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Summary

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THEMATIC ISSUE ON "LABOUR MARKET: ANALYSIS, TRENDS AND NEW SCENARIOS - EDITORIAL"

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The analysis of the labour market has always played an important role in the international scientific debate because of its economic relevance and its social impact and importance.

In particular, in the last two decades in Italy there has been a growing interest in the labour market and all its related aspects, driven by three main issues:

- the new labour market regulations that, since the end of the twentieth century, have changed its functioning and introduced flexibility in the Italian labour market;
- the financial and economic crises that are still occurring today and that have deeply affected the EU and the Italian labour market because of the subsequent long economic recessions and/or widespread unemployment in most regions;
- the technological and digital revolution, together with globalisation and environmental issues, which are constantly evolving the labour market, with new forms of employment and emerging companies,

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and the increasingly widespread use of online recruitment methods.

In this panorama, as expected, the analysis of the labour market is not easy and many questions arise from statistical and economic issues, both methodological and data-driven, and from various social aspects, both ethical and educational.

This thematic issue therefore aims to contribute to the scientific discussion by proposing original papers that cover many of the issues related to the labour market, ranging from statistical methods for labour force analysis to job demand and supply matching, and to employment, unemployment and transitions as driven by labour force policies to education, training and human capital.

This thematic issue brings together nine original papers. It is published in two volumes.

The first volume contains four papers which can be summarised as follows:

- the first paper, by Varriale R., Filipponi D., Garnier-Villarreal M. and Pavlopoulos D., analyses the effect of measurement error on mobility between different types of employment in Italy, using a hidden Markov model with two independent indicators for the employment categories under consideration, i.e. permanent, temporary, self-employed, not employed;
- the second paper, by Menini T., focuses on the professional work of the manager and, in particular, the author identifies a possible new approach to managerial behaviour that can define this professional figure and a first idea of an "open manager" leading to a horizontal and participatory organisation of power;
- the third paper, by Ciaschini C. and Salvati L., examines the spatial regimes and short-term changes of a gross unemployment rate, taken as a representative proxy for the overall performance of 610 local labour markets in Italy, and the authors identify, through a purely exploratory approach, the socio-economic factors that have better characterised the labour market dynamics during the period considered;
- the fourth paper, by Vassallo E., analyses the labour performance in the 610 Italian local labour systems in terms of the activity rate,

the employment rate and the unemployment rate, applying a benefit-of doubt approach in a DEA-type model to obtain a score of "labour performance" and, in particular, the author proposes a composite indicator to synthesise the three above-mentioned rates, based on a robust non-parametric approach of the order m DEA frontiers.

The second volume contains five papers, which may be briefly summarised as follows

- the first paper, by Kahlawi A., Grassini L. and Buzzigoli L., analyses the recent dynamics of the demand for ICT skills in Italy, using online job advertisements, by means of a skill change index at the regional level;
- the second paper, by Marini C. and Nicolardi V., highlights the difficulties arising from the unsatisfactory availability of dynamic databases for analysing the dynamics of the Italian labour force, as a result of the long phase of labour market reform that started at the beginning of the 21st century, and through a graphic-matrix approach the authors show how non-disclosed administrative data, in addition to official statistical data, could support the analysis;
- the third paper, by Leombruni R., proposes a conceptual map of what data are in the field of empirical economic research in order to clarify what are the conditions and possible strategies to fully exploit their opportunities, especially in the case of big data of administrative origin and, in particular, the author discusses the case of labour market research based on social security data;
- the fourth paper, by Barzizza E., Biasetton N., Ceccato R., Fedeli M. and Tino C., examines engineering students' perceptions of the labour market and career planning, where data have been collected through a questionnaire addressed to engineering students, and the authors apply appropriate machine learning models to examine the relationship between students' perceptions of the labour market and career planning and various factors;
- finally, the paper by Maiorino S., Rappelli F. and Giubileo F. examines the employment of people with disabilities through targeted placement services in the Lombardy region, and the

authors show, using administrative data, that there has been an improvement in the probability of finding a job and in the probability of being hired with a permanent contract over the period considered for those registered on the targeted placement lists.

We are grateful to the Association for Applied Statistics (www.sa-ijas.org) for publishing this research in its official journal, and to the authors and referees for making this double issue possible.

The Guest Editors

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HOW "REAL" IS MOBILITY FROM TEMPORARY TO PERMANENT EMPLOYMENT IN ITALY? A FOCUS ON MEASUREMENT ERROR

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Abstract *The aim of this paper is to study the effect of measurement error on mobility between different employment types in Italy. For this purpose, we apply a hidden Markov model with two independent indicators for the employment category (permanent contract, temporary contract, self-employed, not employed). The model takes into account that both sources may not be error-free as well as that measurement error may be correlated over time. The two indicators come from ISTAT administrative data and the Labour Force Survey from 2017 to 2021, linked at the individual level. The results show that neither source can be considered error-free and that measurement error* may *severely bias mobility between employment states.*

Keywords: *Hidden Markov model; Latent variable model; Multi-source data; Employment career Measurement error.*

1. INTRODUCTION

In the last decades, flexible employment has been at the centre of political and scientific debate in Europe. In the countries of the Eurozone, in 2021, 11.4% of all individuals in paid employment were employed with a temporary contract (OECD, 2023). Latner (2022) found that, over time, while the temporary employment rates stagnated, the risk of temporary employment increased. In more detail, following a period of growth (1996-2007), the incidence of temporary employment remained stable in Europe between 2007 and 2019. However, between

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.
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2013 and 2019, the risk of experiencing at least one temporary employment contract increased by 36%. Italy presents an exceptional case in Europe as it is one of the few countries where both the incidence and the risk of temporary employment increased. Specifically, between 2008 and 2019, the incidence of temporary employment increased from 11.4% to 16.4% (OECD, 2023), while the risk of temporary employment from 14.9% to 22.7% (Latner, 2022). Research has also shifted its focus from the incidence of temporary employment to mobility in and out of temporary employment instead. The reason is that, although there is consensus that ceteris paribus, temporary employment is inferior to permanent employment (Amuedo-Dorantes and Serrano-Padial, 2007; Gash and McGinnity, 2007; Gebel, 2010; Mooi-Reci and Dekker, 2015; Pavlopoulos, 2013), there is still debate on the role of temporary employment in the life course. In this, two very different scenarios exist: temporary contracts sometimes serve as a stepping-stone to a permanent job, while other times can lead to a trap of precarious jobs and unemployment (Latner and Saks, 2022). To determine which of the two scenarios prevail, we need reliable estimates of the transition rate from temporary to permanent employment.

As shown by Pavlopoulos and Vermunt (2015), findings on mobility from non-permanent to permanent employment can be biased due to measurement error, usually present in the data used for analysis. In survey data, measurement error is the result of problems related to cognitive processes, social desirability, design and implementation (Groves, 2004; Sudman et al., 2004; Tourangeau et al., 2000). In register/administrative data, measurement error is the result of administrative delays, misregistration or faulty administrative procedures (Bakker and Daas, 2012; Oberski, 2017). This measurement error may be either random or systematic. Systematic error may come in surveys, e.g. due to dependent interviewing, and in registers due to administrative procedures (e.g. when firms report information retrospectively to the Employment Office). Pavlopoulos and Vermunt (2015) find, by employing a hidden Markov model, that random and systematic errors in the Labour Force Survey and the Dutch Employment Register of the Netherlands considerably bias our view for mobility from temporary to permanent employment in the Netherlands. These findings are confirmed by Pankowska et al. (2018, 2021).

In this paper, we build on the approach of Pavlopoulos and Vermunt (2015) and utilize a hidden Markov model to estimate and correct for measurement error in employment mobility in Italy. For this purpose, we use a unique dataset with linked information from the Labour Force Survey (LFS) and administrative data

(AD) provided by the Italian National Institute of Statistics (Istat). Specifically, we aim to determine the "true" size of temporary employment and the "true" transition rate from temporary to permanent employment in Italy. Our analysis spans the years 2017 to 2021. The modeling approach we employ, HMms, offers flexibility, allowing us to refrain from considering any of the data sources as error-free (i.e. "gold standard"). Instead, it enables us to estimate and correct measurement errors within each source. Furthermore, the use of multiple indicators for the phenomenon of interest, namely employment status, enables us to model realistic specifications for measurement errors. This encompasses both random and systematic errors, as discussed in Biemer (2011) and Vermunt (2010).

The rest of the paper is organized as follows. In Sections 2 and 3 we present the data and the HMm, respectively. In Section 4 we describe the results of the analysis and in Section 5 we discuss the conclusions of our research.

2. THE DATA

The Italian National Statistical Institute, Istat, relies on multiple data sources to gather information on employment. The primary source for official labour market statistics is the LFS, which is directly administered by Istat. Additionally, Istat gathers and processes data from various administrative sources as part of its routine operations to provide statistical information on various aspects of the labour market.

The Italian LFS follows the standards set by EU Regulation 2019/1700 of the European Parliament and the Council. The survey is conducted throughout the year and covers approximately 1.2% of the entire Italian population. Each year, it involves approximately 250,000 households and 600,000 individuals residing in Italy, distributed across roughly 1,400 Italian municipalities. The Italian LFS operates on a rotating quarterly scheme. Selected households are interviewed four times within a 15-month period. Each household is interviewed for two consecutive quarters, followed by a two-quarter break and another two consecutive survey quarters. Interviews are spread across all weeks of the quarter. Data collection utilizes a combination of computer-assisted personal interviews and telephone interviews. The information that is collected refers to the time of the interview. For further details on the LFS contents, methodologies and organization see Istat (2006). Italian AD pertinent to labour statistics are collected by social security and tax authorities. Social security authorities release different data sources depending on the type of employment contract, while tax authorities release different data sources depending on the tax deadline. It is important to note that the quality of information differs considerably between administrative sources. Therefore, these data go through different, source-specific editing and harmonization procedures (Baldi et al., 2018; Istat, 2015). Harmonized data is organized within an information system featuring an employer-employee linkage structure. This structure serves as the foundation for extracting information regarding the primary unit of analysis, the "worker". Specifically, for each individual, the primary regular job and its associated characteristics are determined according to the definitions outlined by the International Labour Office, guiding also the classification criteria used also by LFS. Additionally, the treatment of data varies according to the type of employment relationship, i.e. whether this relationship involves self-employment, paid employment, or work as a dependent contractor.

We use linked quarterly data from the LFS and AD for the period from 2017 to 2021. The linkage between the two datasets was conducted at the individual level utilizing an internal statistical code, which facilitates the integration of diverse data sources within the Italian National Statistical Institute. To cope with the growing volume of administrative datasets acquired for statistical analysis, Istat has developed the Integrated System of Microdata (SIM). This system centralizes functions such as data acquisition, storage, integration, and assessment of administrative data quality. The integration process within SIM entails linking and harmonizing microdata sourced from different external data sources in addition to surveys. Tailored integration strategies and algorithms are deployed depending on the available linking variables, ensuring consistent and high-quality data integration (Runci et al., 2018).

The above-mentioned process of linking the LFS and AD results in a total of 20 data points per individual. From the LFS, information from all survey waves in which these individuals participated is retained. The actual number of LFS observations in the data may be less than 4 in case of attrition or in cases where the LFS rotation scheme commenced before 2017 or ended after 2021. For the same set of individuals, quarterly information from the AD is retained, covering all quarters from January 2017 to December 2021. For each individual, there is a maximum of four observations from the LFS, whereas the AD dataset contains no missing data. We include in our data individuals aged 25 to 55 who participated at least once in the LFS within this period. By excluding young workers who frequently exhibit significant mobility and often combine employment alongside education, as well as older workers who are in the preparatory phase for retirement transition, we ensure a more homogeneous population. As our statistical model is computationally demanding, a 10% sample of units was randomly selected.

To ensure that overlap between the LFS and AD is retained for all time points, we stratified the sample by the month of the first LFS interview. This procedure resulted in a sample of 39,847 individuals. A random sample was necessary as the analysis is computationally infeasible with the full sample in any available software. A consequence of this is that the original sample weights are no longer valid; to include sampling weights, we would need to derive new ones, but this extends beyond the scope of this project. Further, as the sampling weights are related to demographic characteristics but are unrelated to the outcome variables of interest, using these weights would not affect the parameters of interest in the model.

From the LFS, we derive information on employment status, the type of employment contract, the number of hours worked during the reference week, and educational level. In addition, we have information on whether the interview was conducted by the individual or by a proxy[2]. From AD, we retain information on the employment status, the type of employment contract, age, gender, citizenship, municipality of residence, and labour income classified into various income classes.

The breakdown of the workforce based on their status in employment is fundamental in labour statistics, as comprehending transitions among different employment categories is essential for thoroughly understanding a country's labour market dynamics. The International Classification of Status in Employment (ICSE-18), established by the International Labour Organization (ILO), comprises 10 distinct categories of status in employment, with the aim of providing a detailed classification that reflects the various working relationships within the labour market. Recognizing the challenge presented by managing these 10 categories, both in terms of classification and statistical dimension, we aggregate them into three main groups: (1) employees with a permanent contract (PE), (2) employees with a temporary contract (FT), and (3) self-employed (SE), which encompasses employers, independent workers without employees, contributing family workers, and dependent contractors. Additionally, our classification includes those who are not employed (NE). The development of this simplified classification is relatively straightforward for LFS data, given that ICSE has been implemented in the LFS and builds upon the prevalent practice of using self-identification questions. Specifically, for the Italian LFS, we utilize questions related to the status

[2]LFS is a household survey. This means that every time one household member provides information for all (relevant) members of the household. This means that for some individuals, information is provided by a different member of the household, a proxy.

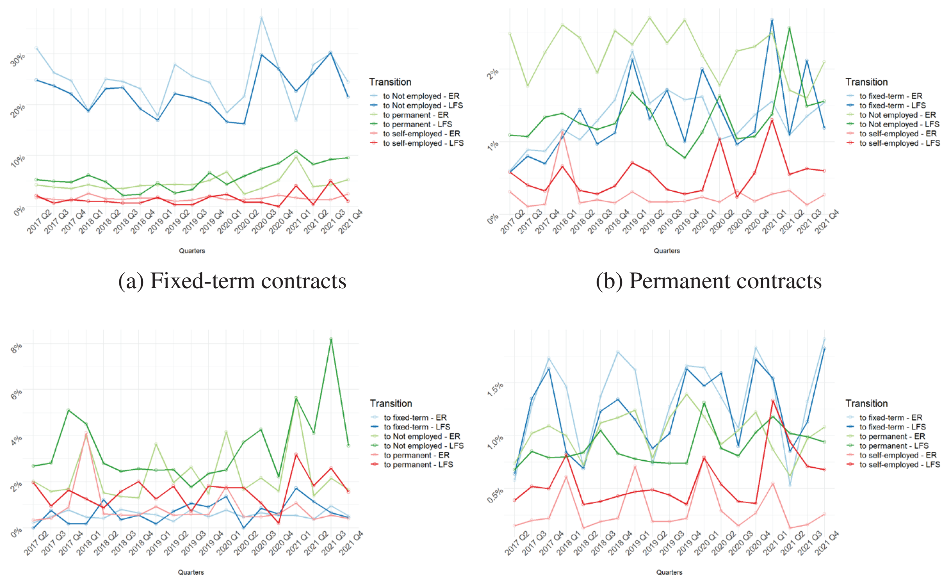
in employment in the main job and the permanency of the main job. However, deriving the status in employment from administrative data poses challenges and remains an ongoing subject of discussion within statistical offices. Additionally, the derivation process varies across European countries and is contingent upon the types of available administrative sources. In Italian AD, employees can be identified through social security data, with further categorization into permanent or temporary based on administrative contract types. Self-employed individuals are identified by integrating various sources such as social security data, fiscal data, and the business register. It is important to note that the administrative classification may not fully align with the self-reported classification in the LFS, as it is based on administrative concepts. Additional conceptual discrepancies between LFS and AD can be attributed to shortcomings in the data collection process. These include e.g. temporal misalignment of sources, particularly for occasional employment, a structural absence of administrative details regarding irregular work, discrepancies in the definition of employment across available sources. Tables 1 and 2 display the transition rates between the different employment catagories in adjacent quarters in the LFS and AD. The disparities between the two transition matrices are relatively minor.

