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More Flexible Yet Less Developed? Spatio-Temporal Analysis of Labor Flexibilization and Gross Domestic Product in Crisis-Hit European Union Regions

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Abstract
This study conducts a spatio-temporal analysis of labor flexibilization and GDP per capita change (gross domestic product) with focus on their interrelation in European Union (EU) regions during 2008–2013. Using a composite index to calculate the dispersion of flexible contractual arrangements and spatio-temporal autocorrelation metrics, it shows that changes in overall growth largely affect the distribution of flexible working patterns across space and time. In particular, regions with high increments in the prevalence of flexible work, thus ranking highest in terms of flexibilization, suffered the most as a result of the productivity and financial crisis during the turbulent 2008–2013 period. Further, applying univariate, bivariate, and differential local Moran's I spatial autocorrelation techniques, this study demonstrates that changes in GDP pca are negatively spatially autocorrelated with flexibilization, while increasing flexibility has no significant positive effect on GDP growth. This major finding contradicts the general belief that more flexible labor environments lead a priori to economic growth, re-emphasizing previous considerations on that matter while also updating existing contributions with a more nuanced and recent account that follows a geographically sensitive methodology. Although many studies have identified that labor flexibilization is not always linked to economic growth, the current study offers recent spatio-temporal evidence that refer to almost all EU regions to complement existing works. Contextualizing these findings, this analysis highlights an increasing schism between the north-central and south-eastern EU regions, with the latter facing poor growth prospects and extensive low-road flexibilization practices. Such a schism, which often transcends national boundaries creating new patterns of sub-national unevenness, challenges the idea of a healthy trade-off between flexibilization and GDP growth and warrants urgent attention.

Keywords Labor flexibilization · GDP · European Union · Economic crisis · Spatio-temporal autocorrelation

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1 Introduction

There are only but a few, if any, official policy documents by the European Union (EU) and the Organization of Economic Cooperation and Development (OECD) that do not boldly mention and highly talk about the importance of "employment flexibilization" for contemporary labor markets. Since the past three decades, the EU and other nations have adopted "employment flexibilization" as an umbrella term for various policies and practices that promote non-permanent employment. In fact, the term has been more intensively applied since the 2008–2009 depression. Being a market-oriented reduction of typical labor protection, often accompanied by unbalanced employee pay-offs in the form of enhanced security, flexibilization has been praised for its ability to eradicate barriers (i.e., rigidities) in labor market entry and boost employability. As recently stated by the European Commission (2015a) "Member States should take into account the flexibility and security principles (flexicurity principles). Employment protection rules, labor law and institutions should all provide a suitable environment for recruitment, while offering adequate levels of protection […]". Thus, flexibilization is largely understood and broadly conceived as an important tool that tackles unemployment and produces GDP growth and economic expansion (European Commission 2015a; Keune and Jepsen 2007).

Flexibilization is commonly distinguished into (1) *external* or *numerical* flexibility, that is, temporary, seasonal, and other casual contracts, (2) *working time* or *qualitative* flexibility, which is related to practices spanning from part-time to overtime work, and (3) *institutional* flexibility, wherein job protection and dismissal regulation are less stringent and the provisions of collective wage arrangements are lower. Despite their important differences, all three types hold something in common; they are not solely considered to be the mere outcome of a new political compromise between capital and labor, nor are they a simple result of "hard political choices" that seek to restore growth after recession (Kalleberg and Marsden 2015). In fact, all flexibilization practices are deeply rooted in certain macroeconomic necessities of contemporary post-industrial societies (Harvey 2010). For example, geographically uneven, productive and exchange networks; advanced communication technologies; outsourcing and vertical disintegration; emerging global asymmetries; and geopolitical hierarchies have together reduced the prevalence of "well-paid and regulated" jobs, thus forcing the local labor markets to adopt more flexible patterns (Markusen 1996; Massey 1996; McGrath et al. 2010).

Despite its increasing prevalence and a certain level of consensus in its definition, flexibilization lacks commonly agreed upon and widely used tools for its measurement. Even though different forms of flexible and atypical labor, such as temporary work, are systematically measured by national and EU authorities, a unified and cohesive measure that accounts for flexibilization per se is absent. Moreover, geographical analyses of flexibilization through spatial statistical analysis remain sparse. Thus, straightforward answers to questions as, "Which and where are the most (least) flexible socio-spatial entities and local labor markets of the EU?" or "What are the spatio-temporal patterns of flexibilization across the EU?" cannot be easily and reliably given. Despite this reality, answering such questions is a pressing task because, among others, it provides a means for a timely evaluation of the efficiency of labor market policies and the overall connection among flexibilization, economic cycles, and growth. Such a task is attempted below.

This study contradicts the general belief that more flexible labor environments lead a priori to economic growth, re-emphasizing previous contributions on that matter (e.g. Barbieri and Cutuli 2015; Gebel and Giesecke 2016) while also updating existing contributions with a more nuanced and recent account that follows a geographically sensitive methodology. More specifically: (1) it provides useful insights on the spatio-temporal trends of labor flexibilization using a unified measure of its dispersion and (2) analyzes the interrelationships between flexibilization and GPD pca change amid a crisis. The former aim is of a methodological nature and significance and is operationalized through the contextualized calculation of composite index (CI) named *Flexible Contractual Arrangements* index (FCA) (Gialis and Leontidou 2016). On the other hand, the latter is of wider sociopolitical importance and addresses the spatially sensitive correlation between regional flexibilization scores and GDP pca data, through the calculation of spatial and spatio-temporal autocorrelation metrics.

FCA index represents the first of the four pillars of flexicurity policies, as officially introduced by the EU's flexicurity agenda. In particular, it is the pillar that accounts for flexible and atypical forms of work, which are, in turn, institutionalized through "modern employment legislation" collective agreements, and the changing work organization in sectors and firms (Viebrock and Clasen 2009). The other three pillars, which mainly concern aspects of employment security, are not included in the present study owing to space and data limitations.

The analysis is performed for 16 EU countries at the Nomenclature of Territorial Units for Statistics-2 (NUTS-2) regional level for 2008 and 2013. The reference year 2008 is selected as the year before crisis started, and 2013 as the year that crisis had already peaked across eurozone members.

