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LABOUR PERFORMANCE INDEX IN THE ITALIAN LOCAL LABOUR SYSTEMS: AN ORDER-M COMPOSITE INDICATOR FROM 2006 TO 2021

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Abstract*. We use a robust Order-m frontier (DEA-type) in a BoD approach to measure the labour performance in the 610 Italian local labour systems (SLL) from 2006 to 2021 with reference to activity rate, employment rate and unemployment rate. We also apply a conditional BoD frontier to take into account environmental factors and a dynamics index which measures the relative improvement or worsening of the SLLs performance scores between 2006 and 2021 and useful for classifying the 610 SLLs into four different clusters.*

Keywords*: labour performance, local labour systems, order-m frontier, data envelopment analysis, efficiency.*

1. INTRODUCTION

In this paper, we analyze some characteristics of the Italian Labor Market Areas with specific attention to three main indicators: activity rate, employment rate and unemployment rate (Istat, 2023a). It is known that work has an important social function both for individuals and for community, it gives a sense of belonging and usefulness and economic resources that allow better access to healthcare and education, it also have a role in establishing strong social bonds (Semenza, 2022). Therefore, a labour market able to efficiently and effectively balance supply and demand in both quantitative and qualitative terms is a desirable condition of a solid economic, social and political system (Kruppe et al., 1998). However, a condition of disequilibrium with high unemployment rates is very common especially in some geographical areas (Eurostat, 2023). In this sense, the Italian labour market is emblematic, often used as an example of rigid market with high barriers to entry and exit and with a strong difference between the Northern regions (higher levels of employment) and the Southern regions (lower levels of employment) (Istat, 2023b); the recent economic crises have exacerbated this geographical fragmentation (Banca d'Italia, 2023). In this paper we are interested in exploring this aspect and the best way is to use an extensive spatial disaggregation that is not limited to the usual and too large geographical boundaries of regions or provinces: it seems natural to refer to the so-called Local Labor Systems (Istat, 2014). Local Labor Systems (Labor Market Areas or SLLs "sistemi locali del lavoro"), are sub-regional geographical areas not identified with an administrative criterion but statistically defined through an algorithm that considers home-work flows. Essentially, SLLs are gravitational areas where a large part of the workforce present in the area finds employment within the same territory; in short, SLLs are sub-provincial municipal aggregations according to European standardized and common definitions and procedures based on a measure of travel to work (Eurostat, 2018). The current home-work flows used in Italy are updated with information from the population census in 2011 and identify 611 distinct areas, later reduced to 610 (Istat, 2018). In this paper, we use official data for these 610 SLLs, the analysis is conducted with the maximum temporal extension from 2006 to 2021 but limited to only the main indicators available in all the SLLs, i.e. activity rate (TA), employment rate (TO) and unemployment rate (TD) (Istat, 2023c). These three indicators represent different and only partially overlapping aspects of the labour market, but they are a good synthesis of its performance because a labour market with greater opportunities and fewer critical issues is always accompanied by higher values in activity rate and employment rate and lower values in unemployment rate; so, to represent a SLL performance profile is useful to synthesize these three indicators TA, TO and TD in a composite indicator (CI). For this goal, we use a Benefit-od-Doubt (BoD) approach in a DEA-type model to obtain a score of "labour performance" for the 610 SLLs (Panwar et al., 2022). In particular, CI proposed here uses a robust non-parametric approach of the order-*m* DEA frontiers able to detect super-performing SLLs (Cazals et al., 2002). The performance of a SLL is certainly greater than other SLLs if, given the same labour market indicators, it records a better condition than its neighbors or with similar economic and social characteristics; so, we also apply a conditional BoD-DEA with spatially lagged indicators and with other economic variables in the SLLs (Daraio and Simar, 2007). Section 2 briefly describes the characteristics of the Italian SLLs, Section

3 illustrates the BoD techniques applied here, Section 4 presents results and Section 5 concludes.

2. THE ITALIAN LOCAL LABOR SYSTEMS

The Italian SLLs are 610 with strong differences in the prevailing economic activity and levels of productive specialization (Istat, 2023c). Only 23.1% of these 610 have an industrial district, i.e. presence of a main industry with auxiliary industries and a narrow specialisation profile (for example, the metallurgical industry in Breno, or leather and footwear in Castelfiorentino, and so on). Majority of the industrial districts are located at the Centre-North; the remaining 469 SLLs do not constitute an industrial district even if they show prevalence of some industrial activity. In detail, 18.5% of the SLLs are without prevalent specialization, 36,6% are non-manufacturing, 31,0% have a prevalent activity in "Made in Italy" (textile, wood, furniture, etc.) and 13,9% are characterized by so-called heavy manufacturing (steel, chemicals, ships, etc.). Furthermore, approximately 45% of the 610 SLLs are small with no more 50,000 residents. We use the latest official data published by ISTAT from 2006 to 2021 for activity rate (TA), employment rate (TO) and unemployment rate (TD) in each of the 610 Italian SLLs (Istat, 2023c). We remember that activity rate (TA) is the ratio between the active population (people in labour force) and the corresponding population, employment rate (TO) is the ratio of employed persons in relation to the corresponding population, and unemployment rate (TD) is the ratio of unemployed persons (looking for a job) in relation to the corresponding labour force. Figure A1 in Appendix classify the 610 SLLs through these three indicators into three quantiles (lighter colors correspond to lower values and darker colors correspond to higher values) at the beginning (2006) and end (2021) of the series, in a period in which different economic crises occurred (a first order queen-type contiguity matrix is used in this paper). The presence and permanence of a strong geographical fragmentation is evident, also with an increase in spatial polarization, especially between the northern and southern regions; this result is confirmed by the LISA clustering (Figure A2 in Appendix) and, of course, by the increase of the I-Moran values in Figure 1 (Anselin and Rey, 2012). We remember that LISA represents the local Moran statistics $I_i = \sum_j w_{ij} z_i z_j \,/ \sum_i z_i^2$, the (global) I-Moran is proportional to the sum of the local statistics and it corresponds with the average of the local statistics, where z_i and z_j are deviations from the mean and w_{ij} is the weight matrix between unit *i* and unit *j* (here, it is a contiguity matrix 0-1); in this formulation, w_{ij} is intended to be standardized by row (the sum of the values in all the columns *j* is equal to 1 for each row *i*), then the LISA clusters are constructed taking into account the significance of the LISA values (measured with a pseudo p-value obtained via permutation technique) and the values "high" or "low" of the variable with reference to its mean. So, high-high and low-low represent spatial clusters whereas high-low and low-high (substantially absent here) indicate spatial outliers.

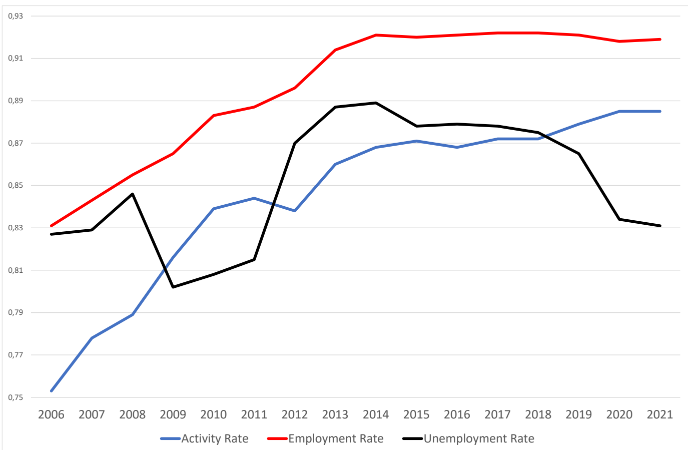


Figure 1: I-Moran for TA, TO and TD (610 SLLs, 2006-2021)

In Figure 1 we note the increase of spatial association in the activity rate and the (more limited) increase in the employment rate that, however, already had a higher starting value, whereas the unemployment rate, that is more cyclical than other two rates, shows values of spatial association that increase and decrease depending on the different territorial impact of the economic cycles; in this regard, the reduction of the I-Moran in 2009 is explained by the financial crisis in 2007 (with repercussions in real economy, for Italy, especially in 2009), whereas oscillations in 2011-2013 are explained by a great turbulence with strong increase in unemployment and further increase of the territorial gaps, while the reduction in 2020 is explained by the covid-crisis. Useful for an overall representation, Table 1 presents the Moran's values also separately by geographical area (1 indicates the SLLs in the North-West, 2 those in the North-

East, 3 those in the Centre area and 4 the SLLs in the South and Islands, i.e. “Mezzogiorno”; for simplicity, from now on, we will consider the terms “South”, “South and Islands” and “Mezzogiorno” to be geographically equivalent).