Table 1: Observed transitions in LFS. Years 2017-2021

Employment category $t-1$	**Employment category t**			
	PE	**FT**	**SE**	**NE**
Permanent contract	0.962	0.012	0.006	0.020
Temporary contract	0.074	0.739	0.013	0.174
Self-employed	0.015	0.010	0.944	0.031
Not employed	0.019	0.063	0.013	0.906

Figures 1 shows the observed transition rates between different contract categories across adjacent quarters from 2017 to 2021. These transition rates are derived from LFS data and ER. In the case of LFS data, transitions are considered only when there are consecutive observations available. Specifically, Figure a) illustrates the transition from fixed-term contracts to other categories, while Figure b) shows transitions from permanent contracts. Similarly, Figure c) displays transitions from self-employment, and Figure d) presents transitions from non-employment.

These figures confirm the findings of Tables 1 and 2 that there are only minor



(a) Fixed-term contracts

(b) Permanent contracts

(c) Self-employer

(d) Not employed

Figure 1: Transition flows from type of contracts by quarter, year 2017-2021

Table 2: **Observed transitions in AD. Years 2017-2021**

Employment category $t-1$	Employment category t			
	PE	TE	SE	NE
Permanent contract	0.966	0.009	0.003	0.022
Temporary contract	0.078	0.717	0.017	0.187
Self-employed	0.011	0.012	0.956	0.022
Not employed	0.030	0.061	0.012	0.897

differences in flow patterns between the LFS and AD. However, notable variations emerge when comparing different quarters. The largest transition rates occur from fixed-term contracts to non-employment and permanent contracts. As far as time differences are concerned, there is an increasing trend in flows from temporary contracts to permanent contracts, coupled with a declining trend in the transition from temporary contracts to non-employment. This consistent pattern is evident in both LFS and AD data, suggesting that there is time dependence in transition probabilities.

Table 3: **Cross-classification of employment status, AD and LFS, frequencies and percentages, years 2017-2021.**

Employment category, AD	Employment category, LFS				
	PE	TE	SE	NE	Total
Permanent	41326	1993	1203	1290	45812
	41.1	*2.0*	*1.2*	*1.3*	*45.6*
Temporary	1217	5442	298	1268	8225
	1.2	*5.4*	*0.3*	*1.3*	*8.2*
Self-employed	748	349	11033	1095	13225
	0.7	*0.3*	*11.0*	*1.1*	*13.2*
Not employed	1942	1394	1876	28066	33278
	1.9	*1.4*	*1.9*	*27.9*	*33.1*
Total	45233	9178	14410	31719	100540
	45.0	*9.1*	*14.3*	*31.5*	*100.0*

Note: every cell reports the relevant absolute frequency and the joint probability in italics

Table 3 presents the cross-classification of employment status from LFS and AD data. The diagonal cells concern cases where the two data sources agree on the classification. In contrast, off-diagonal values represent discrepancies in classification and indicate potential classification errors in at least one of the data sources. As Table 3 illustrates, the two data sources do not align for approximately 14.6% of the total number of cases. Beyond random classification errors, these discrepancies arise from distinct reasons, as suggested by Varriale and Alfó (2023) in their analysis of employment status. Errors in AD are typically attributable to mis-specifications of statistical concepts. For example, AD lack information on irregular work, or it may encounter difficulties in correctly identifying the reference period of the information. On the other hand, errors in the LFS survey may arise from misclassification due to respondents providing incorrect answers or having an erroneous understanding of employment categories.

Table 4: Distribution of employment categories from LFS conditional on AD measurement, years 2017-2021.

Employment category, AD	Employment category, LFS				
	PE	TE	SE	NE	Total
Permanent contract	90.2	4.4	2.6	2.8	100
Temporary contract	14.8	66.2	3.6	15.4	100
Self-employed	5.7	2.6	83.4	8.3	100
Not employed	5.8	4.2	5.6	84.3	100
Total	45.0	9.1	14.3	31.5	100

Table 4 presents the same cross classification as Table 3 but reports the percentage distribution of employment status as measured by the LFS, conditional on the AD measurement. The percentages of observations where the classification of AD employment status agrees with the classification of LFS are shown on the diagonal. Off diagonal cells represent the percentages of observations where the AD employment status is classified differently in the LFS employment status. 90.2% of cases that are recorded as permanent contracts in AD are also classified as permanent contracts according to the LFS. The relevant percentages of classification agreement for the self-employed and not employed are also quite high (83.4% and 84.3%, respectively). Accordingly, the off-diagonal values for permanent contracts, the self-employed and those not employed in the AD are rather low (below 6%). The only exception concerns the cases that are recorded as self-employed in AD as 8.3% of them are classified as not employed in the LFS. The classification mismatches are observed for temporary contracts. In fact, only 66.2% of those recorded as having a temporary contract in AD are observed as having a temporary contract in the LFS, while about 14.8% are classified as having a permanent contract and 15.4% as not employed. Figure 2 provides a temporal perspective on the distribution of Table 4, highlighting the stability of this phenomenon over time.

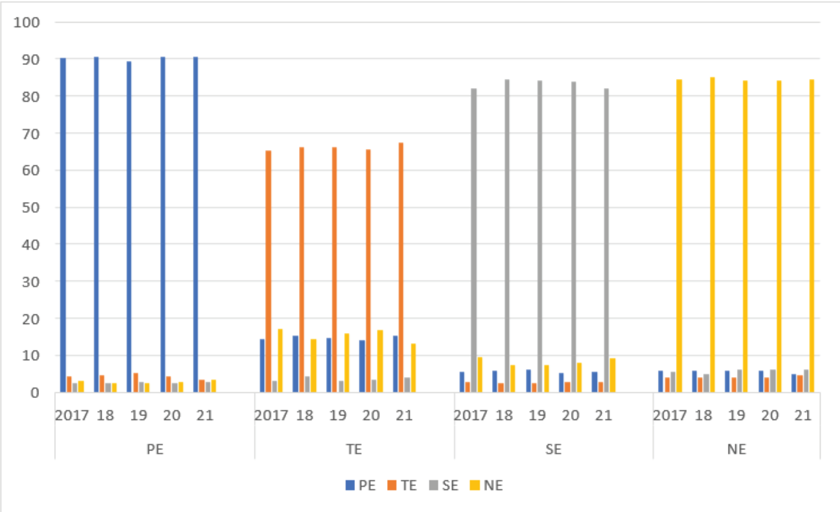


Figure 2: Distribution of employment categories by AD, LFS and year, percentages, years 2017-2021

3. THE HIDDEN MARKOV MODEL

Hidden Markov models (HMms) represent an extension of latent class analysis for longitudinal data. Recently, these models have been applied in the field of employment research to correct for measurement error in mobility between employment states (Bassi et al., 2000) and to estimate employment status in the Italian employment register (Filipponi et al., 2021). Lately, Pavlopoulos et al. (2023) used a mixed HMm to evaluate the effect of measurement error on employment trajectories using linked data from the LFS and the employment register of the Netherlands.

Let us denote X_{it} as the "true" (latent) target variable of the model in the employment category at time t for subject i, where $t = 0,\ldots,T$ and $i = 1,\ldots,N$.

X_{it} has 4 categories, x_t: permanent contract (PE), temporary contract (TE), self-employed (SE) and not employed (NE). We use quarterly data from 2017-2021 and therefore, t runs from 0 to $T = 19$.

The variables C_{it} and E_{it} represent the two measurements for the target variable: C_{it} denotes the observed contract type of person i at time point t according to the AD and E_{it} according to LFS. Also, C_{it} and E_{it} can take the same four values of the target variable. We denote these categories by c_t and e_t. The latent contract type X_{it} follows a first-order Markov process: the true contract at time point t, X_{it}, is only directly related to the previous time point at $t-1$, $X_{i(t-1)}$.

The probability of following a certain observed path of C_{it} and E_{it} over the entire period can be expressed as follows:

$$\begin{aligned} P(\mathbf{C}_i = \mathbf{c}_i, \mathbf{E}_i = \mathbf{e}_i) &= \sum_{x_0=1}^{4} \sum_{x_1=1}^{4} \dots \sum_{x_T=1}^{4} P(X_{i0} = x_0) \prod_{t=1}^{T} P(X_{it} = x_t | X_{i(t-1)} = x_{t-1}) \\ & \prod_{t=0}^{T} P(C_{it} = c_t | X_{it} = x_t) \prod_{t=0}^{T} P(E_{it} = e_t | X_{it} = x_t)^{\delta_{it}}. \end{aligned} \tag{1}$$

$P(X_{i0} = x_0)$ represent the initial state probabilities, $P(X_{it} = x_t | X_{i(t-1)} = x_{t-1})$ are the transition probabilities from $t-1$ to t, $P(C_{it} = c_t | X_{it} = x_t)$ are the measurement error probabilities for the AD, and $P(E_{it} = e_t | X_{it} = x_t)$ are the measurement error probabilities for the LFS. As we deal with categorical indicators, we will use the terms measurement and classification errors interchangeably. The indicator variable δ_{it} takes value 1 if the LFS information is available at time t and 0 otherwise. In the model, we assume the independence of the classification errors (ICE): conditional on the value of the latent variable, the observed states are independent of one another within and between time points.

As in Pavlopoulos et al. (2023), the model in Equation 1 has to be extended to deal with more realistic specifications of measurement error and modelling of longitudinal change in the phenomenon of interest (i.e. employment). One of these extensions is that transition probabilities are modelled as time-varying (conditional on t and t^2), meaning that between each pair of time points we allow the model to estimate different transitions, relaxing the assumption of stationarity of the process over time. Since the ICE assumption is unrealistic, we also introduce across-time correlation in the measurement error of both indicators. The joint probability of having a particular observed state path conditionally on the across-time systematic measurement error can be expressed as follows:

$$P(\mathbf{C}_i = \mathbf{c}_i, \mathbf{E_i} = \mathbf{e}_i) = \sum_{x_0=1}^{4}\sum_{x_1=1}^{4}\dots\sum_{x_T=1}^{4} P(X_{i0} = x_0) \tag{2}$$

$$\prod_{t=1}^{T} P(X_{it} = x_t | X_{i(t-1)} = x_{t-1}, t, t^2) \tag{3}$$

$$\prod_{t=0}^{T} P(C_{it} = c_t | X_{it} = x_t, X_{i(t-1)} = x_{t-1}, C_{i(t-1)} = c_{t-1}) \tag{4}$$

$$\prod_{t=0}^{T} P(E_{it} = e_t | X_{it} = x_t, X_{i(t-1)} = x_{t-1}, E_{i(t-1)} = e_{t-1})^{\delta_{it}}. \tag{5}$$

To take into account that the latent process may depend on time, we add the covariates t and t^2 in the logit modeling the transition probabilities (equation part 3). Furthermore, the error probabilities in both LFS and AD are allowed to depend on the lagged observed and lagged true contract type. Note that $X_{i(t-1)}$ and $C_{i(t-1)}$ can take on 4 values, which implies that there are 16 ($4*4$) different sets of error probabilities in the LFS and AD indicators, one for each possible combination of lagged observed and latent contract. Because it is not meaningful to estimate freely all these error probabilities, we used a more restricted model. Specifically, we defined a constraint logit model when the same error can be made between adjacent time points and otherwise is equal to 0. This model expresses that the likelihood of making a specific error depends on whether *the same error* was made at the previous time point.

Based on a sample of independent realizations from the distribution (equation part 5), estimates of the relevant model parameters can be obtained via maximum likelihood estimation in the Baum-Welch version (Baum et al., 1970). An extension of this algorithm is implemented in the syntax module of the software Latent GOLD v.5.1 (Vermunt and Magidson, 2016). The final model was chosen from various alternatives. Decisions have been taken based on known modelfit measures, i.e. the Bayesian Information Criteria (BIC), the Akaike Information Criteria (AIC) and its modification, as described in Vermunt and Magidson (2016). Missing data were treated as missing at random, handled with full information maximum likelihood. This represents a proper method for recovering model parameters, reducing bias related to the missing value, and retaining all available information (Enders, 2010).

4. RESULTS

In total, we tested 9 HMms. These are presented in Table 5, where we show the log-likelihood, the information criteria and the number of parameters.

In Models 1-3, we allowed for random measurement error. In more detail, in Model 1, we allowed for random measurement error in the LFS, in Model 2 in the AD, and in Model 3 in both data sources. Among the three models, Model 3 is the one presenting a better fit. Therefore, there is evidence that both sources contain at least random measurement error. In Model 4, we also allowed the LFS error to be determined by age and proxy interview. The variable on proxy interview takes the value 1 if another member of the household provided information in the survey on behalf of the reference person. The information criteria suggest that these 2 variables do not improve the model fit. Therefore, this particular error structure is not considered any further. In Models 5-9 of Table 5, we used log-linear restrictions to allow for error autocorrelation. In Models 5 and 6, we estimated an extra error coefficient for the cases where the error that was made in time point $t-1$ could be repeated in t in the LFS (Model 7) or in AD (Model 8). In fact, if an error is made in quarter $t-1$ and the individual remains in the same latent state for two consecutive quarters, it is possible to repeat the same error. In Models 7 and 8, we estimated an extra error coefficient for the cases where any classification error was made in time point $t-1$. In the final model (Model 9), we combined Models 5 and 6, and we estimated an extra error coefficient for the cases where the error made in time point $t-1$ could be repeated in t both in the LFS and in AD. Model fit measures indicate that Model 9 is to be preferred over all other models.

Figure 3 provides a graphical representation of the final model of Table 5, Model 9. Following the conventions, circles represent latent variables, and rectangles manifest variables; arrows connecting latent and/or manifest variables represent direct effects, which do not need to be linear.

The classification error in the two data sources is represented by the conditional probabilities $P(C_{it}=c_t|X_{it}=x_t, X_{i(t-1)}=x_{t-1}, C_{i(t-1)}=c_{t-1})$ (equation part (4)) for AD and by $P(E_{it}=e_t|X_{it}=x_t, X_{i(t-1)}=x_{t-1}, E_{i(t-1)}=e_{t-1})$ (equation part (5)) for LFS. Tables 6 and 7 show the classification error in AD and LFS according to Model 9 of Table 5, where separate error (logit) parameters were estimated for the repetition of the same error between quarters $t-1$ and t. In all other cases, the probability of having an error in quarter t depends only on the

Table 5: **HMm fit measures. LFS and AD data, years 2017-2021.**

Model	LL	BIC(LL)	AIC(LL)	AIC3(LL)	Npar
1	-310888	622443.5	621902.1	621965.1	63
2	-352625	705918.2	705376.8	705439.8	63
3	-294941	590549.2	590007.8	590070.8	63
4	-293821	588372.6	587779.7	587848.7	69
5	-285633	572059.9	571415.5	571490.5	75
6	-279607	560008.5	559364.1	559439.1	75
7	-289556	579906.6	579262.1	579337.1	75
8	-288984	578761.7	578117.2	578192.2	75
9	-276355	553631.5	552883.9	552970.9	87

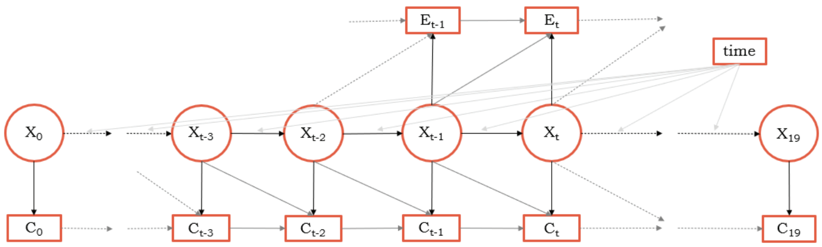


Figure 3: **Path diagram for the (hidden Markov) Model 9**

latent state in quarter t. In more detail, Table 6 presents the probability of being observed in a certain employment category in AD conditional on the true employment category in t, the true employment category in $t-1$, and the observed value in AD in $t-1$. Table 7 presents the probability of being observed in a certain employment category in LFS conditional on the true employment category in t, the true employment category in $t-1$, and the observed value in LFS in $t-1$. Since the number of probabilities estimated is too large, we only present in Tables 6 and 7, the conditional observed probabilities for cases where an error repetition is possible. These probabilities are shown in the shaded cells. For example, the probability of the shaded cell of the first row of Table 6 can be interpreted as follows: if an individual in $t-1$ was employed in reality with a temporary contract but was recorded in AD as having a permanent contract, and in t (s)he is again in reality employed with a temporary contract, then (s)he has a 0.842 probability

Table 6: **Selected conditional probabilities of classification error in AD, Model 9**

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
TE	**PE**	**TE**	0.842	0.128	0.001	0.029
SE	**PE**	**SE**	0.949	0.000	0.050	0.001
NE	**PE**	**NE**	0.737	0.002	0.001	0.259
PE	**TE**	**PE**	0.165	0.834	0.000	0.002
SE	**TE**	**SE**	0.004	0.506	0.485	0.006
NE	**TE**	**NE**	0.006	0.289	0.003	0.702
PE	**SE**	**PE**	0.078	0.000	0.921	0.001
TE	**SE**	**TE**	0.030	0.429	0.446	0.095
NE	**SE**	**NE**	0.001	0.001	0.877	0.121
PE	**NE**	**PE**	0.523	0.001	0.001	0.475
TE	**NE**	**TE**	0.035	0.507	0.005	0.453
SE	**NE**	**SE**	0.002	0.001	0.246	0.751

(see Table 6) of been again mistakenly recorded as having a permanent contract in AD. The full results of these tables are presented in the Appendix (Section 7).