The study draws on previous research on the FCA index and its methodological underpinnings (see Gialis and Leontidou 2016). through which a theoretical framework allowing for flexibilization CIs calculation had been set, and the variables included and rankings produced were statistically tested for their reliability. In the attempt on hand attention is paid to the spatiality of the "flexible work–economic growth" nexus. What we do here is to expand to the geographical and temporal scope of FCA CI, while discussing the potential interrelationship between unevenly dispersed flexibility and GDP pca change. It is noteworthy that this study is among the few attempting the theoretical and empirical application of CIs in the field of employment flexibilization in a geographical context. More importantly, to the best of the authors' knowledge, this is the first study to apply spatial and spatio-temporal autocorrelation techniques to flexibilization issues in relation to GDP pca change at a regional level.

In fact, most of the studies analyzing labor market deregulations are focusing on the national level. Although these studies offer invaluable knowledge about labor flexibilization, they treat regions as homogeneous and cross-sectionally independent, failing to address spatial dependence. The importance of spatial heterogeneity and the influence of meso-level mechanisms (e.g. regional competitiveness and human capital, illicit or informal regional labor market practices etc.) has been highlighted in studies of regional unemployment as well through various implementations of shift-share analysis techniques (Grekousis 2018; Gialis et al. 2017). Although on average, regional flexibilization and unemployment are highly influenced by the national trends, they are also highly influenced by regional industrial composition, local regulating mechanisms as well as by neighboring (national or trans-national) regions as a result of spatial autocorrelation existence (Marelli et al. 2012). As such, regional employment performance is also analyzed at sub-national geographical scales, as for example the NUTS 2 or NUTS 3 ones, for the EU (Grekousis 2018; Bailey et al. 2016; Doran and Fingleton 2016; Netrdová and Nosek 2016; Gilmartin and Korobilis 2012). By the same token, we believe that labor flexibilization analysis on larger spatial scales (i.e., national) fails to study the underlying geographies at play, necessary for uncovering the effects and other casual mechanisms of labor flexicurity. Our hypothesis is that FCA has a strong national component but due to spatial heterogeneities and the effect of regional path-dependence is also highly influenced from regional neighborhood effects. Thus, we analyze labor flexicurity regionally to account for spatial dependence and test whether FCA and GDP exhibit spatial disparities across the EU. We also suggest that mapping potential spatial clustering of FCA and GDP along with their co-location could be the first step for understanding their contextual factors.

Additionally, the regional spatio-temporal analysis of FCA CI and GDP and their interrelations offers valuable findings for policymakers and stakeholders to design better regional labor policies that foster employees well-being. According to OECD (2011) a major response to the economic crisis is the targeted regional polices applied by the countries and the European Union. To this end, our increased knowledge on regional labor flexicurity status is essential for the better regional integration and cohesion in Europe (Psycharis et al. 2014). The selected spatial scale of analysis (NUTS-2 regions) used in this study is in line with such a policy target since NUTS-2 regions have been designed as the appropriate level for socioeconomic analysis for the EU 28 countries (Eurostat 2015). Overall, such a spatio-temporal analysis is original and has been partially overlooked by previous attempts.

The remainder of this study is structured as follows. Section 2 presents the theoretical contextualization of the FCA index, methodological choices, and data used for the analysis. This section pays specific attention to the relevance of spatial auto-correlation techniques for GDP, labor market, and employment flexibility. Section 3 discusses the results and offers a detailed analysis of the findings. Section 4 elaborates on the wider meanings and implications of the overall material.

2 Materials and Methods

2.1 Measuring Flexibilization Using CIs: The FCA Index and Related Data

A composite index (CI) is the statistical aggregate of several variables or indices synthesized in a standardized manner, thus providing a meaningful and cohesive statistical measure of a phenomenon over time. In most cases, a CI is constructed from a large number of variables, which when averaged, represent a generalized quantifier of the phenomenon at hand. The literature contains well-known CIs with wider sociopolitical significance that frequently make headlines. Typical examples are the Human Development Index (HDI; United Nations Development Programme 1990; Osborne and Difei 2010) and the Environmental Sustainability Index (Esty et al. 2005), which estimate and monitor the developmental environment-friendly capacity of nations.

A key advantage of CIs is that they broadly summarize multi-dimensional phenomena using stylized simple measures, thus contributing to comparative analyses and accountability across space and time. On the other hand, a disadvantage is the over-simplistic approach to aggregating different aspects of a phenomenon while frequently presenting false messages to the academia and public. The latter is particularly prevalent in CIs that are poorly constructed or misinterpreted (Saltelli 2007). As has been argued, the calculation of CIs should not be considered the key objective; rather, it is an analysis that "sets the scene" for more in-depth research on the reasons underpinning (changing) socio-spatial structures. In addition, CIs should no longer "stay national" and pay more attention to other scales (i.e., urban and regional). These two remarks signify how we understand (and make progress in) the use of CIs with regards to flexibilization in contemporary labor markets.

In this study, we make use of the FCA CI as proposed in Gialis and Leontidou (2016). The methodological foundations of the FCA CI, in the context of this analysis, are briefly outlined below. In order to calculate the FCA CI, we have (1) selected the appropriate variables following a theoretical contextualization of flexibilization in contemporary labor markets, (2) statistically tested these variables to determine their appropriateness and reliability (e.g. tests for the effects of data gaps, normalized the range of values for reasons of comparability, checks for potential correlations between variables and redundancies),[1] (4) calculated the CI and analyzed results through proper visualization techniques, and finally (5) conducted a comparative analysis of CI relationship with other economic indicators to assess the impact of recession. The latter is mostly performed using advanced spatial autocorrelation techniques.

2.1.1 Data

Scrutinizing the official statistics revealed eight variables/indicators that best describe the phenomenon at hand. These variables are allocated across three dimensions: *external*, *work-time*, *and institutional flexibility.* The dimensions, respectively, denote the diffusion of certain atypical employment forms vis-à-vis permanent employment, changes in average working hours and part-time work, and employment protection during full- and part-time work. The variables are derived from Eurostat Labour Force Survey (LFS), excluding institutional flexibility, for which the data series measured by OECD at a national level is referenced (Table 1).

The eight variables are synthesized to build the FCA CI following an equal weighting scheme (i.e., all indicators of each dimension have equal importance and participate with the same weight) and a linear aggregation method (Table 1). Issues of robustness and sensitivity are also tested using two extra methodologies of normalizing and weighting. Divergences in regional ranking were minor and mainly attributed to the reduced effect of outliers on the CI values.