	TA	TO	TD	TA_1	TO_1	TD_1	TA_2	TO_2	TD_2	TA_3	TO_3	TD_3	TA_4	TO_4	TD_4
sll	610	610	610	106	106	106	119	119	119	105	105	105	280	280	280
2006	0,755	0,833	0,829	0,466	0,484	0,315	0,476	0,487	0,392	0,323	0,396	0,710	0,446	0,537	0,392
2007	0,780	0,846	0,830	0,424	0,464	0,356	0,488	0,498	0,350	0,328	0,394	0,682	0,496	0,581	0,420
2008	0,791	0,858	0,847	0,431	0,472	0,419	0,500	0,517	0,452	0,323	0,386	0,732	0,527	0,604	0,373
2009	0,818	0,867	0,804	0,452	0,466	0,337	0,534	0,564	0,577	0,332	0,378	0,679	0,526	0,570	0,321
2010	0,841	0,886	0,810	0,467	0,492	0,419	0,557	0,596	0,657	0,295	0,384	0,756	0,586	0,620	0,325
2011	0,846	0,890	0,818	0,439	0,449	0,402	0,559	0,585	0,571	0,337	0,405	0,671	0,607	0,649	0,301
2012	0,841	0,899	0,872	0,481	0,479	0,390	0,549	0,583	0,609	0,372	0,436	0,708	0,581	0,678	0,487
2013	0,863	0,917	0,889	0,554	0,575	0,501	0,586	0,638	0,634	0,319	0,407	0,727	0,552	0,679	0,552
2014	0,871	0,924	0,891	0,535	0,582	0,604	0,605	0,656	0,629	0,278	0,374	0,671	0,578	0,695	0,554
2015	0,874	0,923	0,880	0,509	0,522	0,490	0,590	0,647	0,614	0,300	0,438	0,680	0,604	0,713	0,550
2016	0,870	0,923	0,882	0,528	0,573	0,528	0,584	0,628	0,550	0,331	0,441	0,576	0,581	0,714	0,568
2017	0,875	0,925	0,880	0,605	0,660	0,632	0,580	0,627	0,586	0,275	0,409	0,613	0,622	0,727	0,525
2018	0,875	0,924	0,877	0,567	0,649	0,646	0,520	0,588	0,603	0,198	0,374	0,749	0,603	0,731	0,570
2019	0,881	0,924	0,867	0,561	0,646	0,641	0,530	0,580	0,536	0,225	0,364	0,705	0,652	0,746	0,549
2020	0,887	0,921	0,836	0,560	0,638	0,621	0,510	0,553	0,446	0,219	0,369	0,673	0,619	0,728	0,552
2021	0,887	0,921	0,833	0,550	0,609	0,564	0,487	0,531	0,452	0,193	0,371	0,692	0,666	0,753	0,514

Table 1: I-Moran for TA, TO and TD (SLLs by geographical area, 2006-2021)

However, despite the clear and confirmed North-South division, if we compare the ranks of the 610 SLLs for TA, TO and TD between 2006 and 2021, we notice numerous (and even strong) changes in position. In fact, TA, TO and TD show a non-negligible variability over time resulting in a much more varied and articulated geographic map of the 610 SLLs. To adequately represent this map in an easily readable way, it is useful to summarize the three sub-indicators TA, TO and TD in a single score through a composite indicator that, therefore, becomes interpretable as a performance index of the labour market in the SLLs. The best way appears to us a procedure that automatically weighs (without arbitrary external judgments) the three sub-indicatos emphasizing, for each SLL, the best possible result in a Benefit-of-Doubt (BoD) logic (Cherchye et al., 2007). This technique appears particularly advantageous with a large number of sub-indicators where the simple arithmetic mean clearly shows the limits of an approach that attributes the same importance to all indicators in all *i*-th cases. Unfortunately, for the 610 local labour systems in each year from 2006 to 2021, no other variables are available in addition to TA, TO and TD; however, this does not limit the analysis because these three basic indicators are the key components relevant for the structural analysis of the characteristics and evolution of the labour market and, given the high number of units under analysis, the method described in the next section guarantees wide variability of the weighting scheme that adequately takes into account the specific characteristics of each SLL.

3. ROBUST AND CONDITIONAL BOD-CI

There is a large literature on composite indicators (CI) and DEA and it is not the purpose of this paper to review different methodologies and techniques (Panwar et al., 2022). In an extremely concise way, we can say that one of the main advantages in the use of composite indicators consists in reducing the dimensionality of the data without losing too much information; indeed, in some cases, the synthesis allows a measure of a latent construct that is represented, only partially, by individual basic dimensions (i.e., quality of life, well-being, firm performances, etc.). The main problem of CI consists in the aggregation (what type of function?) and in the weighting of the sub-indicators (equal or different weights and how are they chosen?) because there is no method that is always better and preferable than others (Oecd, 2008). Among the alternatives of no weighting and arbitrary or exogenous choice of weights (external experts), it seems more natural (and less subjected to criticism) to choose a method that, with statistical and mathematical criteria, determines these weights endogenously in a data-driven approach; however, as we said, the choice of which criteria to adopt is not neutral (Oecd, 2008). Similarly, the most natural (but also mathematically simplest to manage) choice for aggregation is the sum of the basic components (adequately weighted); there are several alternatives also in this case (Cooper et al., 2002). Among data-driven procedures, the DEA-type techniques in Benefit-of-Doubt (BoD) form have been very successful in the literature (Rogge, 2018; El Gibari et al., 2019): a composite indicator (CI) is constructed so that, from a numerical point of view, is the highest possible combination of sub-indicators (given certain constraints on these sub-indicators and on the weights to be applied); the weights are determined by an iterative procedure, and the CI score for the *i*-th unit is obtained as sum of “weights * sub-indicators”. The connection with the non-parametric DEA techniques is evident in the fact that the sub-indicators represent the outputs y_i of a process whereas the inputs x_i are substantially absent (represented by vectors of values equal to 1) (Zhou et al., 2007). A higher value of the CI represents a higher performance of the unit under analysis, i.e. greater efficiency according to DEA terminology (where we have outputs that are compared with each other for given inputs, or inputs compared for given outputs: precisely the concept of efficiency). The mathematical problem can be formulated in different ways and it allows us to obtain an efficiency score that ranges from 0 (minimum theoretical efficiency) to 1 (maximum theoretical efficiency). The efficiency (or inefficiency) of the unit under examination is obtained by measuring its distance from a frontier built on the best observed units (with the highest output for given inputs if we are interested in output-orientation), so there will certainly be units with values 1 (those on the frontier) while in practice we will never find units with values 0 (zero-efficiency) (Shen et al., 2013). Formula 1 presents the problem to solve in its original DEA formulation (Charnes et al., 1978):

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

s.t.

$$\begin{cases} \dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1; \quad j = 1, \dots, n \\ u_r \geq 0; \quad r = 1, \dots, s \\ v_i \geq 0; \quad i = 1, \dots, m \end{cases} \tag{1}$$

where $x_j = (x_{1j}, \dots, x_{mj})$ and $y_j = (y_{1j}, \dots, y_{sj})$ are input and output for the *j*-th unit. The literature has proposed different formulations to include specific returns to scale, output or input orientation, undesirable outputs (pollution, waste, etc.), multiplicative aggregations, specific constraints on weights, etc.. It is not the purpose of this paper to review a vast literature that presents numerous variations; here, we will focus on the construction of composite indicators exploiting the idea already present in the original formula (1): in this case, the sub-indicators replace the outputs, max h_0 would represent the CI score, while the inputs would be absent. In short, we can write (Zhou et al., 2006)

$$CI_c = max_{w_{c,i}} \frac{\sum_{i=1}^{m} w_{c,i} y_{c,i}}{max_{y_{j,i}} \sum_{i=1}^{m} w_{c,i} y_{j,i}}$$

s.t.

$$\begin{cases} \sum_{i=1}^{m} w_{c,i} y_{j,i} \leq 1 \quad j = 1, \dots, n \\ w_{c,i} \geq 0 \quad i = 1, \dots, m \end{cases} \tag{2}$$

This last formulation is equivalent to the original input-oriented model of Charnes et al. (1978) where outputs are replaced by the sub-indicators with inputs set to 1. Formula (2) can be complicated in various ways, for example by assuming the presence of undesirable sub-indicators (similarly to undesirable outputs in DEA; Allen, 1999; Färe and Grosskopf, 2004), so, the combination that emphasizes the role of "good" sub-indicators and reduces the role of "bad" sub-indicators is rewarded with higher CI scores. Following (Mergoni et al., 2022) and writing the corresponding problem with undesirable sub-indicators in dual version (as typical in DEA), we obtain

$$\min \beta = -\sum_{r=1}^{s} y_{rj_0} u_r + \sum_{k=1}^{l} b_{kj_0} p_k + v$$

s.t.