For both sources, measurement errors are, in most cases, highly autocorrelated. This means that if an error is made in quarter $t-1$ and the individual remains in the same latent state in the following quarter, it is, in most cases, highly probable to repeat the same error in quarter t. For example, if a "truly" self-employed in quarter $t-1$ ($X_{i(t-1)} = SE$) was mistakenly registered in AD as having a permanent contract, and he/she is still "truly" self-employed in quarter t, then he/she has a 0.949 probability (see Table 6) of being wrongly registered again as having a permanent contract in quarter t. The same error structure is observed for almost all combinations of latent/observed contract at $t-1$ and t. An important exception is for individuals who are "really" not employed in quarter $t-1$ while are observed as having a temporary contract: the probability of having the same classification error in quarter t is much lower, as it equals 0.289 (see Table 6). In this situation, the probability of being correctly classified as not employed in t is 0.702 (see Table 6).

In LFS, we observe a different behaviour of classification errors than in AD (Tables 6 and 7). For classification errors with a "persisting" probability greater

Table 7: **Selected conditional probabilities of classification error in LFS, Model 9**

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t PE	TE	SE	NE
TE	**PE**	**TE**	0.673	0.250	0.008	0.07
SE	**PE**	**SE**	0.733	0.003	0.255	0.009
NE	**PE**	**NE**	0.778	0.005	0.007	0.21
PE	**TE**	**PE**	0.237	0.759	0.002	0.002
SE	**TE**	**SE**	0.004	0.823	0.168	0.006
NE	**TE**	**NE**	0.010	0.651	0.011	0.328
PE	**SE**	**PE**	0.287	0.002	0.708	0.003
TE	**SE**	**TE**	0.029	0.229	0.678	0.064
NE	**SE**	**NE**	0.006	0.004	0.806	0.184
PE	**NE**	**PE**	0.490	0.004	0.003	0.503
TE	**NE**	**TE**	0.049	0.389	0.012	0.550
SE	**NE**	**SE**	0.006	0.003	0.232	0.759

than 0.8 in AD, the probability of repeating the same classification error in LFS is slightly lower, such as:

$$
\begin{aligned}
&P(C_{it} = PE \quad | \quad X_{it} = TE, C_{i(t-1)} = PE, X_{i(t-1)} = TE)\\
&P(C_{it} = PE \quad | \quad X_{it} = SE, C_{i(t-1)} = PE, X_{i(t-1)} = SE)\\
&P(C_{it} = PE \quad | \quad X_{it} = NE, C_{i(t-1)} = PE, X_{i(t-1)} = NE)\\
&P(C_{it} = TE \quad | \quad X_{it} = PE, C_{i(t-1)} = TE, X_{i(t-1)} = PE).
\end{aligned}
$$

On the contrary, for classification errors with a “persisting” probability lower than 0.5 in AD, the LFS probability is higher. This is the case, for example, for:

$$
\begin{aligned}
&P(C_{it} = TE \quad | \quad X_{it} = NE, C_{i(t-1)} = TE, X_{i(t-1)} = NE)\\
&P(C_{it} = NE \quad | \quad X_{it} = PE, C_{i(t-1)} = NE, X_{i(t-1)} = PE)\\
&P(C_{it} = NE \quad | \quad X_{it} = TE, C_{i(t-1)} = NE, X_{i(t-1)} = TE).
\end{aligned}
$$

Tables 8 and 9 show the probability of being observed in an employment category in AD and LFS, given the “true” employment status. The correct classification probabilities are on the diagonals, while the off-diagonal cells represent

Table 8: **Classification error in AD, Model 9**

Latent employment category t	**Observed employment category** t			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.667	0.067	0.115	0.152
Temporary contract	0.360	0.398	0.056	0.187
Self-employed	0.403	0.041	0.321	0.235
Not employed	0.309	0.027	0.109	0.555

Table 9: **Classification error in LFS data, Model 9**

Latent employment category t	**Observed employment category** t			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.934	0.017	0.020	0.029
Temporary contract	0.118	0.651	0.032	0.199
Self-employed	0.063	0.021	0.856	0.060
Not employed	0.071	0.027	0.043	0.859

the estimated classification error probabilities. For all categories, the probabilities of correct classification are higher in LFS, and all the classification errors are larger for the AD indicator. The worst-performing category in LFS is temporary employment: as Table 9 shows, individuals who, in reality, are working with a temporary contract ($X_{it} = TE$) have a probability of 0.651 of being observed as being employed with a temporary contract and a probability of 0.199 of being registered as not employed. In AD, these probabilities are 0.398 and 0.187, respectively. In AD (Table 8), we also observe a high classification error for the self-employed. In fact, individuals who are really self-employed have a probability of 0.403 of being observed as working with a permanent contract, which is even higher than the probability of being observed as self-employed (0.321). In LFS (Table 9), the lowest error probabilities are observed for individuals who, in reality, are employed with a permanent contract ($X_{it} = PE$) and those who are not employed ($X_{it} = NE$).

Table 10 shows the distributions of latent ("true") employment state as well as the observed distributions form the LFS and the AD. The estimates are quite

Table 10: Employment categories in LFS, AD and predicted according to Model 9. Years 2017-2021

Employment category	LFS	AD	Latent
Permanent contract	44.99	45.24	43.80
Temporary contract	9.13	8.48	11.39
Self-employed	14.33	13.28	13.56
Not employed	31.55	33.00	31.25
Number of cases	100540	711184	711184

accurate as their standard error is equal to 0.038. The average posterior probability of being employed with a temporary contract is higher than the relevant observed probabilities from the LFS and AD. This finding holds over time, as shown in Table 11. These tables show the importance of accounting and controlling for measurement error when analysing labour statistics.

Transition probabilities between different employment states according to Model 9 are presented in Table 12. As found in Pavlopoulos and Vermunt (2015), these latent transition probabilities are quite different from the relevant observed probabilities in both the LFS and the AD (see Tables 1 and 2). Notably, all values on the main diagonal are higher for the latent transitions than for the observed transition probabilities in LFS and AD. Most importantly, latent transition probabilities from temporary employment to all other states are much lower than the relevant observed transition probabilities in both LFS and AD. For example, the 3-month latent transition probability from temporary to permanent employment is 3.7% (see Table 12), while the relevant observed transition probability is 7.4% in the LFS (see Table 1) and 7.8% in the AD (see table 2) . Actually, this finding illustrates that approximately half of the observed mobility from temporary to permanent employment is not real. Findings for transitions from non-employment to temporary employment are even more interesting. The 3-month latent transition probability from non-employment to temporary employment is just 2.1%, while the observed probability is 6.4% in the LFS and 6.1% in AD. This means that approximately two-thirds of the observed mobility from non-employment to temporary employment is not real.

Table 11: Proportion of temporary contract for the period between January 2017 and December 2021, predicted according to Model 9

t	LFS	AD	Latent
0	7.56	6.49	6.77
1	8.95	8.33	9.30
2	9.15	8.57	10.56
3	8.87	8.55	11.16
4	9.17	8.27	11.6
5	9.58	9.46	12.01
6	10.18	9.40	12.19
7	9.22	9.01	12.09
8	8.96	7.89	11.95
9	9.74	8.94	11.92
10	10.19	8.71	11.85
11	9.99	8.68	11.60
12	8.96	7.77	11.30
13	8.20	7.06	11.09
14	8.57	8.00	11.25
15	8.58	8.12	11.45
16	8.22	7.73	11.46
17	8.87	9.12	11.91
18	9.39	9.51	12.80
19	10.13	10.03	13.89

Table 12: Latent transitions according to Model 9. Years 2017-2021

Latent employment category $t-1$	Latent employment category t			
	PE	**TE**	**SE**	**NE**
Permanent contract	0.988	0.005	0.001	0.006
Temporary contract	0.037	0.939	0.002	0.022
Self-employed	0.001	0.005	0.991	0.003
Not employed	0.005	0.024	0.004	0.967

5. DISCUSSION AND CONCLUSIONS

This paper illustrated the value of using an HMm with multiple indicators in accounting for measurement error on the role of flexible employment in the life course. For our research, we used Italian individual-level data from different sources, namely the Labour Force Survey and administrative sources, for the period 2017-2021. The HMm takes into account the longitudinal structure of the data and allows us to evaluate different measurement error structures in the two data sources. In particular, we studied whether measurement errors in the two data sources can be correlated in time.

As suggested by the literature, our results show that both LFS and AD suffer from measurement error and cannot be used as a "golden standard". Furthermore, the probability of the same error recurring is different in the LFS and the AD. An in-depth analysis of these characteristics may help improve the sources' quality.

The model results can also be used to estimate the error-corrected distribution of employment states as well as the error-corrected transition rates between these states. Notably, in this paper, we found that temporary employment in Italy is much more common according to our HMm than observed in the LFS and AD. Probably the most striking finding of this study is that mobility from temporary to permanent employment is (according to HMm) half of what we observe in LFS or AD. Moreover, mobility from non-employment to employment concerns only transitions to temporary employment. But even then, this mobility is one-third of what we observe in LFS or AD. These results are of utmost importance for policymakers. They show that the Italian labour market is much less mobile than the data suggests.

To provide richer results, the structural part of the model can be extended by introducing covariates and by accounting for unobserved heterogeneity. The measurement part of the model can be enriched by testing more specifications of systematic error. In addition, sensitivity analyses to the model's assumptions can be carried out using Monte Carlo-type simulations.

The paper sheds new light on the role that errors in sources could play in the assessment of labour mobility, the real size of permanent jobs and the specificities of self-employment. Of course, a precise analysis of the causes of measurement errors in sources will be important in order to reduce their occurrence wherever possible. For example, some statistical units are not covered by administrative information, e.g. jobs with a salary below a certain threshold. It will be interesting to analyse whether this information can be obtained from other sources. Furthermore, some discrepancies between the LFS and the AD are due to temporal shifts in the recording of contracts. In the future, it might be useful to try to identify these contracts in order to harmonize their time reference and then evaluate their impact on the results of the HMM.

In the future it will also be important to analyse in detail the situations in which the LFS and the AD report different information. This analysis will make it possible to obtain useful information to try to correct situations where there are systematic differences between LFS and AD coding, e.g. due to definitional problems, which we are not aware of.

6. NOTES

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Any opinions and conclusions expressed are those of the authors and do not necessarily respect the views of the Italian National Institute of Statistics.

7. APPENDIX

Table 13: Selected conditional probabilities of classification error in AD, Model 9 (a)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	TE	SE	NE
PE	PE	PE	0.988	0.002	0.001	0.009
TE	PE	PE	0.988	0.002	0.001	0.009
SE	PE	PE	0.988	0.002	0.001	0.009
NE	PE	PE	0.988	0.002	0.001	0.009
PE	PE	TE	0.054	0.768	0.007	0.171
TE	PE	TE	0.842	0.128	0.001	0.029
SE	PE	TE	0.054	0.768	0.007	0.171
NE	PE	TE	0.054	0.768	0.007	0.171
PE	PE	SE	0.007	0.004	0.978	0.011
TE	PE	SE	0.007	0.004	0.978	0.011
SE	PE	SE	0.949	0.000	0.050	0.001
NE	PE	SE	0.007	0.004	0.978	0.011
PE	PE	NE	0.008	0.009	0.004	0.979
TE	PE	NE	0.008	0.009	0.004	0.979
SE	PE	NE	0.008	0.009	0.004	0.979
NE	PE	NE	0.737	0.002	0.001	0.259
PE	TE	PE	0.165	0.834	0.000	0.002
TE	TE	PE	0.988	0.002	0.001	0.009
SE	TE	PE	0.988	0.002	0.001	0.009
NE	TE	PE	0.988	0.002	0.001	0.009
PE	TE	TE	0.054	0.768	0.007	0.171
TE	TE	TE	0.054	0.768	0.007	0.171
SE	TE	TE	0.054	0.768	0.007	0.171
NE	TE	TE	0.054	0.768	0.007	0.171
PE	TE	SE	0.007	0.004	0.978	0.011
TE	TE	SE	0.007	0.004	0.978	0.011
SE	TE	SE	0.004	0.506	0.485	0.006
NE	TE	SE	0.007	0.004	0.978	0.011
PE	TE	NE	0.008	0.009	0.004	0.979
TE	TE	NE	0.008	0.009	0.004	0.979
SE	TE	NE	0.008	0.009	0.004	0.979
NE	TE	NE	0.006	0.289	0.003	0.702

Table 14: Selected conditional probabilities of classification error in AD, Model 9 (b)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**SE**	**PE**	0.078	0.000	0.921	0.001
TE	**SE**	**PE**	0.988	0.002	0.001	0.009
SE	**SE**	**PE**	0.988	0.002	0.001	0.009
NE	**SE**	**PE**	0.988	0.002	0.001	0.009
PE	**SE**	**TE**	0.054	0.768	0.007	0.171
TE	**SE**	**TE**	0.03	0.429	0.446	0.095
SE	**SE**	**TE**	0.054	0.768	0.007	0.171
NE	**SE**	**TE**	0.054	0.768	0.007	0.171
PE	**SE**	**SE**	0.007	0.004	0.978	0.011
TE	**SE**	**SE**	0.007	0.004	0.978	0.011
SE	**SE**	**SE**	0.007	0.004	0.978	0.011
NE	**SE**	**SE**	0.007	0.004	0.978	0.011
PE	**SE**	**NE**	0.008	0.009	0.004	0.979
TE	**SE**	**NE**	0.008	0.009	0.004	0.979
SE	**SE**	**NE**	0.008	0.009	0.004	0.979
NE	**SE**	**NE**	0.001	0.001	0.877	0.121
PE	**NE**	**PE**	0.523	0.001	0.001	0.475
TE	**NE**	**PE**	0.988	0.002	0.001	0.009
SE	**NE**	**PE**	0.988	0.002	0.001	0.009
NE	**NE**	**PE**	0.988	0.002	0.001	0.009
PE	**NE**	**TE**	0.054	0.768	0.007	0.171
TE	**NE**	**TE**	0.035	0.507	0.005	0.453
SE	**NE**	**TE**	0.054	0.768	0.007	0.171
NE	**NE**	**TE**	0.054	0.768	0.007	0.171
PE	**NE**	**SE**	0.007	0.004	0.978	0.011
TE	**NE**	**SE**	0.007	0.004	0.978	0.011
SE	**NE**	**SE**	0.002	0.001	0.246	0.751
NE	**NE**	**SE**	0.007	0.004	0.978	0.011
PE	**NE**	**NE**	0.008	0.009	0.004	0.979
TE	**NE**	**NE**	0.008	0.009	0.004	0.979
SE	**NE**	**NE**	0.008	0.009	0.004	0.979
NE	**NE**	**NE**	0.008	0.009	0.004	0.979