The reference years used for the calculations are 2008 and 2013 and the spatial scale of analysis refers to the NUTS-2 classification system (Eurostat 2015), that has been designed

[1] Correlations among indicators used were estimated through the Pearson product-moment coefficient in the initial attempt to establish an FCA CI (Gialis and Taylor 2016) and have been re-verified for the new calculation at hand. The qualitative assessment between ‘very weak’ (i.e., $0.0<|R|<0.2$) and ‘very strong’ ($0.8<R<1.0$) of the inter-indicator correlation is defined by diving the range of possible values linearly into five equal intervals. The inter-correlation matrix revealed that FCA2_1 and FCA2_3 very strongly anti-correlate across all study years (2005, 2008 and 2013). Nine other sub-index pairs appear to correlate ‘strongly’ (i.e., $0.6<R<0.8$), including FCA1_2 and FCA1_4. In order to remove or not an indicator that was highly correlated with another, it was necessary to estimate whether both indicators can represent the same phenomenon. For permanent employment (FCA1_4), it was found that a strong negative correlation existed with self-employment (FCA1_2), in turn, related to that high shares of permanent employees are always related to leads minor shares of self-employment. Yet, both indicators were retained as they represent different labor market categories. Also, self-employment captures new trends in flexibility, such as subcontracting or gig-economy work and should be retained. For the redundancy check we applied principal components analysis on the indicators used for the FCA index. It came out that seven of the eight indicators in the correlation matrix have a single strong or very strong component loading, and thus they are accounted for to a large extent by a single principal component As such, there is no opportunity for reducing the dimensionality of the CI and the complete list of indicators has been retained.

Table 1 Flexible contractual arrangements CI: variables per dimension

Variable code	Variable	Short description	Weight within dimension/direction/normalized weight	Source
Dimension 1: External flexibility				
FCA1_1	Temporary[a]	Employees under a temporary or fixed-term form of employment over total employees (%)	0.25/(+)/0.083	Eurostat
FCA1_2	Self-employment	Individually self-employed over total employment (%)	0.25/(+)/0.083	Eurostat
FCA1_3	Family helpers	Contributing family workers over total employment (%)	0.25/(+)/0.083	Eurostat
FCA1_4	Permanent employees	Permanent employees over total employment (%)	0.25/(−)/0.083	Eurostat
Dimension 2: Work-time flexibility				
FCA2_1	Hours worked	Average hours worked above or less than 40-h weeks	0.333/(+)/0.111	Eurostat
FCA2_2	Work-time CV	Average work time coefficient of variation (CV) during the past 4 years	0.333/(+)/0.111	Eurostat
FCA2_3	Part-time	Part-time employment over total employment (%)	0.333/(+)/0.111	Eurostat
Dimension 3: Institutional flexibility				
FCA3_1	Employment protection legislation (EPL)[b]	OECD's employment protection legislation index (absolute value)	1/(−)/0.333	OECD

Data for the eight variables available for 2008 and 2013

[a]Calculated as a share of total employees; all other indicators in FCA1 are calculated over total employment

[b]Values of the EPL index are provided on a national scale; all other variables are on a NUTS-2 level

as an appropriate level for the socioeconomic analysis of the member countries and the implementation of related regional policies.[2] Overall, 16 out of the 28 EU member countries and 239 out of a total of 276 EU28 NUTS-2 regions (86.6%), are included in the study (i.e., Austria, Belgium, Bulgaria, France, Finland, Germany, Greece, Hungary, Italy, the Netherlands, Poland, Portugal, Romania, Spain, Sweden, and United Kingdom). Twelve countries were excluded owing to missing data and space limitations.[3] In addition, remote/island territories (e.g. Portuguese Azores or the Spanish Ceuta) are also removed.

To further analyze FCA CI, GDP pca at current market prices by NUTS-2 regions is used for 2008 and 2013. GDP at market prices is the final result for the production activity of resident producer units (Eurostat 2016). National and regional GDP per capita denote a country or region's standard of living (Grekousis et al. 2016; Eurostat 2015) and have been linked to various geographical studies (Grekousis and Mountrakis 2015). GDP pca offers a solid base for regional analyses and thus, it is adopted as an indicator for EU's regional policies. In particular, regional GDP pca is considered "the most important indicator for the selection of regions eligible for support under the investment for growth and jobs goal of the EU's regional policy" (Eurostat 2016). This research uses regional GDP pca in Euros and not the commonly applied purchasing power standards (PPS). This is because although the calculation of GDP in PPS allows for comparisons across differently sized economies, irrespective of price levels, it is much less suitable for comparative studies conducted over time (Eurostat 2016). The use of GDP pca in Euros allows for diachronic comparisons and calculation of rates, and thus, is more appropriate for the present study. For simplicity, the term GDP pca is used instead of "regional GDP pca at current market prices".

Overall, the FCA CI calculation aims to provide meaningful results that verify established trends for the impact of crisis on contemporary flexibilization and GDP pca and highlight new important ones for regional unevenness. This is further discussed in Sect. 3, after a brief methodological note on spatial autocorrelation.

2.2 Applying Advanced Spatial Autocorrelation Techniques to Regional Flexibilization and GDP PCA Analysis

Spatial autocorrelation is a degree expressing spatial dependency, association or correlation between the value of an observation (referring to an attribute) of a spatial entity and the values of neighboring observations. Positive spatial autocorrelation can be observed if the value in a specific location is similar to those within the neighborhood; in this case, spatial clusters are formed (Dall'erba 2009). Negative spatial autocorrelation exists when a value in a location largely differs from those in the neighboring areas; this indicates potential spatial outlier existence. When there is no association among a value in a location and the values of the surrounding locations, the data exhibit zero spatial autocorrelation.

Spatial autocorrelation can be measured in two ways, globally and locally (Anselin 2017). Both approaches allow for a spatial and temporal correlation analysis based on solid statistical methods (Lloyd 2010). Global spatial autocorrelation measures a statistic for

[2] The administrative boundaries for EU countries are modeled as polygons at the NUTS-2 level and use the geographic coordinate reference system, European Terrestrial Reference System 1989 (ETRS89), for the reference year 2013 at the 1:60 M scale (GISCO 2015). Spatial data were projected to the WGS84 projected coordinate system because spatial statistics require projected data to accurately measure distances.

[3] The following countries are excluded: Czech Republic, Croatia, Cyprus, Denmark, Estonia, Ireland, Latvia, Lithuania, Luxembourg, Malta, Slovakia, and Slovenia.

the entire dataset and produces a single value. However, global measures do not localize a value of autocorrelation or determine where clusters or outliers exist. This gap is filled using local spatial autocorrelation metrics that calculate a value of spatial autocorrelation for each location. To do so, a specific neighborhood should be defined. Defining the size of a neighborhood is not trivial and should be done in a systematical manner. This study uses incremental spatial autocorrelation, which defines the appropriate distance band, to calculate local spatial autocorrelation statistics.