$$\begin{cases} \sum_{r=1}^{s} y_{rj_0} u_r + \sum_{k=1}^{l} b_{kj_0} p_k = 1 \\ -\sum_{r=1}^{s} y_{rj} u_r + \sum_{k=1}^{l} b_{kj} p_k + v \geq 0 \\ v \in \mathcal{R},\ u_r \geq 0,\ p_k \geq 0 \\ j = 1, \dots, n \\ r = 1, \dots, s \\ k = 1, \dots, l \end{cases} \tag{3}$$

b refers to “bad” sub-indicators. The final estimate β* measures the level of inefficiency and the usual CI score between 0 and 1 is obtained as $CI = 1/(1 + \beta^*)$ (Mergoni et al., 2022). We note that in the empirical analysis in this paper we have not used undesirable sub-indicators, however we have preferred to present a more general Formula 3 because there are cases in which some "good" sub-indicators are accompanied by some "bad" sub-indicators (for example, levels of GDP and CO concentration). For labour market, one could hypothesize TA and TO as good indicators and TD as bad indicator, however, due to the meaning and importance of these sub-indicators, for greater adherence to the "theoretical production function", it is appropriate to treat them in the same way as traditional output by changing the direction (polarity) of TD; clearly, if “bad” sub-indicators are absent, Formula 3 collapses to the more traditional case. Formula 3 can be further extended to account for super-efficiency according to the order-*m* technique of Cazals et al. (2002). The Authors propose not to consider all n data to build the frontier but, in a bootstrap approach, a smaller m number of randomly chosen units; the unit j_0 under examination is not included in the sample and this can lead to a lower frontier with respect to "point j", determining a so-called super-efficiency, measured by how much the unit j_0 is above this order-m frontier. In this way, not all the "best" units are necessarily placed on the frontier, some of them will be above and will have a score higher than 1 (signal of super-efficiency); so, it will also be easier to detect outliers and extreme values. Intuitively, the higher m is the more the frontier resembles the traditional case in which all n units are considered; therefore, when m increases the method becomes less sensitive to the presence of super-efficiency. Obviously, just one sample is not enough and this operation is repeated T times (with replacement) obtaining T inefficiency measures for our unit j_0; a mean is calculated on these measures to obtain the final score and, at last, the calculation is repeated for every other unit. Formula 3 is easily adapted to show this order-m DEA-type version of our BoD-CI (Formula 4):

$$\min \beta_{j_0}^{t,m} = -\sum_{r=1}^{s} y_{rj_0} u_r + \sum_{k=1}^{l} b_{kj_0} p_k + v$$

s.t.

$$\begin{cases} \sum_{r=1}^{s} y_{rj_0} u_r + \sum_{k=1}^{l} b_{kj_0} p_k = 1 \\ -\sum_{r=1}^{s} y_{rj} u_r + \sum_{k=1}^{l} b_{kj} p_k + v \geq 0 \\ v \in \mathcal{R},\ u_r \geq 0,\ p_k \geq 0 \\ j \in \Gamma^{t,m} \\ r = 1, \dots, s \\ k = 1, \dots, l \end{cases} \tag{4}$$

The order-m method proposes a random choice of the units in the sample of size m, but, on the contrary, if these m units were chosen according to a specific criterion? For example, a criterion based on a measure of similarity with the j-th unit under analysis. If Z represents the exogenous variables on which to calculate the similarity with the sub-indicators, the implementation of a conditional BoD-CI is immediate (Formula 5) (Mergoni et al., 2022):

$$\min \beta_{j_0}^{t,m} = -\sum_{r=1}^{s} y_{rj_0} u_r + \sum_{k=1}^{l} b_{kj_0} p_k + v$$

s.t.

$$\begin{cases} \sum_{r=1}^{s} y_{rj_0} u_r + \sum_{k=1}^{l} b_{kj_0} p_k = 1 \\ -\sum_{r=1}^{s} y_{rj} u_r + \sum_{k=1}^{l} b_{kj} p_k + v \geq 0 \\ v \in \mathcal{R},\ u_r \geq 0,\ p_k \geq 0 \\ j \in \Gamma^{t,m,z} \\ r = 1, \dots, s \\ k = 1, \dots, l \end{cases} \tag{5}$$

Now is $j \in \Gamma^{t,m,z}$ because the *m* units are chosen among those "most similar" to the unit under analysis. As we will discuss in the next section, we have selected the first *m* more similar units with respect to a decreasing similarity ranking based on two versions of *Z*: in the first case by selecting among the units closer in spatial terms and in the second case among the units with more similar values of two economic indicators of firms. Finally, we observe that in the DEA-type models presented here we use a compensatory aggregative procedure: in brief, the three sub-indicators TA, TO and TD are all equally important but it does not mean (obviously) that they are weighted in the same way: we admit that they can be "compensate" with each other to represent a performance characteristic of the labour market; so, in this context, the compensatory choice seems the most appropriate one. In the next section, we apply the robust and conditional BoD to the 610 Italian SLLs.

4. A PERFORMANCE INDEX FOR THE SLLs

In this paper, we use without distinction of meaning the terms efficiency and performance intending to refer to the best combination of the sub-indicators TA, TO and TD so that the unit under analysis reaches the highest possible score: a higher value of the composite indicator indicates better labour market characteristics compared to a lower value of the BoD-CI. The theoretical values oscillate between 0 (worst condition) and 1 (best condition), but in the order-*m* version they can also exceed the frontier (scores greater than 1) to signal super-performing SLLs. We note that before applying the BoD algorithm, we have range-normalized and rescaled the sub-indicators TA, TO and TD also changing the direction of the unemployment rate, so that all indicators now oscillate between 1 (worst condition) and 10 (best condition) (Oecd, 2008). We do not underline the widely known advantages of range-normalization while we observe that the 1-10 rescaling was not necessary, but it makes the level of the sub-indicators more intuitive, it has consequences on the final scores but not on the relative positioning of the SLLs or on the relative distance from the frontier that is exactly what is of interest here: in brief, the range-normalization and the change on scale 1-10 does not affect the result of the BoD models, but it is useful for comparing sub-indicators and performance scores and for representing results in tables and figures in a more intuitive way. It is also useful for changing the polarity of TD (higher values of the sub-indicator now represent lower levels of unemployment) so that higher scores of any indicator are easily readable and associated with better performance. In particular, it is maintained the variability of the indicators but now with the same minimum and maximum, the data are directly comparable where values closer to 1 represent less favorable conditions and values closer to 10 more favorable conditions (OECD, 2008). In this paper, a value of m=50 was chosen such as to guarantee a maximum of 5% of super-performing units, whereas the value of T is equal to 100. We have done several tests: T=100 is a sufficiently large value, higher values do not give advantages while lower values make the results more variable (and unstable); for m, 50 has the best trade-off between smaller values that produce an excess of super-performing units and larger values that excessively push the SLLs on the frontier. As expected, the robust BoD-CI method shows higher efficiency scores for the SLLs in the Centre-North and lower scores in the South with similar results in each year of the series. The average efficiency for the 610 SLLs is 0.7938, with 0.9150 for the Centre-North and 0.6511 for the South, but we also observe that the product specialization guarantees higher efficiency scores and, in particular, for the SLLs specialized in "made in Italy" (0.8742 vs. 0.6529 for SLLs without specialization) there is no difference between North and South. In general terms, form 2006 to 2021 the efficiency is weakly decreasing at the Centre-North (from 0.9228 to 0.9184) and weakly increasing at the South and Islands (from 0.6438 to 0.6693) (Figure 2); Table 2 presents detail of the values by the 4 geographical suddivisions (North-West, North-East, Centre and South and Islands).

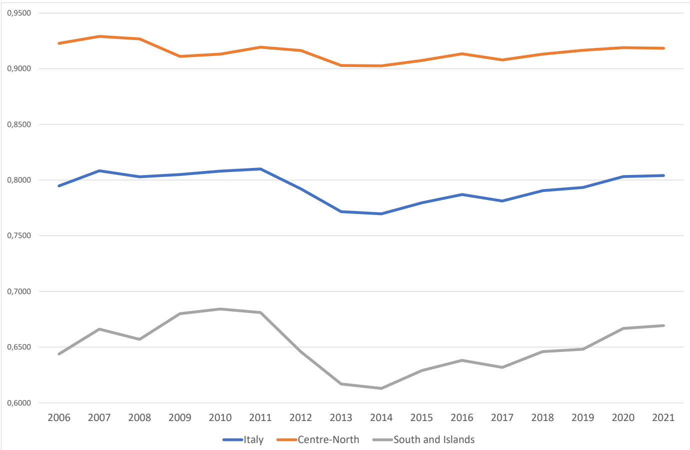


Figure 2: Robust BoD-CI score (m=50, T=100, 2006-2021)

	1: North-West	2: North-East	3: Centre	4: South and Islands	Italy
2006	0,936	0,956	0,872	0,644	0,795
2007	0,931	0,965	0,886	0,666	0,808
2008	0,927	0,968	0,880	0,657	0,803
2009	0,906	0,953	0,869	0,680	0,805
2010	0,908	0,943	0,884	0,684	0,808
2011	0,913	0,960	0,879	0,681	0,810
2012	0,912	0,958	0,874	0,646	0,792
2013	0,901	0,944	0,859	0,617	0,772
2014	0,897	0,949	0,856	0,613	0,770
2015	0,905	0,949	0,863	0,629	0,780
2016	0,914	0,958	0,862	0,638	0,787
2017	0,912	0,953	0,852	0,632	0,781
2018	0,912	0,950	0,872	0,646	0,790
2019	0,916	0,955	0,873	0,648	0,793
2020	0,924	0,950	0,879	0,667	0,803
2021	0,917	0,957	0,875	0,669	0,804

Table 2 : Robust BoD-CI score (geographical area, 2006-2021)

It is interesting to note that in 2009 the performance scores of the Centre-North worsened while those of the South increased. It should be remembered that the 2008-2009 crisis hit the dynamic and productive firms in the North the most and, since the efficiency scores are constructed in relative terms, i.e. comparing all the units with each other with respect to a frontier, the South worsened less than the Centre-North and the performance values showed an increase. As obvious, all the super-performing SLLs are located at the Centre-North. We note that the recent years have a lower number of units above the frontier than the initial years of the series (the minimum is 14 in 2021, the maximum is 31 in 2007); furthermore, the maximum value is about 1.12 (12% above the frontier) and, with a classic BoD, these super-performing SLLs would have obtained a score equal to 1 with excessive approximation. It is interesting to observe that the average efficiency did not register evident worsening between 2007 and 2009 (financial crisis), nor for covid19 in 2020, while an effect appears evident (especially in the South) in correspondence with the 2011-2013 crisis: it must be said that these specific years have recorded a strong increase in the unemployment rate and in North-South gaps, whereas the other crises (particularly in 2020) have affected hours worked with fewer effects on the classic TA, TO and TD indicators.