Table 15: Selected conditional probabilities of classification error in LFS, Model 9 (a)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**PE**	**PE**	0.977	0.008	0.007	0.009
TE	**PE**	**PE**	0.977	0.008	0.007	0.009
SE	**PE**	**PE**	0.977	0.008	0.007	0.009
NE	**PE**	**PE**	0.977	0.008	0.007	0.009
PE	**PE**	**TE**	0.088	0.696	0.021	0.195
TE	**PE**	**TE**	0.673	0.25	0.008	0.07
SE	**PE**	**TE**	0.088	0.696	0.021	0.195
NE	**PE**	**TE**	0.088	0.696	0.021	0.195
PE	**PE**	**SE**	0.022	0.012	0.934	0.031
TE	**PE**	**SE**	0.022	0.012	0.934	0.031
SE	**PE**	**SE**	0.733	0.003	0.255	0.009
NE	**PE**	**SE**	0.022	0.012	0.934	0.031
PE	**PE**	**NE**	0.028	0.021	0.031	0.921
TE	**PE**	**NE**	0.028	0.021	0.031	0.921
SE	**PE**	**NE**	0.028	0.021	0.031	0.921
NE	**PE**	**NE**	0.778	0.005	0.007	0.21
PE	**TE**	**PE**	0.237	0.759	0.002	0.002
TE	**TE**	**PE**	0.977	0.008	0.007	0.009
SE	**TE**	**PE**	0.977	0.008	0.007	0.009
NE	**TE**	**PE**	0.977	0.008	0.007	0.009
PE	**TE**	**TE**	0.088	0.696	0.021	0.195
TE	**TE**	**TE**	0.088	0.696	0.021	0.195
SE	**TE**	**TE**	0.088	0.696	0.021	0.195
NE	**TE**	**TE**	0.088	0.696	0.021	0.195
PE	**TE**	**SE**	0.022	0.012	0.934	0.031
TE	**TE**	**SE**	0.022	0.012	0.934	0.031
SE	**TE**	**SE**	0.004	0.823	0.168	0.006
NE	**TE**	**SE**	0.022	0.012	0.934	0.031
PE	**TE**	**NE**	0.028	0.021	0.031	0.921
TE	**TE**	**NE**	0.028	0.021	0.031	0.921
SE	**TE**	**NE**	0.028	0.021	0.031	0.921
NE	**TE**	**NE**	0.010	0.651	0.011	0.328

Table 16: Selected conditional probabilities of classification error in LFS, Model 9 (b)

Latent empl. cat. $t-1$	Observed empl. cat. $t-1$	Latent empl. cat. t	Observed employment category t			
			PE	**TE**	**SE**	**NE**
PE	**SE**	**PE**	0.287	0.002	0.708	0.003
TE	**SE**	**PE**	0.977	0.008	0.007	0.009
SE	**SE**	**PE**	0.977	0.008	0.007	0.009
NE	**SE**	**PE**	0.977	0.008	0.007	0.009
PE	**SE**	**TE**	0.088	0.696	0.021	0.195
TE	**SE**	**TE**	0.029	0.229	0.678	0.064
SE	**SE**	**TE**	0.088	0.696	0.021	0.195
NE	**SE**	**TE**	0.088	0.696	0.021	0.195
PE	**SE**	**SE**	0.022	0.012	0.934	0.031
TE	**SE**	**SE**	0.022	0.012	0.934	0.031
SE	**SE**	**SE**	0.022	0.012	0.934	0.031
NE	**SE**	**SE**	0.022	0.012	0.934	0.031
PE	**SE**	**NE**	0.028	0.021	0.031	0.921
TE	**SE**	**NE**	0.028	0.021	0.031	0.921
SE	**SE**	**NE**	0.028	0.021	0.031	0.921
NE	**SE**	**NE**	0.006	0.004	0.806	0.184
PE	**NE**	**PE**	0.490	0.004	0.003	0.503
TE	**NE**	**PE**	0.977	0.008	0.007	0.009
SE	**NE**	**PE**	0.977	0.008	0.007	0.009
NE	**NE**	**PE**	0.977	0.008	0.007	0.009
PE	**NE**	**TE**	0.088	0.696	0.021	0.195
TE	**NE**	**TE**	0.049	0.389	0.012	0.55
SE	**NE**	**TE**	0.088	0.696	0.021	0.195
NE	**NE**	**TE**	0.088	0.696	0.021	0.195
PE	**NE**	**SE**	0.022	0.012	0.934	0.031
TE	**NE**	**SE**	0.022	0.012	0.934	0.031
SE	**NE**	**SE**	0.006	0.003	0.232	0.759
NE	**NE**	**SE**	0.022	0.012	0.934	0.031
PE	**NE**	**NE**	0.028	0.021	0.031	0.921
TE	**NE**	**NE**	0.028	0.021	0.031	0.921
SE	**NE**	**NE**	0.028	0.021	0.031	0.921
NE	**NE**	**NE**	0.028	0.021	0.031	0.921

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THE OPEN MANAGER APPROACH: MANAGEMENT STYLES AND CHARACTERISTICS

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***Abstract**. This study focuses on the manager's professional work. In particular, the main focus is to detect the possible new approach in managerial behaviour able to define this professional figure and a first idea of an 'open manager'. Kindness, empathy, and sharing of objectives are characteristics that could revolutionize the figure of the leader. A transformation that moves away from the old models in favour of a horizontal and participatory organization of power. For this reason, the successful leader can interact with the human dimension of employees and guide them towards a shared goal.*

***Keywords**: Labour market, Open manager, Rasch analysis*

1. INTRODUCTION

The great wave of globalization has produced a profound impact on organizations from many points of view. A change is as essential as ever in order to enable those who lead a business today to cope with the difficulties, rethinking management in entirely new ways and logics. Moreover, with the new century, one of the most interesting strategic perspectives in strategic and industrial development research has been developing, namely the phenomenon called Open Innovation (Chesbrough H., 2003). Indeed, it has been realized that it is possible to have an open way of developing innovation through connections and collaborations with research institutes, professionals and companies outside the organization, in order to create a mutually beneficial alliance.

In recent years, it is also applied to the enterprise in its complexity, to relationships with employees and to the way management interprets its role (Bruttini, 2014). Thus, open organization is understood as a complex of practices that can be traced back to organizational models, systems of teamwork functioning and managerial behaviours that seek to provide a concrete response to the need for companies to quickly adapt and evolve, based on market needs (customers and tensions with competitors). It is a fragmented, multifaceted,

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largely unstructured movement (Laloux et al., 2015) that identifies itself in various "buzz words" such as agility, teal and openness precisely.

The market demands that the managerial class requires new skills that until a few years ago were the prerogative of the personal relationships field. To make the most of human capital, organizations have had to adopt approaches involving concepts such as sharing, empathy, and kindness, which should pave the way for the separation between the top and bottom of the corporate pyramid. This change in mentality places human capital, especially at the executive level, as a source of attractiveness and, above all, as a creator of value for companies.

This open manager figure is not clearly defined; thus, it resembles a latent variable in statistical terms. Consequently, we analysed data collected by a 'Confindustria' survey to outline emerging attitudes and behaviors.

As the survey is composed of a set of ordered items, we consider the most proper statistic methodology is Partial Credit Model (PCM, Wright & Masters, 1982).

The paper is structured as follows: after the introduction, a second section is dedicated to data description; the methodology applied to answer the research objectives is described in the third section, whereas a fourth section shows the results, verified by fit statistics.

2. DATA DESCRIPTION

Data was collected by 'Fondirigenti and Confindustria' in 2020 through a structured questionnaire distributed to a non-probabilistic sample of Italian companies and filled in by a managerial internal figure. The total number of managers who responded was 383.

The sample has been extracted from the AIDA (Integrated Automation Customs Excise) database and MISE (Ministry of Economic Development) dataset by filtering the companies presenting open manager skills.

The questionnaire was made up of two sections:

• in the first section there were questions concerning the context in which the firms operate, such as economic sector, dimension, geographical area, as well as the main social demographic characteristics of managers, such as gender, age, education level.

• in the second section there were thirty items describing the managers' business behaviours and attitudes, useful for defining the concept of 'openness' characterizing the figure of the open manager. So, in the second section of the questionnaire, there are 30 different statements. Items were formulated as a 4-point Likert scale, with responses ranging from 1 to 4 where 1 stands for "totally disagree" and 4 stands for "totally agree". For more details see Appendix 1.

The main size characteristics of the companies involved are summarized in the following table.

Table 1: Turnover and employees of companies

Turnover	Employees			
	10-49	50-149	150-249	>250
2-10 mln	76	14	1	2
11-25 mln	11	53	7	5
25-50 mln	3	34	26	9
>50 mln	3	6	22	111

3. METHODOLOGY

The Rasch models can be applied wherever ordered data is obtained with the intention of measuring a latent trait.

The Rasch dichotomous model specifies the probability, P, that person *n* of ability B_n succeeds on item *i* of difficulty D_i. "Success" means "exhibits more of our intended latent variable. "Failure" means "exhibiting less of our intended variable".

So, we must score the observations in accordance with this intention, no matter what values are assigned to the observation during data collection. P is the probability of success, and 1- P is the probability of failure. Success or failure must always happen, as when we add their probabilities they must sum to 1. In other words, success is a score of "1", and failure is a score of "0" on an item. Then the Rasch dichotomous model specifies the probability P_{ni1}, that the person n of ability B_n scores 1 on item i of difficulty D_i while with P_{ni0} the probability of scoring 0. For ordered data "success" means "more of what we are looking for" "failure" means "less of what we are looking for". The difference between "success" and "failure" is qualitative.

The ordering of these different qualities is indicated by scoring them "1" and "0". "1" "indicates more of the latent variable". "0" "indicates less of the latent variable". In the Rasch model, the probability of a correct answer is modelled as a logistic function of the difference between the person and item parameter.

In performance assessment and attitude surveys we encounter rating scales, such as the first "none, some, plenty, and all" and the second "strongly disagree, disagree, agree, and strongly agree" (Rasch, 1993, Bond et al., 2020).

When the items are polytomous, there are several Rasch measurement models for rating scale**s** which we will call "polytomous models". Among these we chose Rasch-Masters partial credit model because we expect the partial-correctness structure to be different for different items.

The partial credit model specifies that the probability, P_{nij} of person *n* of ability measure B_n is observed in category *j* of a rating scale specific to item *i* of the difficulty measure D_i as opposed to the probability $P_{ni(j-1)}$ of being observed in category *(j-1)* of a rating scale with categories *j=0,m*

$$log_e\left(P_{nij}/P_{ni(j-1)}\right) = B_n - D_{ij} \tag{1}$$

It is usually more straightforward to conceptualize and communicate the item difficulty separately from the rating scale structure, so we will use the $D_i - F_{ij}$ notation.

$$log_e\left(P_{nij}/P_{ni(j-1)}\right) = B_n - D_i - F_{ij} \tag{2}$$

The rating scale structure F_{ij} is specific to item *i.* We can think about the item difficulty and then impose the rating scale structure on it, $D_i - F_{ij}$, or we can think about the combination, D_{ij}. Mathematically speaking they are the same thing. The F_{ij} are the points of equal probability of adjacent categories (thresholds). The item difficulty D_i is the point where the top and bottom categories are equally probable.

This means that partial credit items with the same number of categories, and the same total raw "marginal" score, taken by the same people, can have different difficulties if the pattern of category usage differs between the items.

3.1 RASCH DIAGNOSTICS

In literature there are different tools to evaluate the goodness of fit of the model to observed data. Among the most used diagnostics there are reliability statistics which report the reproducibility of the measures. The concept of reliability is defined by the ratio we now express as:

$$\text{Reliability} = \text{True Variance}/\text{Observed Variance} \tag{3}$$

Kuder-Richardson KR-20, Cronbach Alpha, etc. are all estimates of this ratio.

They are estimates because we can't know the "true" variance, as we must infer it in some way. In Rasch models, we also have an item reliability which measures how reproducible the item difficulty order is for the set of items and for the sample of units.

To evaluate the goodness of fit of each item, we apply OUTFIT (Outlier-sensitive fit statistic) and INFIT (Inlier-pattern-sensitive fit statistic, or more technically, Information-weighted fit statistic). OUTFIT is a conventional Pearson chi-square fit statistic divided by its degrees of freedom. This is more sensitive to unexpected remarks by people on items that are relatively very easy or very difficult for them. The INFIT mean-square is the information-weighted average of the squared residuals. This is more sensitive to unexpected patterns of people's observations of items that are roughly targeted at them (and vice versa).

4. RESULTS

In this paragraph we aim to measure the latent trait of openness of Italian managers through the PCM carried out by software Winstep (Linacre, 2004) and library eRm of meta-language R (https://www.R-project.org).

The results of the analysis are summarized and reported in Table 2.

Table 2: Summary statistics

SUMMARY OF 383 MEASURED PERSONS

					INFIT		OUTFIT	
	RAW SCORE	COUNT	MEASURE	MODEL ERROR	MNSQ	ZSTD	MNSQ	ZSTD
MEAN	99.4	30	1.46	0.3	1.03	0.1	0.99	-0.1
S.D.	7.2	0	0.62	0.04	0.37	1.3	0.35	1.2
MAX.	117	30	3.88	0.6	2.68	4.4	2.93	4.6
MIN.	73	30	-0.3	0.23	0.32	-3.6	0.31	-3.6

CRONBACH ALPHA (KR-20) PERSON RAW SCORE RELIABILITY = 0.76

SUMMARY OF 30 MEASURED ITEMS

					INFIT		OUTFIT	
	RAW SCORE	COUNT	MEASURE	MODEL ERROR	MNSQ	ZSTD	MNSQ	ZSTD
MEAN	1269	383	0	0.08	1	0.1	0.99	0
S.D.	119.3	0	0.59	0.01	0.12	1.6	0.15	1.9
MAX.	1457	383	1.42	0.12	1.33	4.6	1.33	4.6
MIN.	958	383	-0.99	0.06	0.88	-1.6	0.81	-2.2

ITEM RELIABILITY= 0.98

Infit and outfit statistics make it possible to evaluate the goodness of fit of the items and the response patterns of managers to the model. Considering the average of non-standardized infits and outfits, 1 and 0.99 for item fit and 1.03 and 0.99 for person fit, these statistics do not show values outside the range proposed by Linacre [0.6; 1.4], consequently the data shows a good fit. On the other hand, as far as the reliability index is concerned, the closer the index is to 1, the more reproducible the test used, i.e. it produces the same results in repeated tests, the analysis has an item reliability of 0.9. As far as the person reliability of 0.76 is concerned, it must be considered that 0.8 is the threshold for strong decision, testifying to the good reproducibility characteristics of the instrument.

The parameters of the model characterize the competence of the interviewees and the difficulty of the items as collocations on a continuous latent variable.

The proposed representation of the results allows us to have at the same time the measure of the behaviours considered prevalent in the definition of open manager, and of the adherence of the managers interviewed to these behaviours. In the variable map (Fig.1), the lower box shows the 30 items, marked with labels ranging from "1" to "30", arranged in ascending order according to their position on the latent dimension; The solid dots indicate the difficulty of each item, while the circles indicate the positions of the thresholds. The top panel (Person Parameter Distribution), on the other hand, shows the distribution of managers' skill from the least skilled (from the left) to the most skilled (right). From the graph you can immediately see how on average the skill of the subjects is greater than the difficulty of the items; therefore, the attitude of the managers interviewed to adopt open attitudes in their professional activity is very high. However, there are items that are difficult even for highly skilled managers, and if you look closer, you can see that these are reverse items.

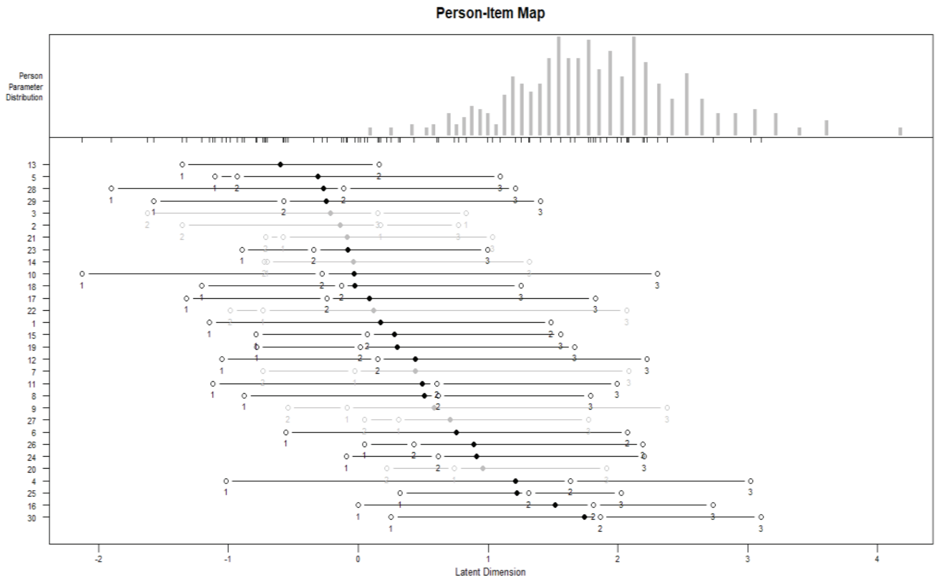

Figure 1: Person and item parameters (items 1-30)

Still referring to the person-item map, it is easy to see how some items (3, 2, 21, 14, 22, 7, 9, 27, 20) have been assigned the colour grey; this is to emphasize that these are items with unordered thresholds, i.e. with one or more redundant categories. There are several diagnostics for the analysis of the individual items.