In addition to defining the neighborhood, multiple testing and spatial dependence should be accounted for when calculating local spatial autocorrelation metrics. Since local spatial statistics apply a test for each single spatial feature in the database, it is possible that objects are categorized as statistically significant only by chance. The probability of rejecting the null hypothesis when in fact is true is high and should be controlled (Castro and Singer 2006). To account for this problem, this research applies a false discovery rate (FDR) correction (Benjamini and Hochberg 1995; Benjamini 2010). FDR correction has been largely used in statistics but not to the same extent in geographical applications (Castro and Singer 2006; Goovaerts 2010).

Moran's I and Getis–Ord Gi* indices are the most well-defined and documented indices used to measure local spatial autocorrelation (Anselin 1994; Getis and Ord 1992). Numerous geographical applications adopt these metrics to analyze for example networks (Yamada and Thill 2007) or income mobility (Rey 2016). However, local spatial autocorrelation techniques are yet to be implemented to flexibilization issues especially in a spatio-temporal context. This study applies local spatial autocorrelation techniques to identify flexibilization and GDP pca patterns as well as to assess their interrelations. These techniques offer more detailed insight into the analysis as they provide a statistical value for each location. As such they can map FCA CI or GPD pca spatial clusters and outliers that originate from different processes running across space, revealing local spatial heterogeneity. This spatial heterogeneity can be further analyzed by studying interrelations among the variables. In this study, the focus is to identify any spatio-temporal linkage between the manner in which FCA CI evolves in relation to GDP pca change by using spatial autocorrelation techniques. To spatially and temporally analyze FCA index and GDP pca we make use of the following spatial autocorrelation techniques (that are briefly explained below): incremental spatial autocorrelation, differential local Morans' I, univariate local Morans' I and bivariate local Moran's I.

Defining the appropriate size of a neighborhood is crucial to the performance and outcomes of a spatial autocorrelation index. A large neighborhood may hide local clusters as it tends to calculate the index at the global level. The further away an object lies, the less impact it has on others. As a result, an index does not need to be estimated when spatial weights are practically close to zero. By contrast, a small neighborhood might lead to objects with few or no neighbors, which results in low statistical accuracy. To determine a trade-off distance between a large and small neighborhood size, this study employs the incremental spatial autocorrelation technique. A global Moran's I value is estimated for a set of increasing distances and a graph of z-scores produced over the increasing distance is used to determine the distance at which the spatial autocorrelation is more intense. The distance at which the first peak of z-score is observed is used as the fixed distance to calculate the weight matrix and spatial autocorrelation index.

The differential local Moran's I is used to test for the spatio-temporal autocorrelation of FCA CI, that is, to trace if changes over time are spatially clustered (Anselin 2005). A differential Moran's I is more descriptive in a spatio-temporal context in comparison to mapping the univariate local Moran's I index of FCA CI for each timestamp. In the context of this research, it tests whether the change in FCA CI at a location between 2008 and 2013 is related to the change in FCA CI in the neighboring locations for the same period. When high values in FCA change are clustered together then we have a high–high type of cluster (hot spots of FCA CI). That is, during a specified time interval, high changes in FCA CI for a location are surrounded by high changes in neighboring locations. Similarly, low changes surrounded by other low changes create low–low clusters (cold spots of FCA CI). Both cases present positive spatio-temporal autocorrelation. Spatio-temporal outliers can be also observed for high–low or low–high formations.

Univariate local Morans' I spatial statistic is used to detect either outliers, or clusters of high or low values of a single variable and most of the times it is just referred to as local Morans' I (Anselin 1994). In this study, local Morans' I is used to test for spatial autocorrelation of the rate of GDP pca change. An index score larger than 0.3, is an indication of relatively strong positive autocorrelation, while a score smaller than -0.3 is an indication of relatively strong negative autocorrelation (O'Sullivan and Unwin 2010). A positive autocorrelation for the rate of GDP pca change would typically mean that entities with either high or low values cluster together.

Bivariate Moran's I is used to identify spatial associations between two variables for the same timestamp (Anselin 2005). This study extends the use of the bivariate local Moran's I in a temporal context to examine FCA change (2008–2013) and GDP pca rate of change (2008–2013). Conceptually this approach explains in a temporal context how the rate of change of GDP pca at a specific location affects the change of FCA CI in its neighborhood within a time interval. As such we test for spatio-temporal autocorrelation. In this study, we also reverse the analysis to study how the FCA change at a specific location affects the GDP pca rate of change in nearby locations within the same time interval.

The rationale behind this switch is that although results are expected to look similar (see Sect. 4), there are key conceptual differences. The first case analyzes the spatial autocorrelation of the GDP pca rate in a specific location with an FCA change in a neighboring location. One can think of the bivariate correlation calculated (and also depicted in a related scatter plot) as the effect of GDP pca change in one location on the FCA change in nearby locations. On the other hand, when switching variables, the bivariate correlation highlights the influence of FCA changes on GDP pca change, thus contributing to growth.

Such an analysis can help develop proper and targeted policies as it signifies, *ceteris paribus*, the measures that should be taken to avoid high flexibilization when GDP pca changes and underlines changes in growth potential as a result of the flexibilization policies adopted. Although changes in GDP and productivity are multivariate, a high FCA CI value reveals changes in employment patterns, wage remuneration, hours worked, and institutional provisions, which in turn, largely influence GDP pca. From a policy perspective, however, the above approach can be used to draw more sophisticated policies based on solid statistical results that reveal high or low degrees of association.

3 Results: Spatialities of Flexibilization, GDP, and their Interrelation

In 2008, high values of the FCA CI were observed in the United Kingdom, the Netherlands, Romania, Poland, and the Check Republic, while low values were mostly concentrated in France, Italy, and Germany (see Fig. 1a). In 2013, there is an expansion of high FCA CI values in southern regions, particularly in Portugal, Spain, and Greece (Fig. 1b). As Fig. 1c depicts, through a simple subtraction of (FCA CI 2013–FCA CI 2008), the