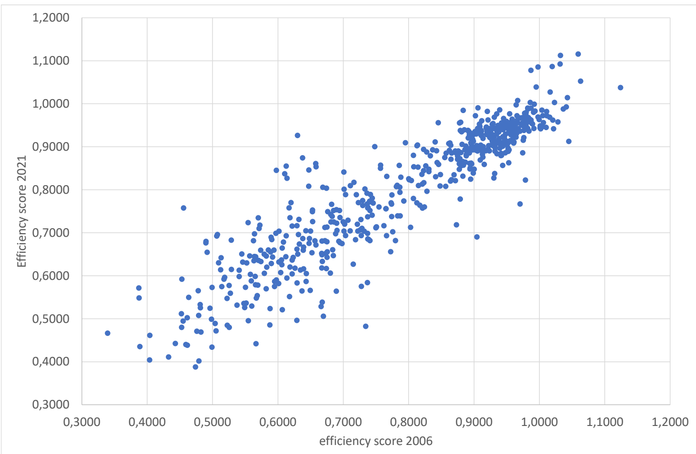


Figure 3: Performance score, robust BoD-CI (610 SLLs, 2006 and 2021)

At last, it should always be remembered that the results must be read in relative terms also with respect to a frontier that shifts every year. Figure 3 reports the efficiency values of the 610 SLLs in the first year of the series (2006) and in the last one (2021), where the super-performing SLLs exceed 1; in Figure 3 it is also evident a high variability mainly (but not only) among the less performing SLLs with numerous changes in position between 2006 and 2021. Contrary to expectations, the other years in the series (even those of strong economic crisis) do not show particular anomalies in the performance scores; therefore, from now on, we will refer to the beginning (2006) and end of the series (2021).

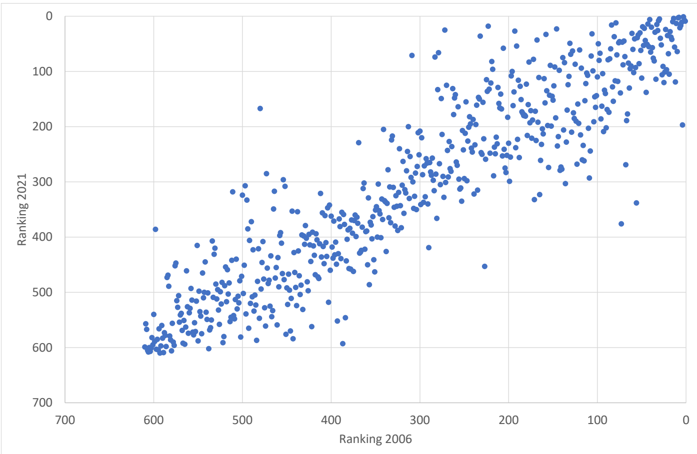


Figure 4: Performance ranking, robust BoD-CI (610 SLLs, 2006 and 2021)

The distribution of the performance scores reflects the temporal and spatial characterization of the sub-indicators, the synthesis proposed by the BoD-CI is consistent with the data and allows us to graduate the SLLs from the most performing to the least performing ones. In this regard, Figure 4 reports the ranks in which we notice (also it happens in the sub-indicators) a significant change in position of some SLLs between 2006 and 2021. All SLLs that are outside the bisector show a change in score (Figure 3) and position (Figure 4) between 2006 and 2021; the SLLs above the bisector present an improvement, those below a worsening. Table A1 in Appendix lists the best and worst SLLs ordered for the 2021 values: evidently, the first positions are occupied by SLLs in the Centre-North (and super-performing) and the last positions by SLLs in the South (*area* indicates the geographical area – 1 north-west, 2 north-east, 3 centre, 4 south). The informative contribution of this BoD-CI can be appreciated by relating the performance scores with the simple arithmetic mean of the three range-normalized sub-indicators TA, TO and TD rescaled on 1-10 values for reading convenience (in this way, 1 represents the worst data and 10 the best data) (Figure 5).

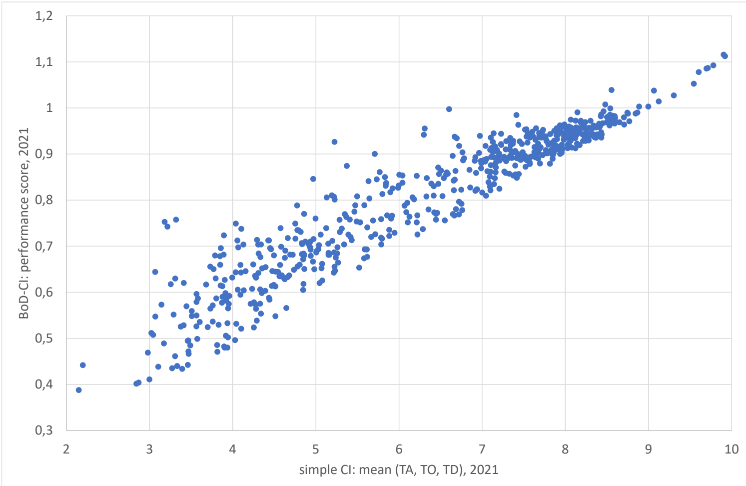


Figure 5: mean-CI and robust BoD-CI (2021)

Figure 5 shows 2021 but other years are not much different; on the contrary, some interesting differences can be seen in the geographical maps: Figure 6 compares 2006 and 2021 for the performance values BoD-CI. In 2006, there is a clearer distinction between low and high performing areas with the North-West and the North-East and some central areas featuring high scores. Over time, the impact of the economic crises have changed the geography of the efficiency scores: the areas of the North, especially in the North-West, appear weaker and we note a higher spatial polarization with the North-East areas who maintain, now almost alone, the top positions, also thanks to the evidence of super-efficiency. Other changes are evident in the South, with some interesting and limited improvements but, in general terms, the South maintains a low level of labour market performance. These conclusions are perfectly reflected in the corresponding LISA clusters (Figure 7).

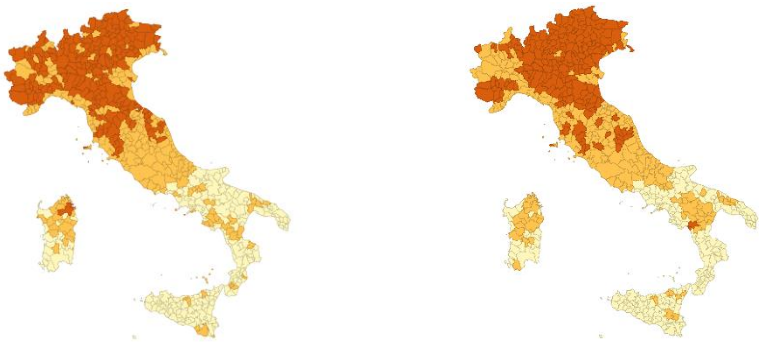


Figure 6: Robust BoD-CI (2006 left panel, 2021 right panel)

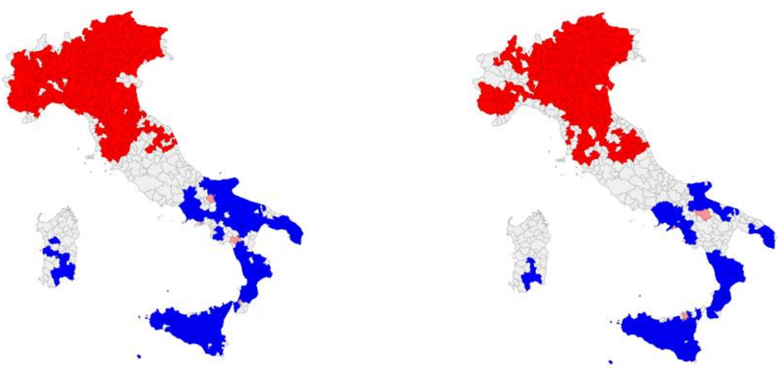


Figure 7: LISA clusters, high-high (red), low-low (blue), robust BoD-CI (2006 left panel, 2021 right panel)