By way of example, the measures of the thresholds between categories and curves are calculated. The graphs of the characteristic curves of the items (CCIs) represents on the axis of measurement of the latent dimension, the probability curves of the categories and the locations of the thresholds that are located at the points of intersection of the curves. By reporting the characteristic curves of the items with unordered thresholds (Figure 2) it is possible to deduce that for these items, Category 1 is not used like the other categories, since it is never the most likely. In this case it is said that that category does not emerge; Therefore, it should be grouped into one of the two adjacent categories.

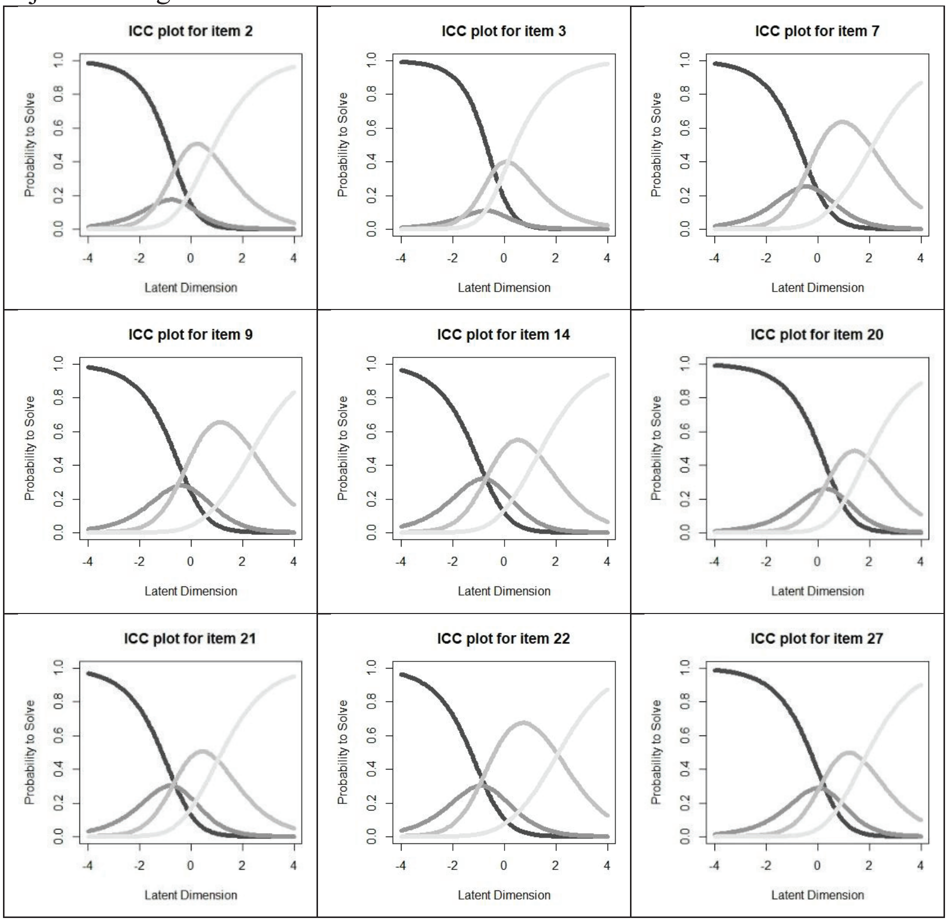

Figure 2: Category probabilities - item 2, 3, 7, 9, 14, 20, 21, 22 e 27.

The graphs of the characteristic curves of the items (CCIs), in which the probability curves of the categories and the locations of the thresholds that are located at the points of intersection of the curves are represented on the axis of measurement of the latent dimension. By reporting the characteristic curves of the items with unordered thresholds (Figure 2) it is possible to deduce that for these items, the answer "Partially disagree" is not used like the other categories, since it is never the most likely. In this case, the category "Partially disagree" is said not to emerge; Therefore, it should be grouped into one of the two adjacent categories.

The results obtained from the Rasch analysis were used to test some hypotheses about the characteristics of managers already identified in Bruttini et al. (2022).

The Rasch analysis results developed the ones of the analysis by Bruttini et al. (2022) on the same dataset. The authors defined six different groups of managers by applying a different methodological approach. In fact, data analysis carried out by Bruttini et al. (2022) applied the agglomerative hierarchical cluster procedure with Ward's method allowing to define six different groups of managers, according to their openness level; instead, our analysis measures the openness level of each manager. Moreover, we tried to identify the different areas of competencies where it is possible to improve the open attitude for every group of managers identified by Bruttini et al. (2022) starting from the measure of item difficulty weighted with scores in the groups (Figure 3).

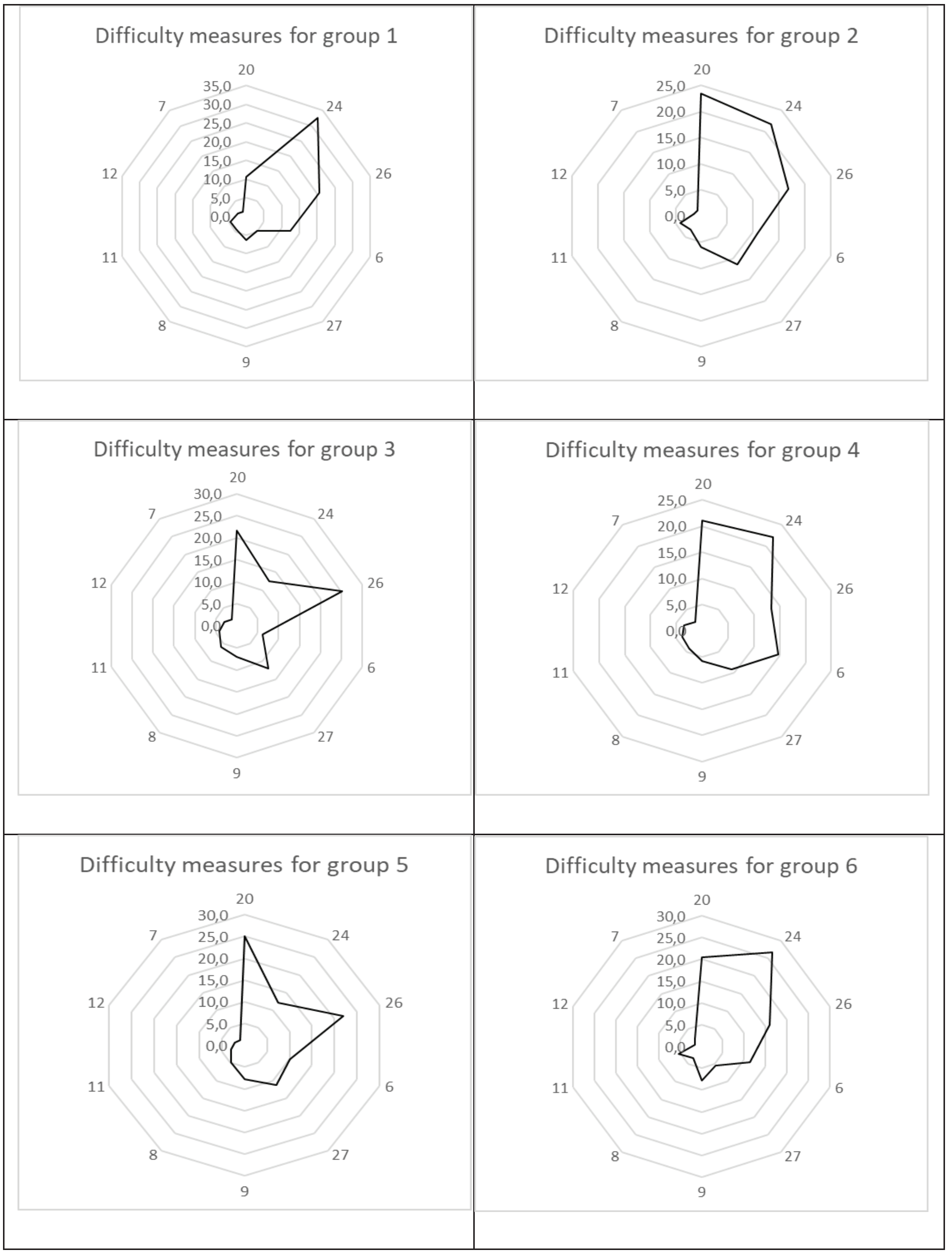

Figure 3: Difficulty measures for groups

5. CONCLUSIONS AND FURTHER EXTENSIONS

The results of the analysis can be used to predict the likelihood of the manager to be open in his activities, based on the pattern of responses to the questionnaire. The guidelines for the managerial staff in the selection phase are useful for a fruitful collaboration or calibrating training interventions on certain aspects of possible improvement of the company management. Using the data collected in the first part of the questionnaire, it is possible to compare groups of subjects with different personal characteristics using differential item functioning (Camminatiello et al., 2014).

The study lends itself to further analysis and application in management and training. For example, once the measurement tool has been also validated by reviewing some critical aspects of the questionnaire, it could be useful to anchor the parameters of the items, to compare personal measures with subsequent surveys and to evaluate the effectiveness of training interventions.

Finally, diagnostic tools of consolidated statistical methods show that the adopted questionnaire is an effective tool for evaluating manager openness. The questionnaire can be improved by changing the number of categories of items.

Appendix 1- Items of the questionnaire

1	I can accept continuous changes in the business world
2	It’s important to admit your mistakes with collaborators
3	I seize all the opportunities that come my way to learn new things
4	I prefer collaborators who can assert themselves over others
5	It’s always appropriate to give visibility opportunities to collaborators
6	In a professional context, I act very quickly
7	In decision-making, I question my own opinions
8	Business today requires the utmost consistency
9	In the face of any critical task, I always know someone who can help me
10	I always manage to develop relationships with interlocutors who can impact the business
11	I encourage collaborators to adopt indicators so they can self-monitor
12	I expect my collaborators to be able to change autonomously
13	For the team to function, it’s always necessary to clarify priorities
14	I’m always careful to identify potential areas of business growth

15	I dedicate regular meetings to review the situation, analyse experiences and learn from mistakes made
16	It's not always appropriate to prioritise the career development of your collaborators
17	In the face of people's resistance, I act to overcome it
18	In every context I go to, I immediately try to create relationships
19	I feel affectionate towards my colleagues in this company
20	Sometimes I personally take care of writing the procedures that regulate activities
21	You have to trust collaborators so they can manage critical situations in the way they find most effective
22	I can create a climate that pushes every team member to innovate
23	I never lose confidence and the idea of being able to do it
24	I often imagine doing things that others consider impossible
25	In decision-making, it's not always necessary to evaluate the impact on others
26	In my work, I know I have to convince even my enemies
27	I feel completely identified with my company
28	To do my job, I need to gain a deep understanding of technologies and organisational processes
29	It's important to create work contexts where people can self-manage
30	It's not always appropriate for subordinates to contribute to important decision-making

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THE IMPACT OF SHORT-TERM EXOGENOUS SHOCKS ON LOCAL LABOUR MARKETS:

AN EMPIRICAL EXERCISE FOR ITALY (2006-2021)

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Abstract

In this paper, we investigate the spatial regime and the short-term changes following both activity and unemployment rates. These rates are taken as proxies of the functioning of 610 local job markets in Italy as reflected in the homogeneous districts delineated by Italian National Statistical Institute and called 'Sistemi Locali del Lavoro'. The time horizon spans over a relatively long time period (2006-2021) encompassing the long economic crisis (2007-2013), a period of economic stagnation or moderate recovery (2014-2019) and the Covid-19 time (2020-2021). Based on a purely exploratory approach, the empirical analysis has identified the socioeconomic factors more effectively characterizing the job market dynamics.

Keywords*: Unemployment rate, Territorial disparities, Economic downturns, Southern Europe.*

1. INTRODUCTION

In recent times, global processes of change underpinning socio-demographic phenomena have been the subject of intense debates in regional science and applied economics (Martin and Sunley, 2015). Changes impacting local job

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markets have demonstrated to consolidate employment disparities over space and affect the distribution of wealth and income across countries and regions (Rodríguez-Pose, 2013). These issues, indeed, revealed as crucial topics in understanding business cycles, industrial restructuring, and spatial relocation of advanced services (Goldblum and Wong, 2000; Winarso and Firman, 2002; Wilkinson and Pickett, 2009). Moreover, regional disparities in employment levels still represent a challenging concern for policy makers in many advanced economies (Veneri, 2010). Following Tselios et al., (2012), 'entrenched and persistent spatial disparities' cannot be neglected for their impacts on both the 'economic geography thinking', and the economic history of countries all over the world. In European Union, the 2007 crisis has affected almost all countries, impairing peripheral regions especially in the Mediterranean basin (Salvati et al., 2017). The main consequences of the great recession in Europe have been reflected in rising spatial disparities, income inequality, and a more polarized distribution of businesses (Pérez, 2010; Piketty, 2014; Ren, 2015). Specifically, as discussed in Cuadrado-Roura et al. (2016), spatial disparities and structural differences in economic production can result in different (often place-specific) reactions to external shocks, possibly undermining the existence of monetary unions. Scholars provided evidence on the role of regional inequalities in political instability and armed conflicts (e.g. Ezcurra and Rios, 2019; Lessmann et al., 2015; Østby et al., 2009). Among others, Stiglitz (2016) raised ethical and economic arguments in favour of a more equitable world, providing the same opportunities to people regardless to their nationality. According to Rodríguez-Pose (2018), persistent inequalities have drawn increased attention for their potential role in the rise of the 'places that don't matter' in the post-Trump and post-Brexit era. In the long-term, the outcomes of divergent regional economic trajectories affected the election results, thus leading to the emergence of a 'geography of discontent' (Dijkstra et al., 2019; Los et al., 2017; Rodríguez-Pose, 2020). Based on these premises, the focus on the main mechanisms of local development and socioeconomic change should be of crucial relevance when dealing with studies in regional science and economic geography (Storper, 2011). Recessions have widely impacted social cohesion, either directly or indirectly, causing poverty, unemployment, social inequities, and conflicts over physical resources (Bathelt and Boggs, 2003). Specifically, social segregation and polarization in wealthy and depressed areas (Massari et al., 2009), as well as other intricate, complex and multifaceted local transformations, significantly affected economic development (Whelan et al., 2015). Nevertheless, crisis-driven socioeconomic changes should provide renewed prospects for local development (e.g. Storper, 1997). Recent studies on the relationship between economic cycles and regional disparities in both income and employment levels have delineated some internal and external factors shaping local systems (UNDP, 2022). Processes of spatial agglomeration and dispersion have been also monitored for their intrinsic role in socioeconomic development (Belussi and Gottardi, 2000; Patacchini, 2008; Salvati, 2016; Lan et al., 2019). The notion of 'spatially balanced growth' has thus become a 'political hymn' in emerging markets as well as in certain advanced economies (Garcia, 2010; Schneider et al., 2010; Rodríguez-Pose, 2012). Local development results from broad, uniform industrialization processes across time, and from spatially balanced population dynamics and economic activity growth and change (Storper, 2011; Kruse et al., 2023). Moreover, the basic mechanisms generating socioeconomic disparities at different spatial scales have been investigated in earlier studies assessing the intrinsic relationship between structure and performance of labour markets (Urso et al., 2019). The economic performance of local job markets can be addressed using refined, and spatially disaggregated, statistical indicators (Mauro, 2004). Among others, change in employment levels over time was assumed as an implicit measure of resistance to economic crises and post-shock recovery (Martin, 2016). Based on these premises, regional science has undertaken enriched explanations of the evolving geography of income and wealth (e.g. Gonzales, 2011). In this perspective, the experience of affluent but largely divided countries in Europe can help elucidating the mechanisms underlying the spatial division of labour (Haggett, 2001). Southern European countries display several, and possibly kaleidoscopic, examples of such dynamics (Dunford, 2008). For instance, Italy has recently shown a regionally unequal development embedded in its historical roots (Dunford, 2002; Daniele and Malanima, 2007; Salvati and Carlucci, 2016). In particular, the economic systems of Northern and Central Italy benefited from agglomeration economies, a high rate of innovation, and improved accessibility (Glaeser et al., 1992; Henderson et al., 1995; Boschma and Iammarino, 2009). These regions play a significant role in the economic structure of the country thanks to a strong relationship between agglomeration and vertical integration, a mix of competition and collaboration, trust relationships over formal contracts, and the effectiveness of existing production systems (Dow et al., 2012; Cainelli and Iacobucci, 2012; Tridico, 2015). According to Salvati et al. (2017), local unemployment statistics in Italy highlight such kind of spatial divides. Nevertheless, before the 2007 recession, a labour market reform, codified in the 'Legge Biagi' (Italian Law no. 30/2003) and in the 'Pacchetto Treu' (Italian Law no. 196/1997), brought about changes to the highly regulated Italian labour market and increased local competition (Mauro, 2004). Further studies on regional job markets in Italy highlight potential losses of relevant opportunities in territorial interactions, for a more effective coordination of innovation policies within each of the two major innovation (sub)systems of Northern and Southern Italy (Gonzales, 2011). Within this context, a quantitative examination of administrative borders carried out for historical and demographic reasons relies on a critical analysis of their functionality for innovation (Leydesdorff and Leydesdorff, 2021). Based on these premises, tour study investigates whether the 2007 recession (and, more recently, the Covid-19 shock) has shaped new geographies of local job markets, reflected in short-term unemployment dynamics at the level of local labour market areas (LLMAs) in Italy. Assuming the indicators of labour market performances (e.g. unemployment rates) as a valid proxy of the functioning of regional job markets (Salvati et al., 2017), results of the analysis provided indirect evidence on the effect of institutional changes on the spatially varying performance of local labour markets to short-term economic shocks (Boschma and Iammarino, 2009). The study identified basic factors influencing the spatio-temporal dynamics of job markets in Italy, by compiling a database with socioeconomic and territorial indicators (e.g. Zambon et al., 2019). Spatial divides in the functioning of local job markets were investigated focusing on changes in unemployment rate between 2006 and 2021, a time period reflecting one of the most severe unemployment crisis since 1977 (Urso et al., 2019).