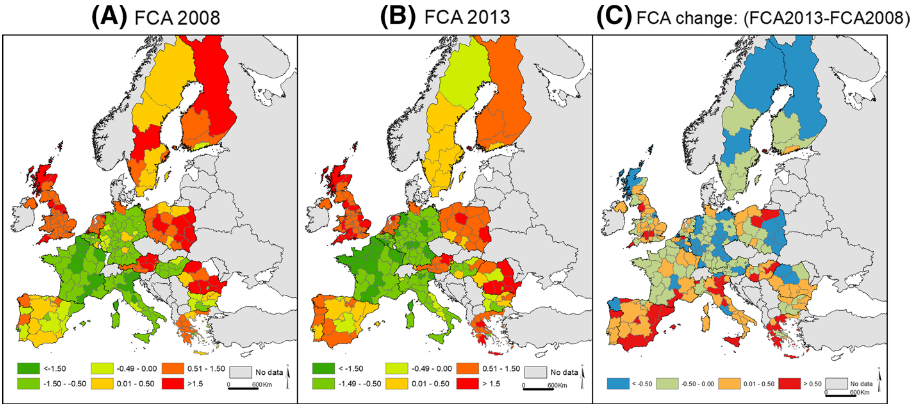

Fig. 1 FCA CI in 2008 (**a**), 2013 (**b**), and FCA change for 2008 and 2013 (**c**)

larger positive FCA changes are gathered in southern Europe, while many northern regions experience a retreat to lower positions of the flexibilization ranking. Of the 57 regions belonging to Portugal, Spain, Italy, and Greece, 49 regions (86%) increased their FCA CI values. Other regions with increased FCA CI are located in the United Kingdom, France, Romania, Bulgaria, and Poland. For instance, 25 of the United Kingdom's 40 regions (63%) reported higher FCA CI in 2013. On the other hand, FCA CI comparative diffusion mainly decreased in central European (e.g. North-western France, Germany, Austria, or Poland) and Scandinavian regions. Of the regions with large FCA CI decrements (i.e., more than 0.50), 42% (19 out of 45) are located in Germany. In total, during 2008–2013, 97.3% (37 out of 38) of Germany's regions have relatively lower positions on the flexibilization hierarchy, while only one holds a slightly higher position.

In addition, changes in the per capita GDP hierarchy of EU regions are important and depict the turbulence that EU regions experienced during the study period. To better examine the emerging ranking, the regions are classified into five categories: very low GDP pca (i.e., with less than 10,000 euros pca), low GDP pca (10,000–15,000 euros pca), average GDP pca (15,000–20,000 euros pca), high GDP pca (20,000–25,000 euros pca), and very high GDP pca (exceeding 25,000 euros pca).

In 2008, a majority of the regions in ex state socialist countries of eastern EU, for example, Romania, Hungary, and Poland, have very low GDP pca (Fig. 2a) with Bulgarian regions holding the lowest values ranging from 3500 to 4500 euros pca. On the other hand, regions with the largest values are located in the United Kingdom, Belgium, and Germany. In general, very high GDP pca regions run from northern Italy through Austria, France, western Germany, Belgium, the Netherlands, Finland, and Sweden. The southern European regions of Greece, southern Italy, and southern Spain mostly have average GDP pca values.

Similar geographical patterns, yet more uneven, are revealed for GDP pca in 2013. For this year there is a more pronounced distinction between Eastern Europe with very low GPD pca and central and northern Europe with high-to-very-high GPD pca. A major difference is also observed in the southern European regions. Although only three regions (2 in Portugal and 1 in Greece) had low GDP pca in 2008, there are 14 in 2013, 11 of which are in Greece (see Fig. 2a, b). It appears that severe austerity measures, imposed labor flexibilization norms, and increased unemployment are associated with the sharp fall in GDP in the Greek regions (i.e., more than 20%; see Fig. 2c). Greece is the only country in the

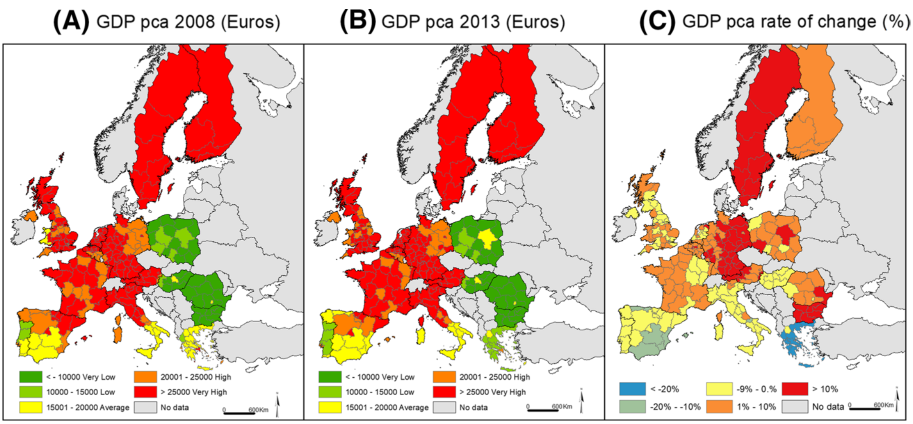

Fig. 2 GDP pca in Euros in 2008 (**a**), 2013 (**b**), and GDP pca rate of change for 2008 and 2013 (**c**)

study area that experienced such a dramatic change in GDP pca within the 5-year period. During the same period, the country was several times at the risk of bankruptcy. Spain also experienced considerable decrease in GDP as half of its regions reduced their GDP pca by 10–20% and the other half by up to 10%. All Portuguese regions decreased their GDP pca by almost 10%. In total, 54 out of 57 (95%) regions in Portugal, Spain, Italy, and Greece reduced their GDP pca during 2008–2013. On the other hand, in Germany, 23 out of 38 regions (61%) increased their GDP pca by at least 10% and the rest increased it up to 10%. Notably, Sweden, Austria, and Belgium increased their GDP pca as well.

3.1 Spatial Patterns

A spatial autocorrelation analysis of FCA CI (see Table 2 and Supplementary Figures S1 and S2) and GDP change (see Table 2 and Figures S3) revealed important underlying mechanisms that transform existing groupings of the EU's regional labor markets.

First, the incremental spatial autocorrelation technique is applied (locational outliers—one located in Finland and one in Sweden—were temporarily excluded from the analysis). Results of the FCA CI during 2008 show a peak at distance 704.81 km with a statistically significant z-score and a Moran's I index value of 0.35. The global Moran's I values larger than 0.3 are typically interpreted as strong positive autocorrelation (O'Sullivan and Unwin 2010). The FCA CI results for 2013 are similar: the first peak is located at the same distance with a Moran's I index value of 0.41. Thus, 705.0 km is set as the FCA CI scale of analysis for the study period. This value is a reasonable distance to build neighborhoods suitable for NUTS-2 scale spatial statistics. It should be mentioned that the scale of analysis might change as spatial autocorrelation intensifies or becomes lax over time. In the present case, the spatial autocorrelation value of a global Moran's I increases from 0.35 to 0.41, indicating that the FCA CI is more positively spatially autocorrelated in 2013 than in 2008, albeit without an effect on the scale of analysis. Such an increase in spatial autocorrelation denotes that the underlying processes, such as the productive and financial crisis, are also spatially clustered. The GDP pca changes studied hereinafter shed light on the issue.