The conditional BoD-CI presents different results; it is exactly what was expected. We have constructed two different exogenous Z matrices always with m=50 and T=100. The first Z matrix is composed of the three spatially lagged sub-indicators TA, TO and TD (as before, a weight matrix based on the first-order queen contiguity was used). The underlying idea is to highlight specific performances, if any, with respect to the surrounding areas that generate natural spillover and contagion effects. The South can only, necessarily, record low performance scores due to the presence of two different labour market regimes (North and South): the frontier can only (and always) be determined by the best areas of the North, but if we take into account the values of the neighboring areas, somehow, we construct a local frontier of spatial proximity. This can highlight some good performances of the South compared to its neighbors and that, with a frontier always determined by the Centre-North, we may not be able to see. In particular, in the first Z matrix, the sub-indicators TA, TO and TD are spatially lagged, range-normalized and a mean is calculated; similar mean is calculated for the *i*-th SLL on the not lagged range-normalized sub-indicators. For each SLL, the units with means more similar to that of the *i*-th SLL are preferred and extracted to build the frontier. Due to the geographical characteristics of the data, this essentially guarantees the choice of spatially close units in the construction of the frontier. Other criteria based only on spatial proximity or combining proximity and values of these means, generate frontiers substantially overlapping without enriching the analysis. Table A2 in Appendix reports the spatially conditioned BoD-CI values in 2006 and 2021 for the first and last SLLs sorted by 2021 scores. The top positions are occupied substantially by SLLs to which is attributed a score equal to 1, that is SLLs exactly on the frontier (or almost). This is obvious because the frontier specifically takes into account the scores of the already highly performing neighbors and it never be too different or far from these data, and this also explains the substantial absence of super-performing SLLs, that is SLLs above the frontier. Among the best units we also note the presence of SLLs from the North-West that, unlike the case with unconditional frontier, is now no longer overshadowed by the performance of the North-East SLLs. This application appears particularly useful for the less performing SLLs that in the classic BoD suffer the most from comparison with frontiers very far from them. Now, even the frontier of the SLLs in the South is closer to them; in some way, it takes into account the environmental conditions and does not compare the SLLs performance with an limit set by benchmarks in other areas: we can say that the frontier takes local conditions into consideration. In this way, we can better see the SLLs in the South with better performance than their neighbors and some units, which seemed very far from the first frontier, now do not appear to be so poorly performing. Figure 8 highlights the differences in the results between the robust BoD-CI and the conditional BoD-CI; it reports the ratio of the two scores on the ordinate and a mean of the spatially lagged (range-normalized and scaled on 1-10) sub-indicator values on the abscissa in 2021. Confirming what was said, the ratio between robust performance scores and conditional performance scores is less than 1 except for very efficient environmental conditions (the performance of neighbors) typically located in the North; other years show no notable differences.

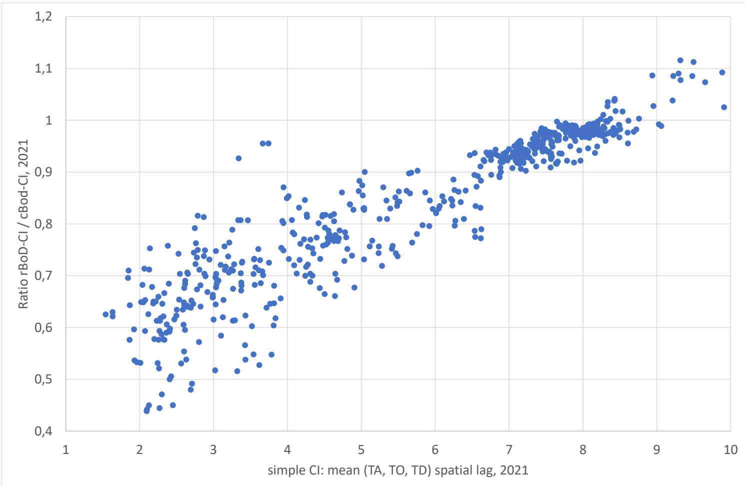


Figure 8: mean-CI and ratio robust / conditional BoD-CI (spatial lag, 2021)

Spatial proximity is not always a sign of similarity even if nearby areas tend to be more similar than distant areas (first law of geography; Tobler, 1970); this is certainly true in the case of the SLLs labour market indicators. Of course, similarity of the SLLs could be measured through other social or economic characteristics; unfortunately, there are not many variables available with SLL detail, but two of these seem particularly interesting to us: added value per employee (VAE) and compensation of employees (divided by number of employees) (COE). The first one is a typical measure of labour productivity, the second one is the total remuneration for work done by an employee and it represents a measure of labour costs; these two variables are excellent proxies for the economic development of a community and the presence of a mature production system. We apply the conditional BoD-CI again and this time we use these two variables VAE and COE in a second version of Z to compare the 610 SLLs and to identify their greater or lesser similarity. It is well known that the richer areas of the North have higher values of both labour productivity and labor costs, but we wonder if the resulting geographical map shows new dynamics that are different from the previous ones. Therefore, after we have range-normalized the two variables and calculated their mean, as before, we compare the SLLs by selecting the frontier units among those that have greater similarity on these average values. As before, Figure 9 crosses the arithmetic mean of the two exogenous indicators VAE and COE (range-normalized on scale 1-10) and the performance score of this conditional BoD-CI. Data availability is limited to the time interval from 2015 to 2020, and the last year corresponds to the stop to production activities due to covid19. It is reasonable to expect a different behavior in 2020 compared to past years, but this does not happen: the relationship represented in Figure 9 remains almost unchanged over time except for the presence of some extreme values on the abscissa. Table A3 in Appendix reports the corresponding conditional performance values in 2015 and 2020 for the first and last SLLs sorted by 2020 scores.

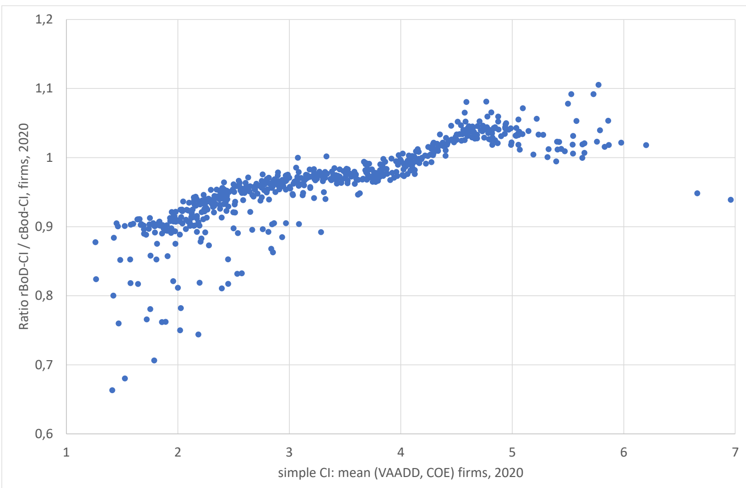


Figure 9: mean-CI and ratio robust / conditional BoD-CI (firms, 2020)

Once again, when Z takes on lower values, and in this case not only in southern areas, the ratio between robust and conditioned values is lower too highlighting the presence of very different regimes, whereas with higher values of Z the ratio reaches and exceeds the value of 1 demonstrating how the context can have a very strong influence on the performance measures when there are different economic and social regimes due to different structural characteristics and spatial positioning of the territories that, for spillover effects, remain trapped in differentiated development dynamics. It would be natural to infer that the best way to measure the labour market performance of the 610 SLLs is to use the conditional BoD-CI; in fact, exactly the opposite. It is true that there are different regimes between North and South and the regions are rather heterogeneous but this does not mean at all that they should not have the best areas in the North as their horizon. The usefulness of the conditional approach is to highlight how complex it is, in practice, to undertake an improvement path when spatial - or other - conditioning exist. But if the local context becomes a privileged point of reference then it will always be difficult to find the best units to imitate in search of a path of convergence and continuous improvement. Therefore, the best way to represent the differences among SLLs is to use the robust unconditional order-*m* BoD-CI that, beyond the banal and well-known result about the North-South distinction, helps us to provide a more articulated and detailed representation of the characteristics of the SLLs.

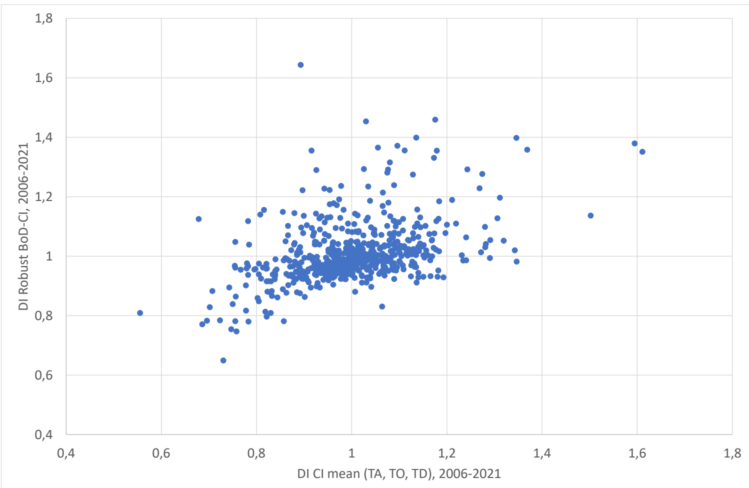


Figure 10: Dynamics Index for sub-indicators and robust BoD-CI (610 SLLs, 2006-2021)

In conclusion of this paper, it is useful to build a "dynamic index" on the changes in value in an SLL between one year and a previous year, compared to the change referring to all the SLLs. Thus, our dynamics index that compares time t and time t-h will be $DI_i = (a_{i,t}/a_{i,t-h})/(a_{\cdot t}/a_{\cdot t-h})$ where $a_{i,t}$ is the performance score or the mean of the sub-indicators for i-th SLL at time t. This dynamics index DI has a numerator greater than 1 if the variable for year t is greater than that of year t-h, otherwise it will be less than 1; its denominator makes a similar comparison but refers to the average values of all the SLLs. So, a DI greater than 1 between *t* and *t-h* indicate better dynamics in the *i*-th SLL compared to the average of all the SLLs and, conversely, a DI less than 1 indicates worse dynamics. Here, the DI is calculated on the mean of TA, TO and TD (with range-normalised values) and on the order-*m* performance scores between the first year 2006 and the last one 2021 (Figure 10). The calculation is made considering only 2006 and 2021 (without considering the intermediate years) because it is particularly interesting to highlight the final positioning of the SLLs compared to their initial position.