The article is organized as follows. Section 2 is devoted to the methodology adopted in the study. Results are shown in Section 3 and further discussed in some problematic aspects (Section 4). Section 5 finally drew some conclusions after having briefly discussed the most relevant findings of the study in a regional science perspective.

2. METHODOLOGY

2.1 STUDY AREA

Italy is a Mediterranean country covering 302,070 km^2 of which 23% are lowlands, 42% uplands and 35% mountainous areas (Dunford, 2002). Spatial divides in Italy exert a wide-range impact on metropolitan structures and socioeconomic processes at different geographical scales (Bonavero et al., 1999). The economic gap between Northern-Central and Southern regions (including the two main islands, Sicily and Sardinia) reflects the long-established industry-service dichotomy still existing in this country (Daniele and Malanima, 2007). Northern Italy includes the large, accessible flat area corresponding with the Po basin valley (Dunford, 2008). The mountain range of the Apennines separates Northern Italy from Central Italy, a polarized area in urban and rural districts and a diversified economic structure centred on small-scale manufacturing, tourism, and high-quality agricultural productions (Patacchini, 2008). Finally, Southern Italy is a marginal and economically disadvantaged context with younger population, and a productive structure centred on low-income agriculture and traditional tertiary activities (e.g. commerce) concentrated in the main cities (Mauro, 2004).

2.2 THE ISSUE OF DATA AVAILABILITY

Over the last few decades, official statistics have become more important in economies and societies, and their position as the most reliable source of information has been increasingly put to the challenge (European Commission, 2020). The increasing demand for statistical data is in line with the recommendation of the 2030 agenda on Sustainable Development - demanding hundreds of indicators designed in coherence with the fundamental principles of official statistics and human rights (United Nations, 2015). A fundamental part of official statistics is grounded on labour statistics (Patacchini, 2008). These statistics describe both micro- and macro-dimensions and all the economic actors (individuals, enterprises and public sector), detailing the labour market framework as well as its socioeconomic context (Salvati et al., 2017). Labour statistics enable the design of policy measures dealing with the main issues connected to job markets (Wulfgramm, 2014). The specific reference to International Standards of labour statistics allows the international comparability of data and methodological coherence, proved to be crucial in the collection of reliable data (Istat, 2015). Shifting to the local dimension, the design of indicators to monitor progress under geographical and territorial aspects relies, especially for European countries, on census and administrative registers (Magrini et al., 2015). Unfortunately, gathering this kind of data is very time- and money-consuming, which makes it difficult to create a comprehensive database for precise estimations (Chieppa and Panizon, 2001). The Europe 2020 strategy addresses the issue of enhancing the territorial dimension in official statistics (Franconi et al., 2017). In the European cohesion policy, the chosen geography reflects the inherent structure of the socioeconomic reality (Schneider et al., 2010). Within this context, local labour market areas (LLMAs) are defined as functional regions whose main distinctive trait is self-containment (Smart, 1974), stemming from the aggregation of elementary geographical units (municipalities, economic districts, census tracks) on the basis of their level of spatial interaction measured by commuting to workflows (Ichim et al., 2017).

2.3. DATA DESCRIPTION AND BACKGROUND VARIABLES

To explore the local job market in periods of economic expansion and recession, variables covering socio-demographic and economic aspects were tested for their impact on labour dynamics in Italy (Salvati et al., 2017). Contextual indicators fixed over time (namely, structural characteristics of each area) were calculated at the local district scale (Table 1) from a database of official statistics released by Istat. The spatial scale adopted in this study relies on 610 LLMAs identified by Istat on the base of commuting data collected in the 2011 National Census of Population. LLMAs have extensively been used as relevant spatial units to analyse regional development of Italy (Pellegrini, 2002), specialization in the primary sector (Giusti and Grassini, 2007), and the impact of land quality on economic development (Salvati et al., 2014). The unemployment rate (DIS) has been adopted as a key indicator of job market performances (Salvati et al., 2017). The annual value of the three indicators has been retrieved, for the time period between 2006 and 2021, in the Istat labour force survey. Participation rate (ATT) is the ratio of total workforce (employed and unemployed) to the total resident population in working age (> 14 years and < 74 years) at any year considered. Employment rate (OCC) is calculated as the percentage of workers in total resident population. Unemployment rate indicates the ratio of population actively searching for a job to the total workforce.

Table 1: Variables adopted in this study to assess the background socioeconomic context of local labour markets in Italy, using economic districts as the elementary spatial unit

Acron.	Variable	Source
Dis	Unemployment rate, gross	ISTAT, Labour Force survey
Occ	Employment rate, gross	
Att	Participation rate, gross	
Sud	A dummy indicating Southern districts in Italy (= 1)	ISTAT, Territorial statistics
Tur	Tourism specialized districts (dummy	ISTAT, statistics on LLSs
Mad	Made-in-Italy districts (dummy = 1)	
Dit	Industrial district (dummy = 1)	
Agr	Agricultural district (dummy = 1)	
Des	Non-specialized district (dummy = 1)	
Urb	Urban district (dummy = 1)	
Com	Number of municipalities per district	ISTAT, territorial statistics
Are	Area (km^2) of local district	ISTAT, population register and census

As highlighted in Table 1, the spatial dimension has been preliminary introduced through a dummy variable (SUD) that classifies the Southern Italian districts with the numerical code '1' ('0' otherwise). Six dummy variables, when equal to 1, have qualified the specialisation of each district under scrutiny (Salvati and Carlucci, 2016). Namely, TUR indicates tourism-specialised districts, MAD delineates the specialization in 'Made in Italy' industries, DIT and AGR respectively define the industrial and agricultural districts, while DES refers to unspecialised districts. Finally, URB qualifies the urban districts. Data on the logarithm of the number of municipalities per district, COM, have been retrieved from the Istat database of territorial statistics dated 2022, while the information on the extension of the area of each district (km^2) was retrieved from Istat population register and decadal censuses (Patacchini, 2008). Given the complexity of Italian local contexts, the selected indicators provide an overview of socio-demographic characteristics and the economic structure typical of each LLMAs (Salvati et al., 2017).

2.4. STATISTICAL ANALYSIS

An exploratory framework based on descriptive and multivariate statistics was adopted in this study (Zambon et al., 2017). This approach allows evaluating the role of variables supposed to be directly or indirectly correlated with job market dynamics, emphasising latent conditions of regional disparities in Italy (Masini et al., 2019). Similar approaches have been used in earlier studies focusing on the resilience of local economic systems (Salvati et al., 2017). The selected indicators have been earlier adopted in several regional studies (e.g. Soares et al., 2003; Del Campo et al., 2008; Salvati et al., 2014), especially focusing on unemployment differentials (Faini et al., 1997; Cracolici et al., 2007; Dallara and Rizzi, 2012). Changes in labour market performances between northern and southern Italian regions have been quantified considering the intrinsic variability of unemployment rates over time (Dunford, 2008). The methodological part, therefore, develops in two different steps. The first phase consists of a comparative analysis of descriptive statistics (Table 2). A principal component analysis was later run with the aim at refining and summarizing the results of descriptive statistics, better contextualizing the outcomes to the local socioeconomic background through the use of specific indicators for each district and year. Components with eigenvalues > 1 were retained and analysed using graphs plotting loadings (rows: years) and scores (columns: descriptive statistics) within the same factorial plane. A minimum spanning tree algorithm was used to delineate the most representative time sequence within the observation years. In a second exercise, a PCA was run on a data matrix whose rows report the values of the twelve indicators of Table 1 for each of the 610 Italian labour systems at the beginning (2006) and the end (2021) of the study period.

Table 1: Descriptive statistics adopted in this study

Variable	Gross unemployment rate for each of the 610 local labour system in Italy
Minimum	Minimum value of the spatial series at each year
Maximum	Maximum value of the spatial series at each year
Mean	Average value of the variable at each year
Normalized	Normalized range [(max-min]/mean] of the variable at each year
Median	Median value of the variable at each year
Median/mean	Median-to-mean ratio of the variable at each year
75pc-	Interquartile range over the median ratio of the variable at each
Kurtosis	Kurtosis of the variable's distribution at each year
Asymmetry	Asymmetry of the variable's distribution at each year
Coeff.Variation	Coefficient of variation of the variable at each year
North/South	Ratio between the values of the variable in northern and southern districts
North-South	Diff. between the aggregated values of the variable in northern and southern districts at each year

Components with eigenvalues > 1 were retained and analysed using graphs plotting loadings (rows: background indicators) and scores (columns: local labour systems) within the same factorial plane.

3. RESULTS

3.1. THE STATISTICAL DISTRIBUTION OF LOCAL UNEMPLOYMENT RATES IN ITALY

Gross unemployment rate includes all job types, e.g. both fixed-term employment and precarious work, but, as a crude rate, it does not consider the peculiarities of each job type. Considering the detailed spatial scale adopted, quarterly statistics are not accessible at the local level, and thus the analysis was based on annual data. Table 3 reports selected descriptive statistics of gross unemployment rate computed for each of the 610 local labour systems in Italy between 2006 and 2021. The time period under scrutiny corresponds with the end of the most recent economic expansion (basically, 2006), being connected to the sovereign debt crisis, particularly in Mediterranean countries. It also covered the Lehmann Brothers crisis' time, since 2007. In that year, Italy reached its highest peak of employment and occupation and its lowest rate of unemployment (around 6%). This scenario is fostered by labour market flexibility measures and the creation of temporary job seats, affecting both male and female employment. Since 2007, gross unemployment rates increased because of the economic crisis culminated in the beginning of the 2010s. These years featured notable political instability in Greece, an increasing public debt in Spain, and debt overexposure in Portugal. Within the Italian context, the relevant political instability has been also complemented by a differential of 500 points between Italian bond and German Bunds. This circumstance caused a further increase in unemployment rates, reaching the maximum value in 2013, being recovered partially in the subsequent years.

Table 1: Descriptive statistics adopted in this study

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Minimum	1.4	1.4	1.8	2.2	2.5	2.8	3.8	3.6	3.1	2.5	2.4	1.9	1.5	1.2	1.0	1.2
Maximum	23.6	23.2	25.2	27.2	29.6	29.4	34.1	37.1	38.8	38.1	39.2	38.5	37.9	36.0	34.0	34.2
Mean	7.3	6.6	7.4	8.4	9.1	9.1	11.8	13.5	14.1	13.2	13.0	12.5	11.6	11.0	10.2	10.2
Normalized range	3.0	3.3	3.2	3.0	3.0	2.9	2.6	2.5	2.5	2.7	2.8	2.9	3.1	3.2	3.2	3.2
Median	6.0	5.4	5.9	7.4	8.0	7.9	10.1	11.4	11.9	11.1	10.6	10.7	9.7	9.1	8.6	8.3
Median/ mean	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.8	0.8	0.8	0.8	0.9	0.8	0.8	0.8	0.8
75pc 5pc/ median	1.1	1.1	1.2	0.8	0.8	0.8	0.8	0.9	0.9	0.9	1.0	1.0	1.0	1.0	0.9	1.0
Kurtosis	-0.2	0.1	-0.3	0.3	0.3	0.1	-0.3	-0.6	-0.6	-0.4	-0.4	-0.5	-0.2	-0.1	0.3	0.1
Asymmetry	0.8	0.8	0.7	0.8	0.8	0.7	0.7	0.6	0.6	0.7	0.7	0.6	0.7	0.8	0.9	0.8
C.V.	57.4	57.9	55.9	45.7	45.1	45.2	44.0	44.3	45.1	46.4	48.6	50.4	52.9	53.9	52.4	51.9
N/S	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4
N-S	-6.9	-6.2	-6.9	-6.2	-6.6	-6.8	-8.8	-10.1	-10.8	-10.3	-10.6	-10.7	-10.3	-9.8	-8.5	-8.5

Assuming an asymmetric distribution of local unemployment rates over Italian districts throughout the time series, the coefficient of variation (CV) of that rate – a measure of the spatial dispersion evaluating both unemployment growth and decrease – was stably around 44%. CV values highlighted a reduced (geographical) variability during crisis, further increased during non-crisis times, when dynamic territories started to recovery, more or less rapidly, while pushing disadvantaged districts in a sort of downward economic spiral.

Therefore, considering the unemployment rate, while crisis led to a flattened and homogenized trend across the entire national territory, economic expansion led to relevant spatial inequalities. Lastly, Covid-19, a transitory shock in comparison to the great crisis (2007-2012), altered the unemployment rate in a lighter way. The negative effects observed in 2020, were overcame in 2021. Indeed, the established public subsidies to economic activities, even causing an additional debt exposure, preserved most of economic sectors, allowing the consolidation of higher employment rates in 2022 and 2023, as the preliminary estimations from Istat may delineate.

3.2. EXPLORING CHANGES IN THE DISTRIBUTION OF UNEMPLOYMENT RATES IN LOCAL LABOUR MARKETS

Figure 1 displays the results of a principal component analysis describing the latent relationships between the descriptive statistics of gross unemployment rates in the 610 Italian local labour market systems. The PCA biplot associated the descriptive statistics in Table 2 with each observation year between 2006 and 2021. Observation tears with similarities in descriptive statistics have been connected in the plot through a minimum spanning tree delineating the most representative development trajectory. PCA results identified two years of economic expansion, 2006 and 2007, and a break point in 2008-2009. Hence, the pre-crisis 2008 spatial path was different from the subsequent one (2009-2021). This spatial pattern has not changed in relation to Covid-19, since its contingent nature does not appear to have exerted any important (medium-term or long-term) effect on unemployment rates in Italy.

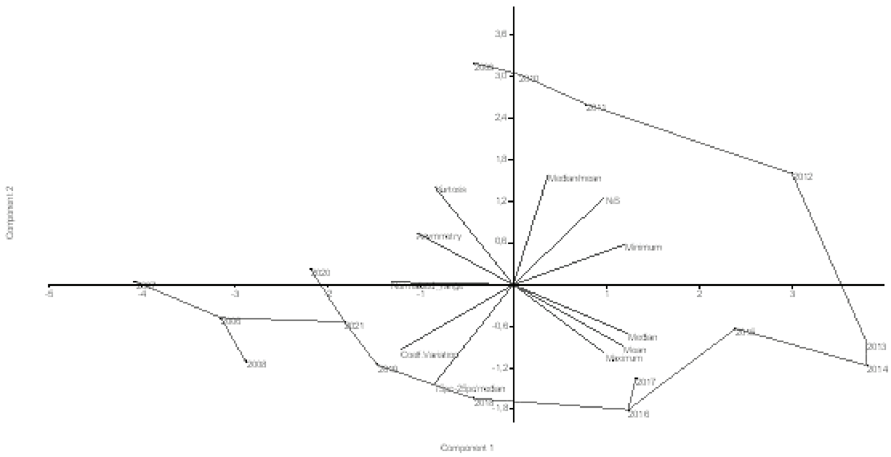

Figure 1: Biplot of a principal component analysis delineating the latent relationships between descriptive statistics of gross unemployment rates in local labour systems of Italy; results of a minimum spanning tree algorithm connect observation years and thus indicate the most representative development trajectory over time.