Table 2 Moran's I for incremental distances for FCA2008, FCA2013, and rate of GDP pca change

Distance (km)	FCA 2008		FCA 2013		GDP pca change 2008–2013	
	Moran's I	z-score	Moran's I	z-score	Moran's I	z-score
400.00	0.50	14.99	0.56	16.81	0.68	20.50
552.40	0.40	17.27	0.48	20.06	0.61	25.72
704.81	0.35	18.47	0.41	21.64	0.54	28.63
857.22	0.29	18.13	0.34	21.48	0.46	28.36
1009.63	0.25	17.87	0.28	20.09	0.39	27.46
1162.04	0.21	17.22	0.22	18.23	0.34	27.43
1314.45	0.17	16.04	0.17	15.80	0.29	27.00
1466.86	0.13	13.89	0.12	12.48	0.26	27.13
1619.26	0.10	12.05	0.08	9.65	0.22	27.65
1771.67	0.06	9.21	0.04	6.11	0.19	27.09

p values are statistically significant at the 0.01 level

Although GDP pca shows no big difference in terms of spatial distribution, between 2008 and 2013 (i.e., low or high values are clustered in similar areas; see Fig. 2a, b), GDP changes demonstrate a significantly different spatio-temporal behavior. In particular, there is a positive spatial autocorrelation that is impressively more evident at the same distance as the FCA CI distance, that is, 705 km (Figure S2 and Table 2). As such, the scale of analysis is common for both the FCA CI and GDP change rate. The global Moran's I at this scale is a considerable 0.54, which indicates that change in the GDP pca rate is spatially clustered with a positive spatial autocorrelation sign. These findings are supported by the following local indices of spatial autocorrelation.

3.2 Spatio-Temporal Analysis

The spatial autocorrelation of the FCA 2013–FCA 2008 difference, also known as differential spatial autocorrelation, is applied using 705.0 km as the appropriate distance band along with FDR correction. As depicted by the map and Moran's I scatter plot, there is positive spatial autocorrelation and clear spatial pattern formed in FCA CI's changes (see Fig. 3a, c). In other words, FCA changes over time are spatially clustered. Indicatively, southern European regions with a highly increasing FCA CI value are also surrounded by regions with high FCA CI increments. Almost all regions in Greece, southern Italy, Spain, and Portugal are included in this high–high grouping. The reverse pattern is observed in Germany and certain nearby regions of Poland, Austria, and France, where low negative changes in FCA CI form a sufficient low–low spatial cluster.

Results for GDP pca change reveal a high positive spatial autocorrelation (Moran's I value = 0.49) that is more intense than that observed in FCA change (see Fig. 3b, d). Regions in Greece, southern Italy, and Spain have negative or low GDP pca rates and are surrounded by similarly characterized regions. On the other hand, in Germany and Sweden large positive GDP pca rates are surrounded by regions with similarly large values. In other words, during 2008–2013, GDP pca changes are spatio-temporally clustered with their extremes observed either through south EU's low values or Germany and Sweden's high ones.

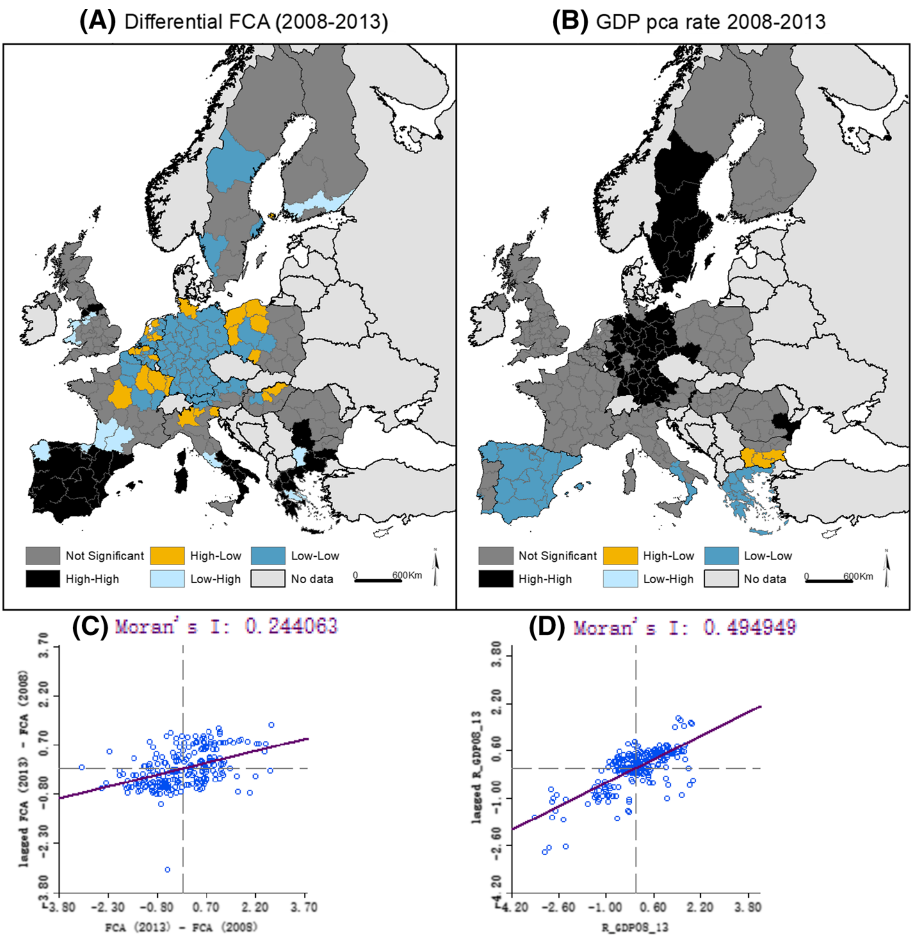

Fig. 3 Differential spatial autocorrelation of FCA (**a**) and univariate spatial autocorrelation for the rate of change in GDP pca for 2008–2013 (**b**). All z-scores are statistically significant at less than the 0.001 level. Moran's I scatter plots for each case are also presented (**c**, **d**)