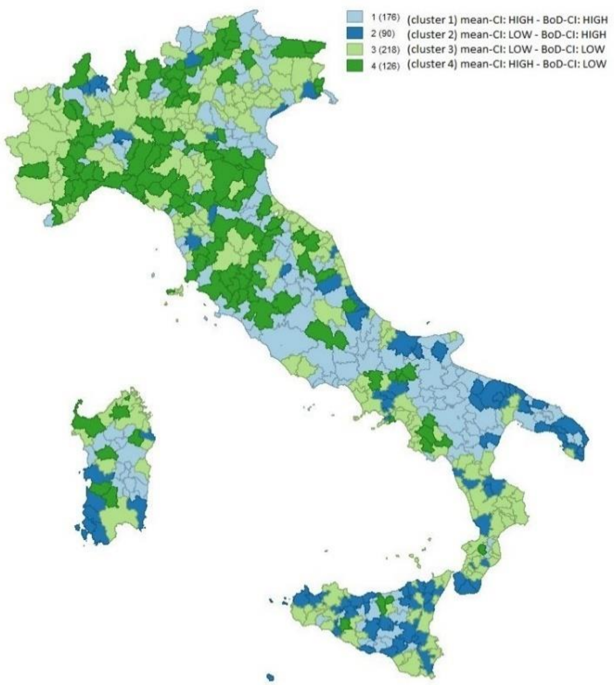


Figure 11: Dynamics Index (DI), clusters (2006-2021)

The dynamics index DI allows us to classify the SLLs into clusters based on the temporal comparison between performances and sub-indicators with reference to the average values of all the SLLs. Therefore, we will have four groups (Figure 10): the first group is made up of SLLs that between 2006 and 2021 show better DI values in both sub-indicators and performances (scores greater than 1 on both the abscissa and ordinate); the second group includes SLLs with worse DI for sub-indicators but better for performances (abscissa less than 1 and ordinate greater than 1); the third group includes SLLs with worsening in both sub-indicators and performances (abscissa and ordinate less than 1); the fourth group includes SLLs with better dynamics in the sub-indicators but worse in performances (abscissa greater than 1 and ordinate less than 1). Figure 11 shows the group to which each SLL belongs, and a list with the first and last SLLs is reported in Appendix in Table A4: cluster 1 has high mean-CI and high BoD-CI, cluster 2 has low mean-CI and high BoD-CI, cluster 3 has low mean-CI and low BoD-CI, cluster 4 has high mean-CI and low BoD-CI. This result is interesting: in the South there is a very high presence of SLLs with positive dynamics in both DI indices (group 1) and positive dynamics for performance and negative dynamics for the sub-indicators (group 2), while the Centre-North is characterized more by negative performance dynamics (group 3 and group 4). However, we should not be surprised: this map represents a very different result from those analyzed so far, because it simultaneously refers to the 2006-2021 variations in performance and sub-indicators compared to the average dynamics of all the 610 SLLs. In this regard, Figure 12 shows the distribution of the two DI over three quartiles (darker values correspond to higher values).

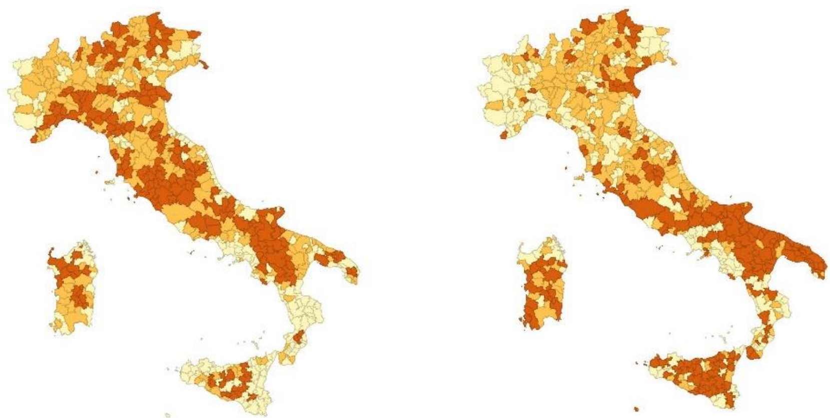


Figure 12: Dynamics indices (DI) for sub-indicators mean-CI (left panel) and performance BoD-CI (right panel) (610 SLLs, 2006-2021)

The two maps show higher values in the Centre and the South for the sub-indicators (Figure 12 left panel) and particularly in the South for performances (Figure 12 right panel). The efficiency of the South is lower than Centre-North and it has not shown paths of convergence but, also, we have observed a greater polarization with an increase in efficiency within the South. This increase, especially compared to the sub-indicators dynamics, explains the reason for a better relative dynamics in the "Mezzogiorno"; after all, when many SLLs in the Centre-North are already at full efficiency and even super-performing, there is no room for further improvement.

5. CONCLUSIONS

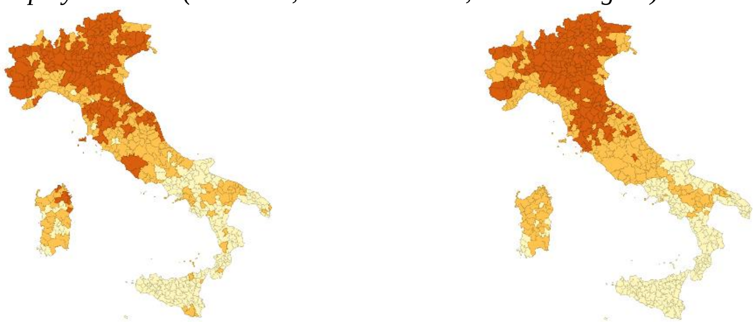
In this paper, we used some DEA-type methods to build a ranking of the Italian SLLs with respect to the three classic indicators of the labour market: activity rate (TA), employment rate (TO) and unemployment rate (TD); we used the official data released by Istat for the period 2006-2021 and for all the 610 Italian SLLs. The application of a BoD (Benefit-of-Doubt) technique made it possible to obtain a performance score between 0 (worst conditions) and 1 (best conditions) for each SLL in each year and, therefore, to map in detail the territorial gap which, beyond the known North-South divide, presents noteworthy articulations. It is interesting to note that, although there were several economic crises in the period 2006-2021, the performance scores did not show significant reductions in value; this is especially true in 2020 with the covid crisis. It must be said that crises have not always had a clear effect on the indicators mentioned above (TA, TO and TD) and, consequently, on the performance scores; for example, in 2020, the largest effect was on hours worked and not so much on the rates. Furthermore, the performance scores are constructed in a BoD logic with DEA-type methods which implies the construction of relative frontiers with which to compare the individual SLLs, and with data-driven frontiers determined by the same units under analysis and frontiers that can shift year after year. This is an interesting aspect of these approaches, because they propose a measure to the best of possibilities (benefit of doubt), that is combining in the best possible way sub-indicators with weights defined endogenously by the procedure; so, we have a measure of efficiency (or performance) that is higher when the unit under examination is closer to a specific frontier (obtained for those units and for that historical period). Therefore, the SLLs very close to the frontier obtain a score equal to 1, but this excessively crushes the best units on a single indistinguishable score and hides extreme performances, the knowledge of which is also useful for obtaining information on the presence of potentially anomalous values and which, in turn, influence the frontier. To eliminate this risk, here it is applied a robust method that defines the frontier on a subset of the 610 SLLs extracting *m* units *T* times according to Monte Carlo technique and excluding the unit under analysis from the sample. In this way, the unit under analysis can also position itself above the frontier (because it does not participate in its construction) and, if this is the case, a super-performance score is obtained with a value greater than 1 the more the SLL is above the frontier. The application of this robust technique has highlighted the presence of some extreme values, the number of which grows following an economic crisis that tends to lower the frontier; paradoxically, this leads to some increases in performance in some SLLs but that should not be surprising if we think of the score as a relative value that takes into account the positioning of the unit, that could relatively improve even with a general - in absolute terms - worsening of the labour market indicators; we add that this is precisely the interesting aspect of this approach. However, the frontier remains substantially unique for all the units, i.e. the subsample of SLLs is extracted from the entire population which is rather heterogeneous and, therefore, typically the frontier obtained is always much higher than the SLLs in the South. This is certainly the correct approach, but we could ask ourselves how the context influences the result knowing that the southern SLLs are trapped in a context that, due to contagion effects, pushes them to maintain a lower level, unlike the SLLs in the Centre-North where environmental factors are more favorable (many nearby units with high performance values). To underline the role of the context, the robust approach was conditioned, first, on the values of the neighboring SLLs and, then, on two economic variables (labour productivity and labour costs), so that the frontier is constructed by selecting the *m* units based on a similarity criterion. This implies, also given the strong spatial polarization of the data, the identification of frontiers with SLLs from the North for the Centre-North and from the South for the South: the obvious consequence is a generalized increase of the performance scores in the South. The comparison between robust and conditional results allows us to measure the contribution of the "environmental context" and its evident braking factor, in our case, for the SLLs in the South. Clearly, the reference scores for ranking and analysis of the 610 SLLs remain the results of the unconditional robust BoD. At last, we have built a dynamics index