The latent relationship between descriptive statistics of gross unemployment rates in local labour systems of Italy, 2006-2021, were also reflected in the ordination plot illustrated in Figure 1, with explained variance 56.4% and 25.5% respectively extracted by Component 1 and 2. The minimum spanning tree path indicated the highest similarity among component scores, reflecting heterogeneity in unemployment distribution over economic districts of Italy. The observed symmetric distribution of the ratio between median and mean values, which is distinctive of 2010 and 2011, was also illustrated in the plot. Unemployment divides in Northern and Southern Italy reached the widest level during this time period. In recognition of the mechanism of economic convergence, persistent growth in northern regions and even stronger employment increases in southern regions have helped to reduce the north-south divide during economic expansion. Northern districts resisted to unemployment, while the disparities deepened, and southern areas started diverging even more throughout the crisis. The variability coefficient between more dynamic locations in the north and less dynamic areas in the south rose sharply and reached a peak in 2019. The biplot also showed how the ratio between the 75th and 25th percentiles and the median unemployment rate approached the greatest values in 2018. Between 2015 and 2017, extreme values, especially the maximum unemployment rate in local districts, but also mean and median values, followed the same pattern. Due to the sluggish recovery, the normalized range, a measure of regional variability, reached its peak later on, in 2020–2021. The economic crisis brought on by the Covid-19 pandemics had exerted only a temporary impact on gross unemployment rates. However, the pandemic's effects were especially severe in some regions, possibly fuelling both asymmetry and kurtosis of unemployment rates. Particularly, Covid-19 had a significant influence on specific northern sectors (Bergamo and Brescia, in Lombardy, and, to some extent, Verona and Padua in Veneto). Other regions were affected significantly less from Covid-19, such as Liguria and Central Italy. From an economic perspective, southern regions have not been as significantly impacted. As a result, going beyond the north-south gradient, unemployment rates in places with high employment and a dynamic economy have been moderately altered. Within this context, subsidies failed to fully compensate for the jobs that were only partially subsidized.

3.3. JOB MARKET PERFORMANCES AND THE BACKGROUND LOCAL CONTEXT

A second PCA exercise was run with the aim at revealing the latent relationship between local job markets' performances and the related background context, extracting, on the first two axes, about the 50% of the total variability. Figure 2 shows the biplot of two principal components in the context of the 610 Italian local labour systems respectively in 2006 (a) and 2021 (b). Italian labour market systems are indicated with dots; Component 1 is associated with activity rate and unemployment rate; Component 2 is related to urban regions and population density of local systems. The two components explain respectively 36.1% and 13.2% of the total variance in the case of Figure 2(a), 37.3% and 13.8% in the case of Figure 2(b). In general, urban districts (URB) were associated with denser local areas but there is no clear path connecting urban regions and unemployment, since it also depends on the geographical location of each district. Component 2 (URB) had strong upward connections to urban regions and denser local systems. However, tourism-specialized systems were ordered in opposition with urban system along Component 2. The activity rate and the unemployment rate were, on the contrary, associated with Component 1, although in the opposite direction. In particular, on the negative side of Component 1, unemployment rate (DIS) was associated with the dummy variable delineating southern districts. The unemployment rate increased in Southern Italy and decreased in Central and Northern Italy. Increases in activity rates corresponded to decreases in unemployment rates and vice-versa. In particular, when there are more clearly defined economic dynamics, there was an increase in labour market participation and a moderate decline of unemployment. This demonstrates the accuracy of statistics delineating the intrinsic functioning of regional economic systems. Industrial districts (DIT), as having high levels of specialization and business density, primarily found in Northern and Central Italy, performed higher rates of activity and employment. Similar to this path, manufacture (MAD) districts developed occasionally in Southern Italy, and more regularly in Central and Northern Italy. Regardless of the geographical gradient, unemployment rose in the South, following similar paths also in Northern and Central Italy as far as unspecialized districts (DES) are concerned, which are economic spaces dominated by basic services including constructions, public administration, wholesale, and retail trade. The number of municipalities (COM) in each local system and the share of agriculture (AGR) in total product seem to have no impact on these dynamics, when focusing on the dualism between wealthy and disadvantaged areas.

The PCA biplot also highlights the importance of areal size and geographical characterisation of employment and unemployment within the Italian context, with a clear connection with both the north-south gradient and the productive specialisation gradient. By the end of 2021, the economy was in a situation of moderate economic expansion, as shown in Figure 2(b). The variance extracted from the first two components increased slightly in respect with 2006. The geographical gradient was still significantly associated with Axis 1, illustrating the dichotomy between southern regions with lower employment rates and northern regions with a consistent participation in the labour market. The second axis showed a high loading for urban (and functionally mono-centric) areas. Nevertheless, this axis also depicted unspecialised systems. This context finally emphasized a high degree of spatial variability, the dualism between wealthy and disadvantaged areas, respectively with specialized and less specialized activities, and the lack of a clear trend in employment and unemployment. Through the lens of unemployment dynamics, Italy's development reflected a complex path over time and, due to the short-term crisis of Covid-19, the dualism of participation and unemployment rates seems to persist as partly decoupled from economic specialization. In other words, dynamic and less dynamic areas do not follow exquisitely economic dynamics, while adapting to non-linear paths with a strong spatial heterogeneity and localism.

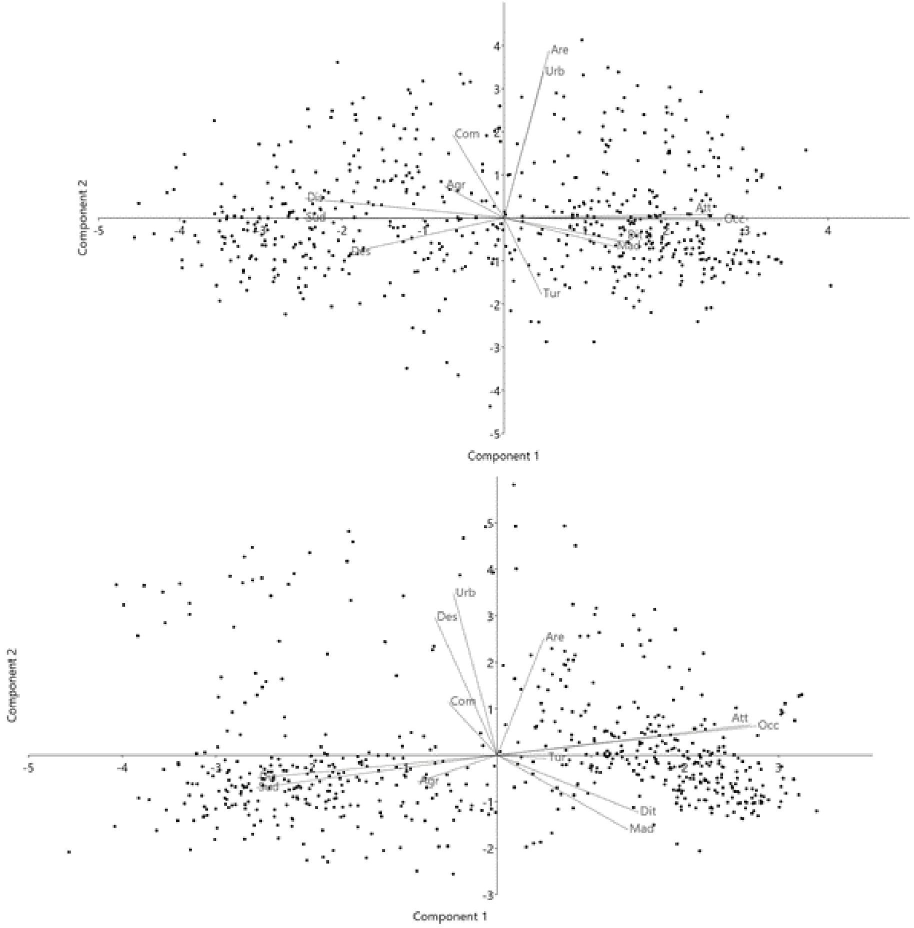

Figure 2. Principal Component Analysis of unemployment rates in local labour systems of Italy in (a) 2006 and (b) 2021.

4. DISCUSSION

In a pre-crisis stage, there were two ‘Italies’ running at different economic speed, as far as unemployment levels are concerned (Dunford, 2008). Dynamic territories coexisted with less dynamic ones, with higher unemployment rates (Dunford, 2002). The labour force was unequally distributed throughout the country following sharp urban-rural differentials, or industrial-service gaps against agricultural specialisation (Patacchini, 2008). The 2007 crisis triggered a sort of homogenization between dynamic and less dynamic territories, possibly narrowing urban-rural differentials (Mauro, 2004). Within this context, the most dynamic areas have experienced a higher burden rather than the remaining districts in the country (Salvati et al., 2017). After the crisis, namely between 2015 and 2019, the economic system was unable to recovery at the pre-crisis level. In the last decade, the market share of the industrial sector, and especially the ‘Made in Italy’ businesses, experienced important losses compared with the past (Urso et al., 2019). Conversely, the potential of tertiary sectors, as tourism and related sectors, increased (Cainelli and Iacobucci, 2012). The present work provides an original view to interpret territorial inequalities in the Italian job market and, more in general, in other European countries where territorial disparities in employment and unemployment strongly affect economic dynamics, as in Spain and England (Gonzales, 2011). In these economies, social and economic factors sharpening territorial differences over time are recognized to be of particular relevance when designing policies for their containment (Salvati et al., 2018; Masini et al., 2019; Zambon et al., 2019). These measures should, in turn, warrant more efficiency in the dynamics of regional and local economic systems (e.g. Chelleri et al., 2015). Territorial disparities have been based on the efficiency of labour markets, according to indicators of participation, employment, and unemployment (Salvati et al., 2017). These measures are easily retrieved by official statistics, by means of internationally standardized methodologies, and are available to sectoral experts and political stakeholders (e.g. Carlucci et al., 2018). The adoption of labour systems as a spatial analysis’ unit is not new (Chieppa and Panizon, 2001). Nevertheless, recent Istat data releases offered a comprehensive overview of the employment/unemployment scenarios in Italy (Franconi et al., 2017). The investigated time window allows a comparative analysis of economic growth, culminated in the 2008 crisis, and the effects of the great crisis on the labour market regulated by two reforms, namely ‘Pacchetto Treu’ and ‘Legge Biagi’, examining as well the recent crisis brought by Covid-19 (Cracolici et al., 2007). In general, the observation time adopted in our study reflects the impact of multiple economic downturns (Frenken et al., 2007). Such impacts have been evaluated not only on the level of unemployment but also on the intensity of territorial disparities (Glaeser et al., 2014). Our analysis discriminated ‘leading’ regions, i.e. those who improved their development path, from the ‘laggers’, i.e. regions with poor market performances and recognized to be more sensitive to short-term shocks (Martin and Sunley, 2015). The novelty of this work lies in the identification of the effects of short- and medium-term shocks (Boeri and Jimeno, 2016), highlighting in turn the importance of carrying on the continuous production and release of historical series of labour market indicators with a strong spatial detail (Patacchini, 2008). The empirical results of this study also remark the significance of a comparative and contextual analysis of multiple indicators, such as participation, unemployment, and employment rates jointly, to delineate the functioning of local labour markets (Veneri, 2010). An accurate collection of data from official statistics under a geo-economic perspective facilitates the design of a set of contextual variables (Bande and Karanassou, 2013), further integrated with newly available indicators retrieved from different administrative (economic/demographic) archives (Salvati, 2016). The elaboration of new indicators to implement comparative analysis should be advisable at the European level (Ciommi et al., 2019). Unfortunately, the geography of labour systems is codified in a very partial and fragmented way in Europe, and it is explicitly adopted only in some national statistical systems (Chieppa and Panizon, 2001). The English system widely benefited from the geography of local labour systems (Cainelli and Iacobucci, 2012). In this system, indeed, travel to work areas represented, for several years, an accurate analysis’ unit (Battaglia and Iraldo, 2011). Research trials have also been performed in Spain and France, among others (Franconi et al., 2017). The relevance to have some more detailed spatial units for statistical reporting than provinces/prefectures (NUTS-3 level), being in turn less detailed than municipalities (NUTS-5 level), is a relevant challenge in official statistics (Ciccone, 2002). This is because, if on the one side there is an increasing demand for official statistics, on the other side the demand of municipal-scale indicators cannot be satisfied in the case of sampling surveys (Cracolici et al., 2007), where the sample size is not enough to disaggregate the most relevant variables to geographically detailed reporting scales.

5. CONCLUSIONS

Local labour systems represent a valid compromise between different disaggregation levels, since they provide an enough articulated geographical picture of territorial disparities at an appropriate level of spatial disaggregation. The adoption of local labour systems represents a basic step for future developments of homogeneous official statistics in Europe. At a country level, more efforts should be placed in the elaboration of geo-referenced statistics to reach and cover wider administrative domains. Scholars, practitioners and policymakers would benefit from this implementation program, since they need continuous information for socioeconomic policies responding (and possibly adapting) to the heterogeneous characteristics of each target area.

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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

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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. Ingrandire scritte grafici riprodurre a colori

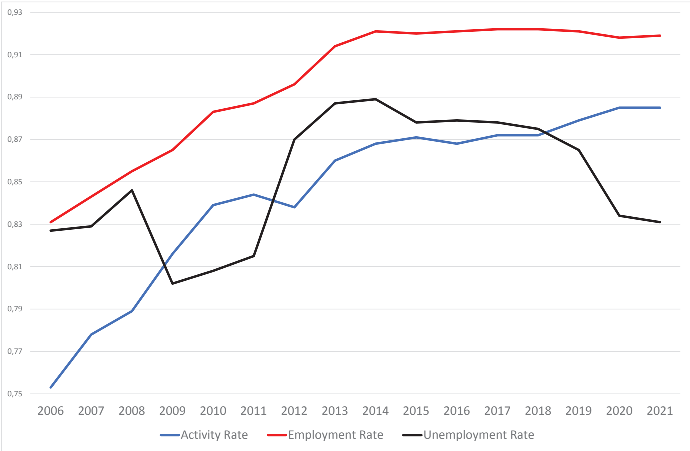


Figure 1: I-Moran for TA, TO and TD (610 SLLs, 2006-2021)

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):

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

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

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 do not affect the result of the BoD models, but are 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).

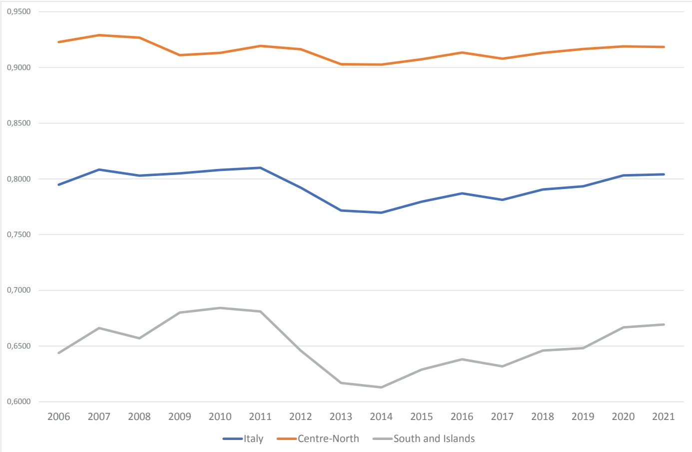


Figure 2: Robust BoD-CI score (m=50, T=100, 2006-2021)

	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.

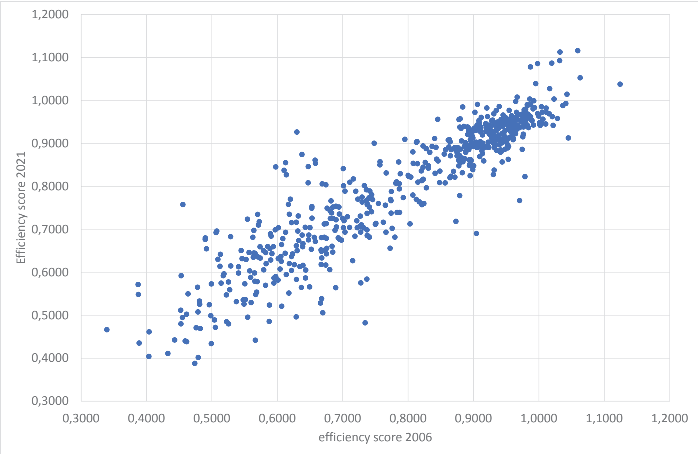


Figure 3: Performance score, robust BoD-CI (610 SLLs, 2006 and 2021)

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).