3.3 Investigating Interrelations

To better assess the potential spatio-temporal linkage between, FCA CI and GDP pca the spatial autocorrelation between the variables "FCA change" and the "GDP pca rate of change" for 2008–2013 is examined using a bivariate local Moran's I. The results show a negative spatial autocorrelation between the GDP pca rate of change (x axis) and FCA changes (change of FCA is calculated as the abstraction: FCA2013- FCA2018) (y axis) (see Fig. 4a, c) with a local Moran's I value of −0.36. Regions in Greece, Spain, Portugal, and south Italy form a low–high cluster. That is, they have low GDP pca rate of change and high FCA change values and are surrounded by regions with similar values. The high values of GDP pca rate of change with low FCA CI changes are also clustered in the central and northern EU regions of Germany, Austria, Poland, and the Netherlands. In addition, certain regions in Bulgaria are mostly outliers because they have high values in both GDP pca rates and FCA change (this is due to their small absolute GDP, approx. 3500 euros pca, leading to relatively high percentage

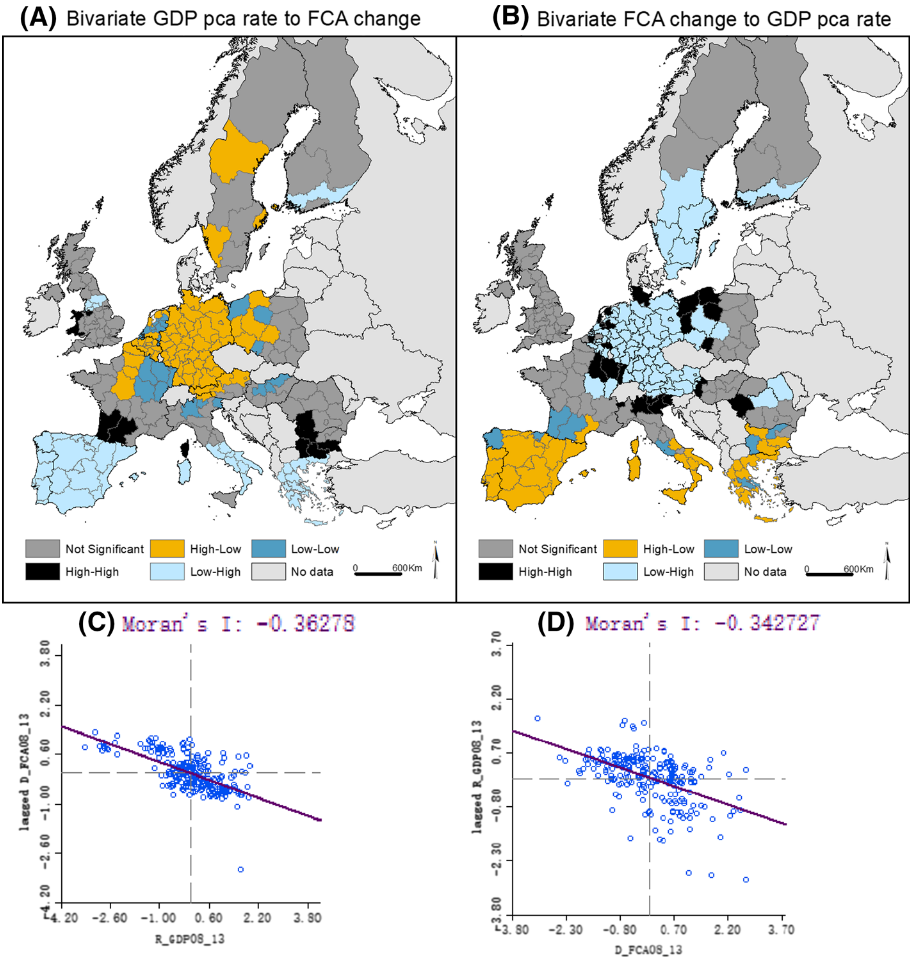

Fig. 4 Bivariate spatial autocorrelation between GDP pca rate of change and FCA change between 2008 and 2013 (**a**) and FCA change and GDP pca rate of change for 2008–2013 (**b**); all z-scores are statistically significant at less than the 0.001 level. Moran's I scatter plots for each case are also presented (**c**, **d**)

increments). Similar outcomes are also presented for the bivariate correlation between FCA change (x axis) and GDP pca rate of change (y axis) (Fig. 4d), suggesting that regions in southern Europe have high FCA change values and are surrounded by low or even negative GDP pca changes. The inverse trend applies for central and northern regions. The bivariate negative spatial autocorrelation is evident in the scatter plot with a Moran's I value of −0.34 (Fig. 4b, d).

4 Discussion and Conclusions: Increasingly Flexible Yet Less Developed

Empirical analysis revealed that changes in the uneven hierarchy of EU regions due to crisis-triggered labor flexibilization are significant. It also highlighted the close interrelationship between labor flexibilization and regional GPD pca change during the turbulent 2008–2013 period. The results showed that the economic crisis, which largely affected southern economies, also had a profound effect on labor flexibilization and GDP pca. A total of 49 out of the 57 regions across Spain, Portugal, Italy, and Greece increased their FCA CI. Of these, Italy has constantly low FCA CI values, despite it being severely hit during the crisis. Nevertheless, 17 out of its 21 regions reported an increased FCA CI rate as a result of flexibilization-related intensification during the crisis.

In addition, there is a clear spatial pattern of how GDP pca is distributed across the EU regions. The pattern is similar for both timestamps (2008 and 2013), that is, eastern regions with very low GDP pca, southern regions with average-to-low GDP, and central and northern regions with high-and-very-high GDP. Still, the GDP gap increased between the southern regions and central and northern regions during the five-year period. In particular, southern regions experienced a large GDP pca decrease, while central and northern regions increased their GDP pca. Ex-Eastern European countries, on the other hand, experienced an increase in GDP pca in most regions. Combining the FCA CI and GDP pca results for the southern regions evidences that labor flexibilization intensification lead in GDP pca decline.

For a more thorough analysis, global and local spatial autocorrelation indices were applied. This allows for a more rigorous statistical analysis than the visual inspection performed using maps. For example, by mapping FCA CI and GDP pca (Figs. 1, 2) we can visually identify some clusters that overlap at some extent, indicating a potential association. Nevertheless, these types of associations can be quantified only when using a statistical test such as a spatial autocorrelation measure. Between 2008 and 2013, the global Moran's I value for FCA CI increased from 0.35 to 0.41, suggesting that FCA CI is more positively spatially autocorrelated in 2013 than 2008. As a result, the clustering of FCA CI values is more evident in 2013. The intensification of clustering reveals that various underlying processes trigger the increase in spatial autocorrelation. This study reveals that GDP pca change as a result of the financial crisis largely affects the distribution of FCA CI across space and time.