(DI) that compares the performance of an SLL between a time *t* and a previous time *h* (contiguous or not) and relates it to the results obtained for all the SLLs. So, lower performance values but with positive dynamics (approaching the frontier) and greater than better performing units (which, moreover, if already close to the frontier have little margin for improvement) leads to higher scores of the dynamics index. In particular, useful here for evaluating the overall dynamics, DI is calculated over the entire period 2006-2021 and it allows us to highlight some very interesting positive dynamics in the South that are not evident in the static approach. In conclusion, the South certainly performs worse and over time it has not shown evident improvements, but this also depends on the fact that the North and the South are very different and distant in terms of the labour market and, in effect, when we contextualize the frontier the results improve; furthermore, in dynamic terms, we discover a liveliness of the SLLs in the South which makes the interpretation of the territorial gaps in the labour market less dramatic. Finally, in this paper we have highlight a series of specificities and articulations beyond the classic North-South gaps and this also with some obvious limitations in the analysis. For example, the use of only three sub-indicators can be criticized because they only capture some aspects of the labour market but, on the other hand, no other information is available with the necessary spatial and temporal detail and, anyway, the three sub-indicators TA, TO and TD represent the most typical and significant structural characteristics of the labor market. But, it is also true that economic policies do not have great margins of influence on these indicators, the value of which also depends greatly on the structural and demographic characteristics of the different territories. Unfortunately, the choice of the data depends greatly on the limited availability of variables for all the 610 SLLs over a large time interval, and this also applies to the data used in the conditional approach. Also, one could criticize the aggregation and weighting used here: BoD is a less arbitrary method than other techniques to build composite indicators but certainly not without a priori decisions of the researcher, such as the choice of a compensatory aggregative approach here justified by the fact that the sub-indicators TA, TO and TD are all considered relevant and their relative improvements and worsening are assumed directly comparable (and replaceable) in terms of performance. At last, the choice of an order-*m* approach has the advantage of not crushing the super-performing SLLs on the frontier (giving them all an indistinct value of 1) but introduces a minimum of randomness due to the Monte Carlo technique used to determine the robust frontier also with respect to the choice of the values of m and T. Therefore, the robust approach used here is not always preferable, and in general terms we cannot say that it is better or worse than the classical approach BoD, because it depends on the cases, the purpose of analysis and the data used. Here, given the high number of units, we have considered the order-m approach particularly useful for its ability to highlight and differentiate the SLLs also with reference to the super-performing ones. In conclusion, despite the presence of some limitations, the analysis discussed in this paper appears of interest because it provides a non-trivial mapping of the 610 Italian SLLs and highlights their evolutions in recent years also with reference to the various economic crises.

APPENDIX

a) Activity rate (610 SLLs, 2006 and 2021, darker is higher)

b) Employment rate (610 SLLs, 2006 and 2021, darker is higher)



c) Unemployment rate (610 SLLs, 2006 and 2021, darker is higher)

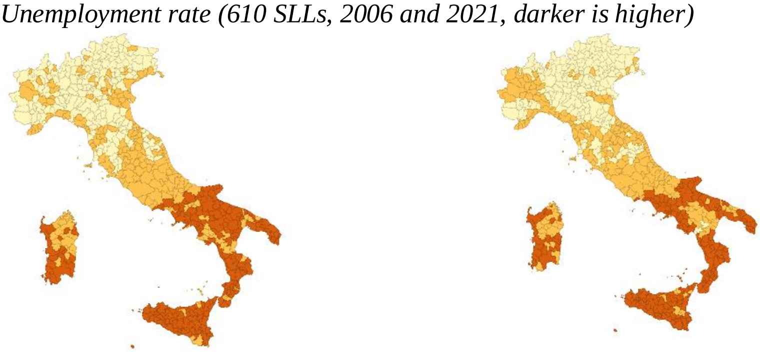
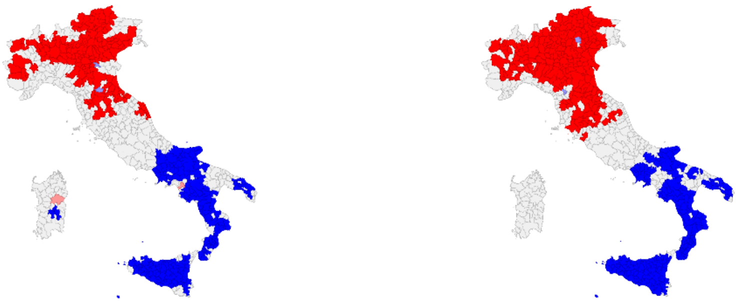
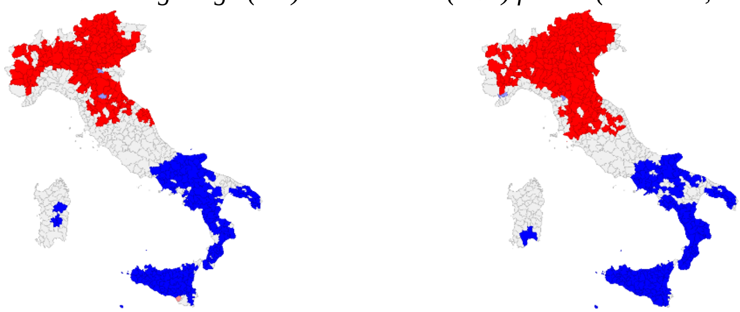


Figure A1: Activity rate, employment rate and unemployment rate (610 SLLs, 2006 and 2021)

a) LISA cluster high-high (red) and low-low (blue) for TA (610 SLLs, 2006 and 2021)



b) LISA cluster high-high (red) and low-low (blue) for TO (610 SLLs, 2006 and 2021)



c) LISA cluster high-high (red) and low-low (blue) for TD (610 SLLs, 2006 and 2021)

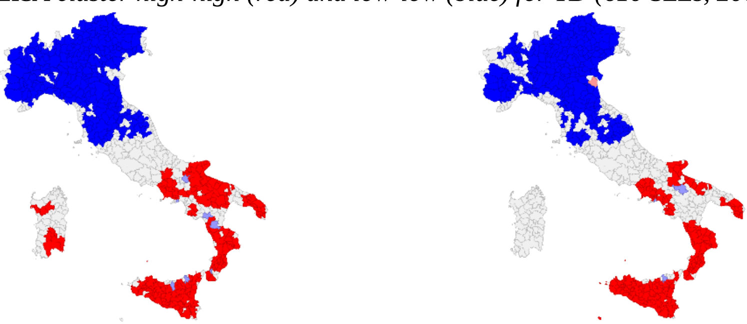


Figure A2: Local index of spatial association (LISA clusters, 2006 and 2021)

Table A1: Robust BoD performance score (rBoD) and ranking (R) (best and worst SLLs, 2006 and 2021)

Istat code	SLL name	area	rBoD06	rBoD21	R-2006	R-2021
410	SAN LEONARDO IN PASSIRIA/ST. L.P.	2	1,0594	1,1157	3	1
407	MALLES VENOSTA/MALS	2	1,0323	1,1125	8	2
404	BRUNICO/BRUNECK	2	1,0316	1,0924	9	3
409	SAN CANDIDO/INNICHEN	2	1,0196	1,0865	14	4
411	SILANDRO/SCHLANDERS	2	0,9979	1,0855	30	5
401	BADIA/ABTEI	2	0,9870	1,0777	41	6
403	BRESSANONE/BRIXEN	2	1,0630	1,0526	2	7
834	MODIGLIANA	2	0,9951	1,0389	31	8
343	CASTEL GOFFREDO	1	1,1241	1,0377	1	9
405	CASTELROTTO/KASTELRUTH	2	1,0164	1,0271	15	10
412	VIPITENO/STERZING	2	1,0429	1,0141	5	11
835	SANTA SOFIA	2	0,9668	1,0075	79	12
419	MOENA	2	1,0231	1,0030	11	13
406	EGNA/NEUMARKT	2	0,9861	1,0030	43	14
518	AGORDO	2	0,9921	0,9991	33	15
911	SAN MARCELLO PISTOIESE	3	0,9644	0,9974	84	16
317	GRUMELLO DEL MONTE	1	1,0412	0,9927	6	17
529	PIEVE DI SOLIGO	2	0,9060	0,9904	223	18
814	MIRANDOLA	2	0,9821	0,9899	49	19
528	ODERZO	2	0,9872	0,9897	39	20
1925	MESSINA	4	0,5876	0,4857	522	591
1521	TORRE DEL GRECO	4	0,5225	0,4849	567	592
1970	PACHINO	4	0,7342	0,4824	387	593
1971	SIRACUSA	4	0,5255	0,4800	565	594
1952	TROINA	4	0,4528	0,4799	601	595
1832	ROCCELLA IONICA	4	0,5055	0,4718	577	596
1814	SAN GIOVANNI IN FIORE	4	0,4760	0,4709	592	597
1838	CROTONE	4	0,4823	0,4692	586	598
1945	MAZZARINO	4	0,3394	0,4664	610	599
1938	LICATA	4	0,4041	0,4615	605	600
1933	AGRIGENTO	4	0,4431	0,4424	603	601
1907	BAGHERIA	4	0,5665	0,4419	538	602
1840	PETILIA POLICASTRO	4	0,4591	0,4401	597	603
1935	CAMMARATA	4	0,4615	0,4385	595	604
1949	LEONFORTE	4	0,3889	0,4352	607	605
1517	NAPOLI	4	0,4991	0,4339	580	606
1953	ADRANO	4	0,4328	0,4111	604	607
1833	ROSARNO	4	0,4038	0,4042	606	608
1807	CETRARO	4	0,4792	0,4016	589	609
1502	MONDRAGONE	4	0,4738	0,3879	593	610