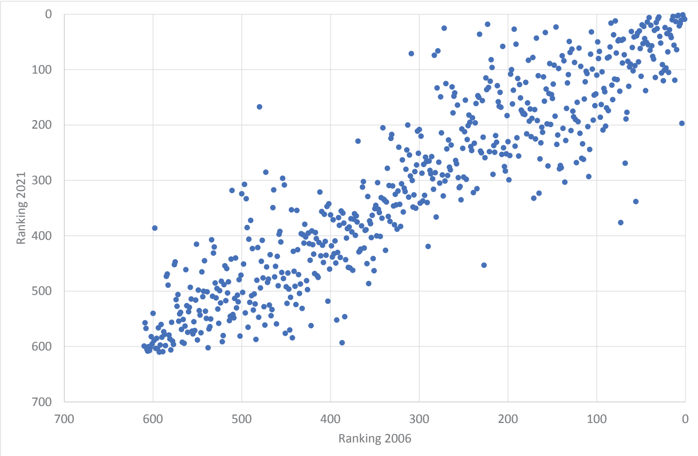


Figure 4: Performance ranking, robust BoD-CI (610 SLLs, 2006 and 2021)

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

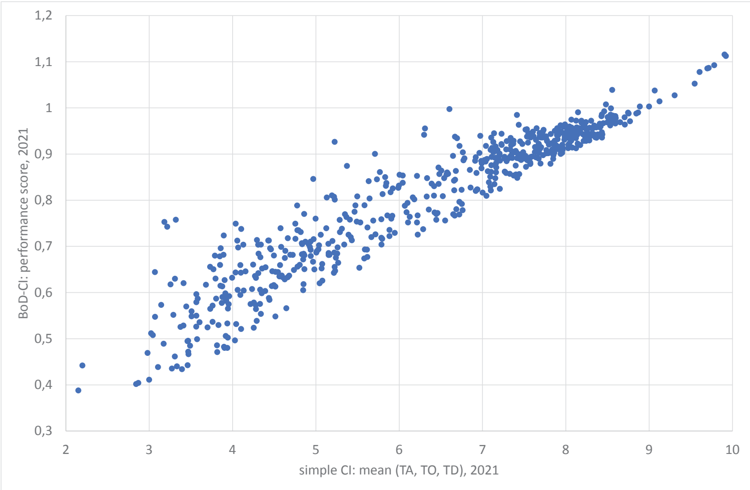


Figure 5: mean-CI and robust BoD-CI (2021)

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).

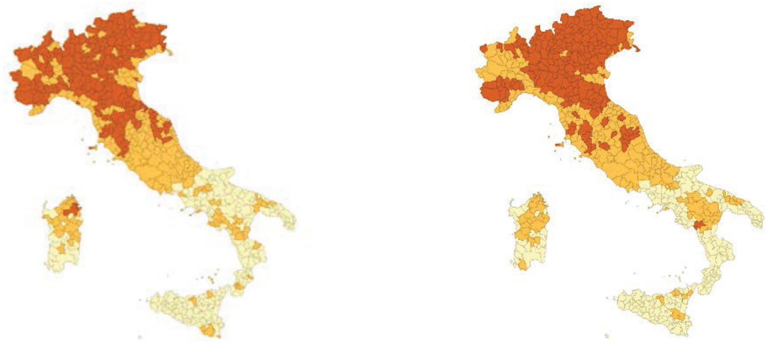


Figure 6: Robust BoD-CI (2006 left panel, 2021 right panel)

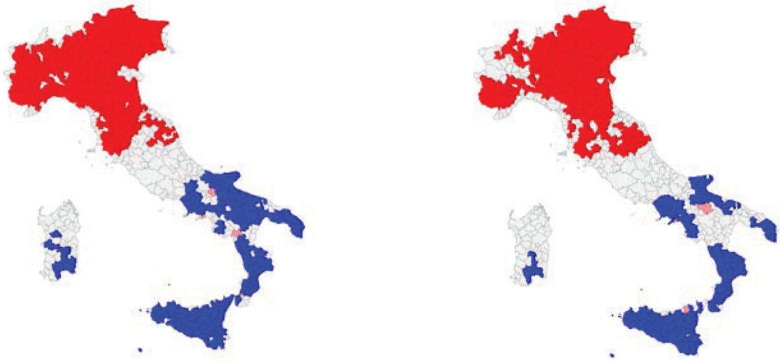


Figure 7: LISA clusters, high-high (red), low-low (blue), robust BoD-CI (2006 left panel, 2021 right panel)

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 neighbouring areas, somehow, we construct a local frontier of spatial proximity. This can highlight some good performances of the South compared to its neighbours 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 neighbours 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 a 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 neighbours) typically located in the North; other years show no notable differences.

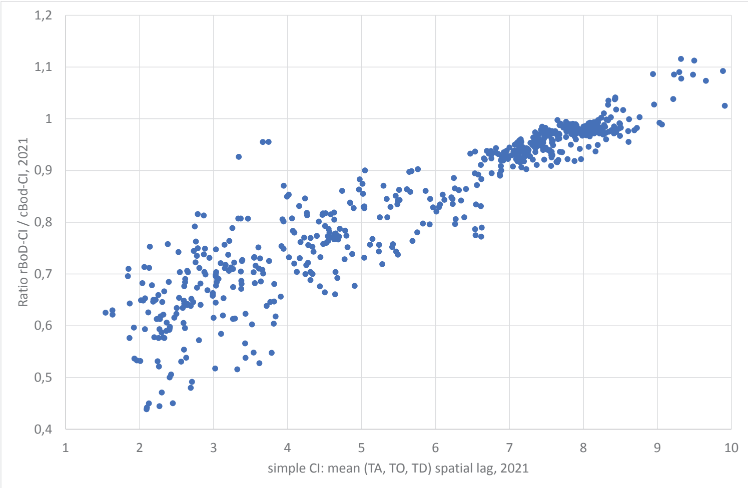


Figure 8: mean-CI and ratio robust / conditional BoD-CI (spatial lag, 2021)

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 labour 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 behaviour 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.

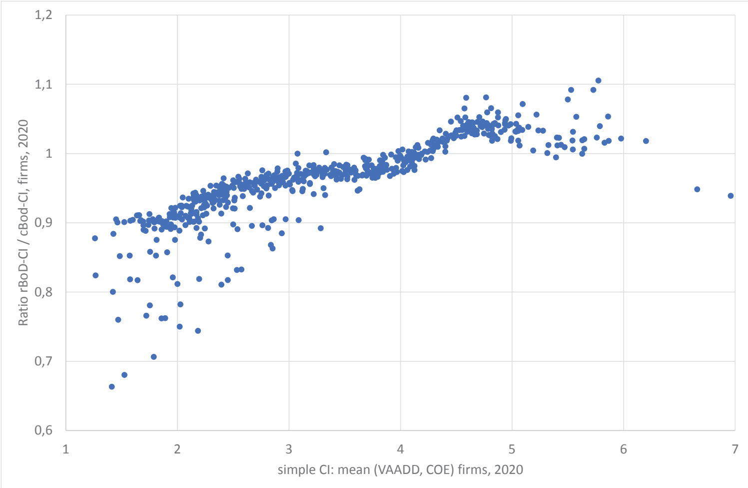


Figure 9: mean-CI and ratio robust / conditional BoD-CI (firms, 2020)

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.

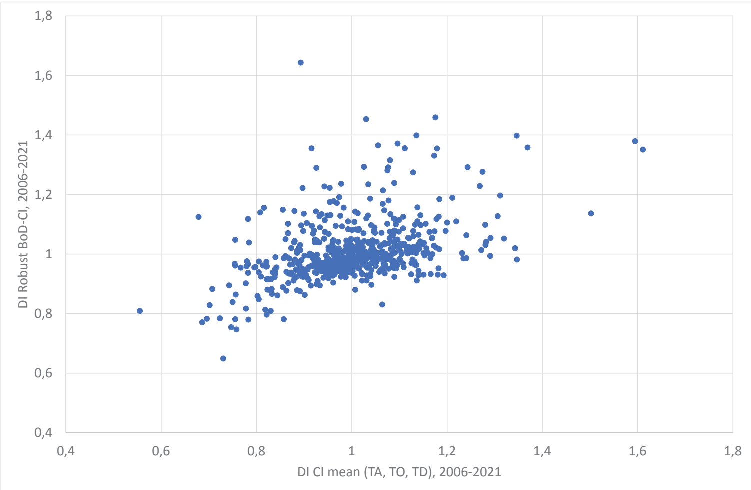


Figure 10: Dynamics Index for sub-indicators and robust BoD-CI (610 SLLs, 2006-2021)

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.

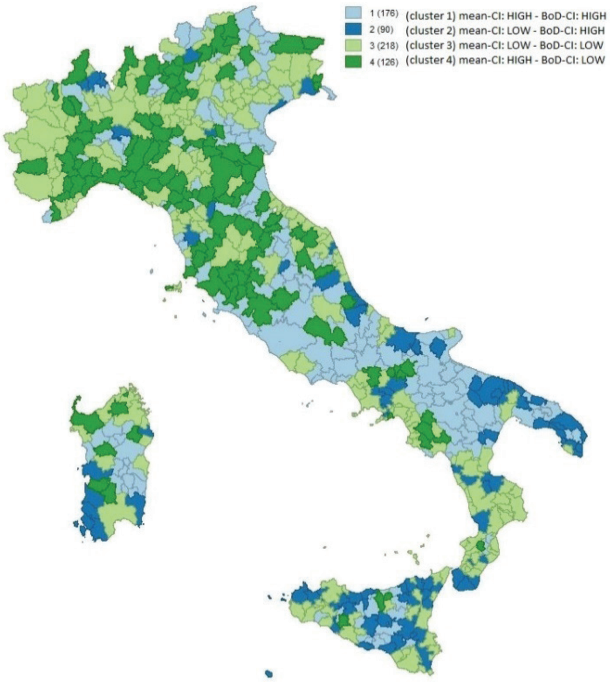


Figure 11: Dynamics Index (DI), clusters (2006-2021)

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 analysed 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).

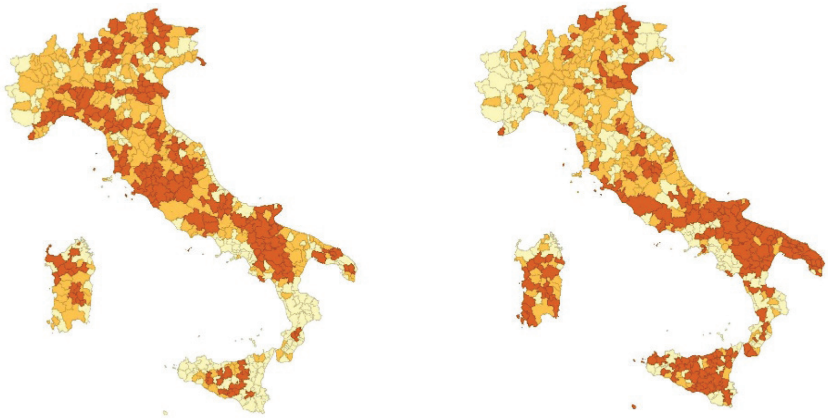


Figure 12: Dynamics indices (DI) for sub-indicators mean-CI (left panel) and performance BoD-CI (right panel) (610 SLLs, 2006-2021)

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.

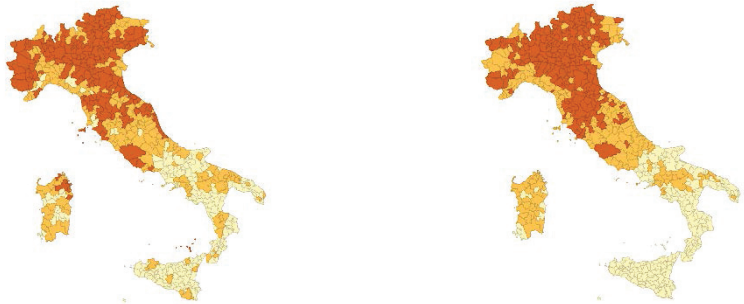
5. CONCLUSIONS

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

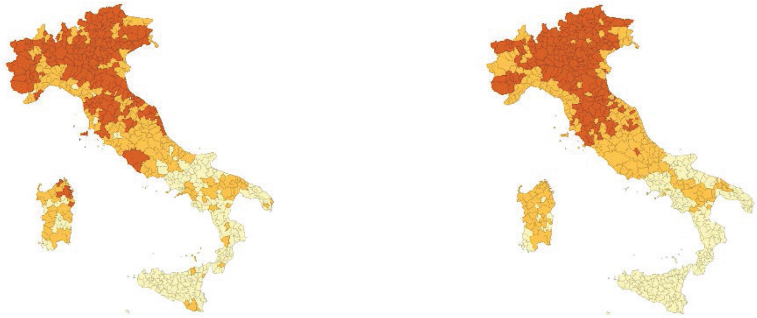
(DI) that compares the performance of an SLL between a time *t* and a previous time *h* (contiguous or not) and relates it to the results obtained for all the SLLs. So, lower performance values but with positive dynamics (approaching the frontier) and greater than better performing units (which, moreover, 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 highlighted 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 labour 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)

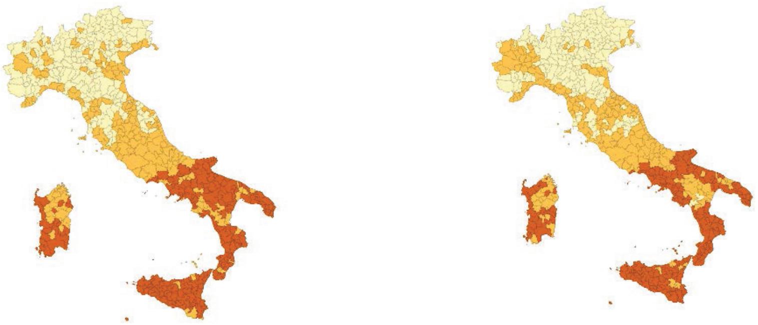
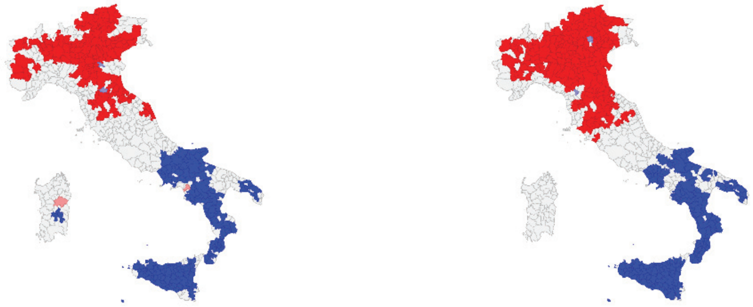
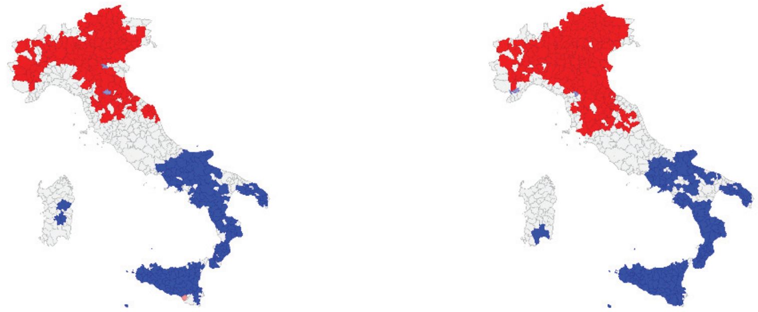


Figure A1: Activity rate, employment rate and unemployment rate (610 SLLs, 2006 and 2021)

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)

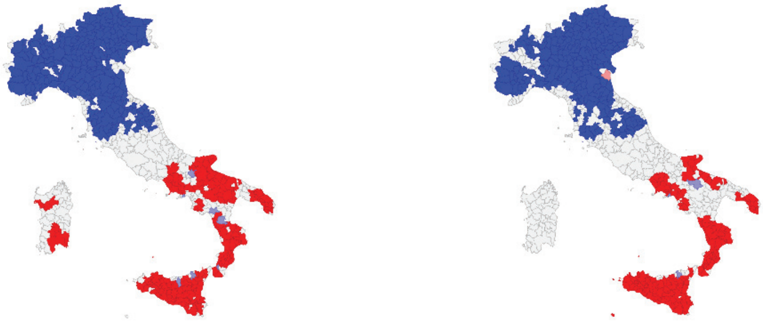


Figure A2: Local index of spatial association (LISA clusters, 2006 and 2021)

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

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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