.360	0.779
	(0.005)	(0.150)	(0.142)	(0.162)	(0.386)	(0.486)
GFCF (ln)	0.006***	-0.262***	-0.250***	-0.036	-0.146	0.592***
	(0.001)	(0.058)	(0.065)	(0.050)	(0.108)	(0.157)
Labour Income Share	-0.014	-0.588	0.862	0.035	-0.125	-1.038
	(0.036)	(1.026)	(1.002)	(1.972)	(2.232)	(3.397)
Constant	1.468***	-42.783***	-14.541	-4.165	-13.691	115.367**
	(0.511)	(14.352)	(12.678)	(16.643)	(36.952)	(49.969)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
chi2	30162.5***	1126497.3***	43122.0***	39114.2***	48755.5***	10334.6***
R-Sq.	0.452	0.426	0.424	0.360	0.456	0.441
Obs.	293	293	293	293	293	293
Regions	50	50	50	50	50	50
RMSE	0.020	0.774	0.645	0.688	0.851	1.740

Notes: panel corrected standard errors method by Beck & Katz (1995) using panel-specific AR(1) autocorrelation structure option.

Table A6: Panel Corrected Standard Errors 2000-2013

PANEL A	Change in Gini, 2000-2013	Changes in quintile shares, 2000-2013				
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value	-0.505***	-0.442***	-0.804***	-0.706***	-0.923***	-0.538***
	(0.161)	(0.157)	(0.218)	(0.228)	(0.222)	(0.173)
GDP per capita (ln)	-0.209***	7.373***	3.746**	1.683	4.797	-18.637***
	(0.025)	(2.010)	(1.715)	(1.519)	(3.518)	(2.709)
GDP per capita squared (ln)	0.010***	-0.353***	-0.167*	-0.079	-0.257	0.912***
	(0.001)	(0.100)	(0.086)	(0.094)	(0.191)	(0.131)
GFCF (ln)	0.004*	-0.203**	-0.370***	-0.128	-0.255***	0.624***
	(0.002)	(0.099)	(0.105)	(0.160)	(0.056)	(0.200)
Labour Income Share	0.008	-1.259	1.622*	-0.344	0.866	-0.343
	(0.019)	(1.208)	(0.853)	(1.403)	(1.033)	(1.950)
Constant	1.171***	-33.424***	-9.639	3.889	-1.181	113.774***
	(0.153)	(9.875)	(9.739)	(7.056)	(16.154)	(17.854)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
chi2	190712.4***	10120723.3***	291411.2***	32777.2***	3987965.8***	21646.9***
R-Sq.	0.408	0.331	0.471	0.377	0.526	0.375
Obs.	392	392	392	392	392	392
Regions	98	98	98	98	98	98
RMSE	0.018	0.679	0.662	0.772	0.805	1.646
PANEL B						
	GINI INDEX	QUINTILE 1	QUINTILE 2	QUINTILE 3	QUINTILE 4	QUINTILE 5
Initial value	-0.549***	-0.503***	-0.831***	-0.726***	-0.957***	-0.578***
	(0.165)	(0.167)	(0.217)	(0.229)	(0.221)	(0.180)
GDP per capita (ln)	-0.137***	5.152***	0.408	-2.858	1.419	-11.618***
	(0.032)	(1.753)	(1.901)	(2.208)	(2.532)	(2.870)
GDP per capita squared (ln)	0.007***	-0.250***	0.002	0.153	-0.075	0.546***
	(0.002)	(0.091)	(0.105)	(0.125)	(0.144)	(0.154)
GFCF (ln)	0.005**	-0.251**	-0.376***	-0.082	-0.249***	0.652***
	(0.002)	(0.098)	(0.093)	(0.130)	(0.050)	(0.168)
Labour Income Share	0.008	-1.287	1.875**	-0.248	0.504	-0.014
	(0.019)	(1.262)	(0.818)	(1.437)	(1.156)	(1.895)
Tech. innovation (ln)	-0.003**	0.135**	0.083*	0.083	-0.066	-0.146
	(0.002)	(0.061)	(0.050)	(0.065)	(0.076)	(0.139)
Tertiary education (ln)	-0.013***	0.196	0.336	0.457	0.842**	-1.252**
	(0.004)	(0.234)	(0.206)	(0.322)	(0.388)	(0.524)
Population density (ln)	0.004**	-0.091	-0.136*	-0.230**	-0.171***	0.484**
	(0.002)	(0.066)	(0.071)	(0.090)	(0.049)	(0.192)
Constant	0.863***	-22.190**	5.516	24.256**	13.044	86.468***
	(0.111)	(8.855)	(10.605)	(12.228)	(12.750)	(11.313)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
chi2	3378.0***	12013.9***	11741.8***	679.7***	1.54e+10***	3686.1***
R-Sq.	0.433	0.361	0.477	0.396	0.542	0.394
Obs.	392	392	392	392	392	392
Regions	98	98	98	98	98	98
RMSE	0.018	0.680	0.658	0.764	0.794	1.622

Notes: panel corrected standard errors method by Beck & Katz (1995) using panel-specific AR(1) autocorrelation structure option.