Table A2: Conditional BoD performance score (cBoD) and ranking (R) (best and worst SLLs, 2006 and 2021, spatially conditioned)

Istat code	SLL name	area	cBoD06	cBoD21	R-2006	R-2021
317	GRUMELLO DEL MONTE	1	0,9998	1,0006	127	1
114	CEVA	1	1,0000	1,0000	1	2
203	COURMAYEUR	1	1,0000	1,0000	1	2
205	VALTOURNENCHE	1	0,9527	1,0000	364	2
333	VESTONE	1	0,9813	1,0000	246	2
343	CASTEL GOFFREDO	1	1,0000	1,0000	1	2
401	BADIA/ABTEI	2	1,0000	1,0000	1	2
404	BRUNICO/BRUNECK	2	0,9953	1,0000	173	2
406	EGNA/NEUMARKT	2	0,9709	1,0000	292	2
407	MALLES VENOSTA/MALS	2	1,0000	1,0000	1	2
409	SAN CANDIDO/INNICHEN	2	1,0000	1,0000	1	2
410	SAN LEONARDO IN PASSIRIA/ST. L.P.	2	1,0000	1,0000	1	2
419	MOENA	2	1,0000	1,0000	1	2
528	ODERZO	2	0,9558	1,0000	356	2
529	PIEVE DI SOLIGO	2	0,9323	1,0000	430	2
703	SANREMO	1	1,0000	1,0000	1	2
705	ALBENGA	1	1,0000	1,0000	1	2
814	MIRANDOLA	2	1,0000	1,0000	1	2
817	PIEVEPELAGO	2	0,9951	1,0000	174	2
826	GORO	2	0,9873	1,0000	217	2
1950	NICOSIA	4	0,9648	0,8102	313	591
1926	MILAZZO	4	0,8147	0,8091	576	592
1938	LICATA	4	1,0000	0,7987	1	593
2032	PERDASDEFOGU	4	0,7158	0,7941	601	594
1838	CROTONE	4	0,7801	0,7922	584	595
1822	BIANCO	4	0,7301	0,7914	600	596
1820	SOVERATO	4	0,9981	0,7861	153	597
1818	CHIARAVALLE CENTRALE	4	0,5991	0,7797	610	598
1845	CORIGLIANO-ROSSANO	4	0,9061	0,7748	486	599
1811	PAOLA	4	0,9805	0,7745	250	600
1604	FOGGIA	4	0,8358	0,7704	565	601
1610	VICO DEL GARGANO	4	0,9990	0,7695	143	602
1807	CETRARO	4	0,8944	0,7551	507	603
1805	CASSANO ALL'IONIO	4	0,9898	0,7368	201	604
1514	CASTELLAMMARE DI STABIA	4	0,8994	0,7230	497	605
1826	LOCRI	4	0,8170	0,7221	575	606
1937	CANICATTÌ	4	0,9285	0,6898	439	607
2026	BUDDUSÒ	4	0,6716	0,6817	607	608
1502	MONDRAGONE	4	0,8202	0,6301	574	609
1833	ROSARNO	4	0,6730	0,6002	606	610

Table A3: Conditional BoD performance score (cBoD) and ranking (R) (best and worst SLLs, 2015 and 2020, firms)

Istat code	SLL name	area	cBoD15	cBoD20	R-2015	R-2020
1201	ACQUAPENDENTE	3	1,1091	1,0732	1	1
135	SANTA MARIA MAGGIORE	1	1,0160	1,0492	10	2
410	SAN LEONARDO IN PASSIRIA/ST. L.P.	2	1,0129	1,0350	14	3
407	MALLES VENOSTA/MALS	2	1,0313	1,0339	4	4
834	MODIGLIANA	2	0,9845	1,0269	37	5
326	LIMONE SUL GARDA	1	0,9806	1,0236	39	6
409	SAN CANDIDO/INNICHEN	2	1,0380	1,0214	3	7
331	PONTE DI LEGNO	1	0,9895	1,0166	34	8
308	LIVIGNO	1	1,0224	1,0164	6	9
425	TONADICO	2	1,0127	1,0119	15	10
1123	MONTEGIORGIO	3	0,9653	1,0118	62	11
832	CESENATICO	2	1,0218	1,0116	7	12
911	SAN MARCELLO PISTOIESE	3	0,9939	1,0112	30	13
944	MANCIANO	3	1,0062	1,0081	16	14
1701	LAURIA	4	0,9692	1,0058	55	15
1002	CASCIA	3	0,9987	1,0037	25	16
835	SANTA SOFIA	2	0,9671	1,0037	60	17
524	PIEVE DI CADORE	2	0,9677	1,0027	59	18
539	MONTAGNANA	2	0,9773	1,0021	47	19
935	MONTALCINO	3	0,9635	1,0019	65	20
1971	SIRACUSA	4	0,5677	0,5457	580	591
1521	TORRE DEL GRECO	4	0,5633	0,5384	582	592
1825	GIOIA TAURO	4	0,5510	0,5314	590	593
1914	PALERMO	4	0,4984	0,5232	602	594
1815	SAN MARCO ARGENTANO	4	0,5292	0,5230	596	595
1807	CETRARO	4	0,5562	0,5101	587	596
1944	GELA	4	0,4602	0,5085	607	597
1811	PAOLA	4	0,5897	0,5084	574	598
1935	CAMMARATA	4	0,5016	0,5066	601	599
1933	AGRIGENTO	4	0,5181	0,5050	597	600
1938	LICATA	4	0,5351	0,5043	594	601
1816	SCALEA	4	0,5140	0,4936	598	602
1812	PRAIA A MARE	4	0,5043	0,4901	599	603
1517	NAPOLI	4	0,5395	0,4754	593	604
1949	LEONFORTE	4	0,5038	0,4658	600	605
1840	PETILIA POLICASTRO	4	0,4561	0,4624	608	606
1953	ADRANO	4	0,4974	0,4542	603	607
1502	MONDRAGONE	4	0,6173	0,4438	565	608
1838	CROTONE	4	0,4380	0,4137	609	609
1833	ROSARNO	4	0,4049	0,4038	610	610

Table A4: Dynamics Index for sub-indicators (DIm) and robust BoD scores (DIeff) and ranking (R) (best and worst SLLs, 2006-2021)

Istat cod.	SLL name	area	DIm0621	DIeff0621	R-m	R-eff	Cluster
1962	SCORDIA	4	0,8928	1,6432	512	1	2
1947	RIESI	4	1,1756	1,4590	37	2	1
1702	MARATEA	4	1,0300	1,4533	229	3	1
1951	PIAZZA ARMERINA	4	1,1356	1,3986	68	4	1
1714	TRICARICO	4	1,3462	1,3979	6	5	1
1713	STIGLIANO	4	1,5946	1,3791	2	6	1
1644	SAN FERDINANDO DI PUGLIA	4	1,0961	1,3716	108	7	1
1958	GRAMMICHELE	4	1,0550	1,3651	178	8	1
1945	MAZZARINO	4	1,3690	1,3584	4	9	1
1705	POTENZA	4	1,1113	1,3555	91	10	1
1960	PATERNÒ	4	0,9157	1,3552	488	11	2
1703	MARSICOVETERE	4	1,1789	1,3549	34	12	1
1602	CASALNUOVO MONTEROTARO	4	1,6110	1,3512	1	13	1
1706	RIONERO IN VULTURE	4	1,1729	1,3309	39	14	1
1604	FOGGIA	4	1,0803	1,3155	138	15	1
1709	MATERA	4	1,0258	1,2933	238	16	1
1606	MANFREDONIA	4	1,2430	1,2920	19	17	1
1708	SENISE	4	1,0764	1,2917	146	18	1
1622	MANDURIA	4	0,9256	1,2899	472	19	2
1704	MELFI	4	1,0749	1,2812	147	20	1
1533	CAPACCIO	4	0,8439	0,8614	553	591	3
1517	NAPOLI	4	0,8023	0,8593	581	592	3
1809	COSENZA	4	0,8048	0,8486	580	593	3
1965	RAGUSA	4	0,7499	0,8391	600	594	3
714	LEVANTO	1	1,0640	0,8308	169	595	4
1807	CETRARO	4	0,7018	0,8284	606	596	3
1925	MESSINA	4	0,7779	0,8169	591	597	3
2029	SAN TEODORO	4	0,8186	0,8133	573	598	3
1502	MONDRAGONE	4	0,5552	0,8092	610	599	3
1536	NOCERA INFERIORE	4	0,8300	0,8091	565	600	3
1641	UGENTO	4	0,8214	0,7969	570	601	3
1811	PAOLA	4	0,7232	0,7843	604	602	3
1966	VITTORIA	4	0,6958	0,7832	607	603	3
1804	CARIATI	4	0,8573	0,7816	549	604	3
2027	OLBIA	4	0,7553	0,7812	597	605	3
1963	COMISO	4	0,7830	0,7801	585	606	3
1907	BAGHERIA	4	0,6861	0,7711	608	607	3
1540	POSITANO	4	0,7469	0,7544	601	608	3
1967	AUGUSTA	4	0,7578	0,7469	594	609	3
1970	PACHINO	4	0,7304	0,6494	603	610	3

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