A global Moran's I for the GDP pca rate of change is significantly high (0.54), indicating a positive spatial autocorrelation. Likewise, GDP pca changes are also spatially clustered. Put simply, large positive changes in GDP pca are surrounded by large positive rates in the neighboring areas. On the other hand, regions that largely decrease their GDP pca are surrounded by those with similarly negative high rates. In addition, local spatial autocorrelation indices were used to support this finding.

A differential local Moran's I was applied to assess the spatial autocorrelation of FCA change during 2008–2013. As shown, FCA change is positively spatially autocorrelated. Regions in southern Europe, that is, in Greece, Italy, Spain, and Portugal, experienced significant increases in FCA CI, creating spatio-temporal clusters. On the other hand, regions in Germany experience spatio-temporally clustering of low values of changes of FCA CI (i.e., negative changes surrounded by negative changes). Finally, the GDP pca rate of change is positively spatially autocorrelated and forms cluster of southern regions with low values, that is, Greece, Spain, and Italy, and those of regions with high values, including Germany and Sweden.

From a broader perspective, this study shows that the crisis has significantly altered the uneven spread of GDP pca and flexible work practices and patterns across the EU, thus intensifying existing geographical divisions while bringing to the fore new hierarchies of socio-spatial fragmentation. The results reveal that this schism between the two edges of the uneven spread, for example, that between northern and southern spatial entities, is most prevalent at the regional level. Further, emerging sub-national divisions, often ignored by contemporary flexibilization accounts which tend to be nationally bounded, redraw the contours of division across EU's regional markets. The pre-crisis patterns of unevenness are altered following different rates of GDP change, which for a majority of the regions lay somewhere between "deep recession" and "anemic growth". In particular, pre-crisis divisions are redrawn following the patterns of production fall and economic downturn, causing many regions with highly negative growth changes to exhibit highly positive flexibilization and vice versa.

This strong inverse association between GDP change and flexibilization demonstrated in the current data analysis is an outcome of the differentiated terrain of flexible work expansion and this has created a new mosaic of labor market inequalities that transcend national boundaries despite state-level similarities. From a statistical perspective, spatial autocorrelation does not reveal causation but association. In this respect, and from a policy viewpoint, we can infer that there is a negative association between flexibilization and GDP pca rate of change. For example, intensified flexibilization policies were widely applied in regions with low GDP pca as for example in Greece, Portugal or Spain in anticipation of economic growth. Nevertheless, this did not lead to the desired outcome, wherein the economy can create more jobs and thus, increase GDP pca. On the contrary, the majority of the regions that reported intensification of flexicurity between 2008 and 2013 experienced a severe decrease in their GDP pca for the same period. While a GDP decrease cannot be solely attributed to increased flexibilization, the above analysis shows that it does not contribute to a GDP increase either.

This major finding does not only contradicts the prevailing beliefs (at least from the European Commission side and related policies implemented) that support flexibilization as a remedy to economic recessions and an instrument that boosts employment and productivity (European Commission 2015a; Keune and Jepsen 2007) but it also offers updated trans-regional evidence that the negative effects of EU employment flexibilization on growth are spatially and temporally clustered and are also spreading outwards like an outbreak. According to the European Commission, member states that applied comprehensive labor market reforms were able to better support employment (European Commission 2016). However, the current findings revealed in a spatio-temporal context that the more flexible a labor market becomes, the wider the gap between its GDP growth and that of less flexible markets. In fact, a less flexible labor environment tremendously decreases GDP pca during the study period.

The fact that labor market flexibilization does not always come with relevant improvement in overall employment rates and economic growth is not new (Gebel and Giesecke 2011, 2016; Noelke 2015; Barbieri and Cutuli 2015; Boeri 2010). Most of the relevant studies apply regression, multilevel, or other econometric models at the country level to assess the effects of changing employment protection legislation (EPL) in labor force participation, to conclude that EPL reforms had no statistically significant effect on unemployment rates mitigation. For example, Gebel and Giesecke (2016) showed that deregulating EPL actually increased youth unemployment in 19 European countries. Barbieri and Cutuli

(2015) detected no macro effects of marginal EPF reforms in the southern European countries with signs of employment growth partially confirmed only for the northern European countries having more resilient economies. The current study complements such works in several aspects. First, it applies spatial analysis techniques that not only estimate the linkages between flexibilization and GDP but also locate the entities in which these linkages are more evident. Second, it explicitly considers spatial heterogeneities on flexibilization, GDP, and their cross-regional comparison up until 2013. Third, it adds to the analysis of how labor flexibilization affected GDP in a time of harsh economic crisis across EU and abroad. As such, it offers new evidence supplementary to current studies focusing mostly on less countries or EU regions than the ones discussed herein, and less-turbulent economic periods.

Concluding, the present empirical analysis and related interpretations addressing the sub-national impact of FCA to GDP focus on the identification of spatial dependency and spatial clustering from a spatiotemporal perspective. The approach implemented, located where spatial clusters exist, expand, diminish or co-locate, something that is rarely taken into account when analyzing the effects of labor flexibilization. The empirical analysis of FCA as shown above, provides evidence that regional disparities do exist, and aims to guide policies related to labor flexicurity, growth and their interplay. Such analysis (through spatial autocorrelation statistics) has its own importance (and is missing from the literature) as most of the studies analyzing labor market deregulation in relation to GDP, unemployment or other variables use econometric modelling mainly at the country level. This type of modeling is very informative, includes many variables, and uncovers casual mechanisms, but it fails to address a deeper understanding of the underlying spatial processes at play. The present study addresses this topic from a different perspective. Instead of applying econometric-modelling to identify causes and effects it focuses on the spatio-temporal relations between FCA and GDP. In this respect, tracing, mapping and analyzing spatio-temporal clusters of FCA and GDP could be the first step in the processes of identifying the causes and effects of labor flexicurity. To better identify causes and effects in a quantifiable way we should include more independent variables and apply related techniques as for example econometric modelling that is planned for future research.

The overall results of this study strongly support the wider skepticism that has recently developed about the need to reassess adopted economic policies for labor market regulations and evaluate their performance and if necessary, promote a change (OECD 2017: 1). This is also in line with the need to pursue actions that will eventually foster both growth and labor protection by conducting more detailed analyses (European Commission 2015b). This study is aligned with this concept as it delves deeper into the relationship between labor flexibilization and GDP pca and it evolves during a crisis by performing a spatial analysis at the regional level. As such, policymakers may account for the abovementioned findings and move toward policies that do not widen economic and labor standard gaps between European regions.

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