Do "good neighbors" enhance regional performances in including disabled people in the labour market? A spatial Markov chain approach

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ABSTRACT

The purpose of this study is to examine whether the performance of regions in providing employment of disabled people according to Law 68/99 can be affected by the performance of neighbouring regions. Hence, we propose a two-step analysis focusing on the Italian regions for the years 2000-2009.

In the first step, we verify by means of the Stochastic Frontier Approach that the regions of Central and Northern Italy are more efficient in the matching process between demand and supply of jobs for disabled people than the regions of Southern Italy. Then, the efficiency results are analyzed using a Markov Spatial Transition Matrix in order to provide insights into the transitions of regions between efficiency levels, taking their local context into account. The results of this analysis show that good neighbors are important in promoting the improvement of the performance of the regions. However, the effects produced by bad neighbors should not be underestimated, especially when they are concentrated in an area of the country and have a time-space persistence.

The effect of a persistent dualism on the performance of the regions with respect to the application of Law 68/99 is a problem that must be seriously considered by policy makers; especially when the regions with a low efficiency score are surrounded by neighbors with poor efficiency score and show an unhealthy poorly performing labour market.

***Keywords**: Disabled People, Public Policy, Non-Labour Market Discrimination, Stochastic Frontier Approach, Spatial Markov Chain.*

JEL classification: *J14, J48,C23, C61.*

1.INTRODUCTION

In the '90s the promotion of laws in favor of disabled people - first in the United States in 1990 with the *American with Disabilities Act*, then in Italy with Law 104/1992, a frame law on assistance, social integration and rights of handicapped people, then in the UK in 1996 under the *Disability Discrimination Act* - has encouraged the development of empirical literature in order to study the impact of this legislation on the employment rates of disabled people (Acemoglu and Angrist, 2001; Stock and Beegle, 2004; Bell and Heitmuller, 2005). A key issue for policy-makers is to determine the extent to which such reforms have achieved their objectives (Jones et al., 2003; Jones et al., 2007; Jones and Sloane, 2009). In particular, Acemoglu and Angrist (2001) show for the USA that although the *American with Disabilities Act* had the objective of increasing the employment of disabled people, its effects were ambiguous; in particular, after this law, there was a severe reduction in the employment of disabled workers. For the UK, Bell and Heitmuller (2005) show that the *Disability Discrimination Act* did not have an impact on the employment rate of disabled people.

The causes of these results are different (Jones et al., 2003):

- Via legislation to promote employment of people with disabilities encourages people to report a disability;
- some who previously reported a disability prior to the legislation may not do so subsequent to its introduction if improvements to the workplace do not limit them in their work any longer. (Jones et al. 2003);

- the analysis of the effects of legislation that promote the employment of disabled people is confounded by changes in the composition of those reporting disabilities; in fact legislation to promote employment of people with disabilities encourages people to report a disability .

In Italy, Law 68 of March 12, 1999 (from now on Law 68/99) aims at the regulation and promotion of the employment of persons with disabilities. Law 68/99[1] is fully embedded in the complex process of reform of services for the Italian labour market which has been occurring since 1997. This law has contributed significantly to the employment of disabled people, and consequently to their social inclusion (Orlando and Patrizio 2006). More specifically, it pivots on the concept of "targeted employment", so that the employment of disabled people is based on quotas of compulsory hiring, but also on a careful assessment of their residual ability, on providing, where necessary, training courses, internship and business mentoring, and on special three sided employment contracts.

The study of the functioning of this law is linked exclusively to monitoring activity and the only empirical work with parametric approach is restricted to the province of Bolzano (Orlando and Patrizio, 2006), where Law 68/99 appears to have a positive effect especially in the employment of disabled people with physical impairments. More recently further studies have been developed to evaluate the ability of Italian regions to efficiently coordinate the various actors involved in the employment of disabled people according to Law 68/99 *in order to reach the matching between demand and supply of jobs for disabled*[2], (Agovino and Rapposelli, 2011; 2012a, 2012b), and have provided useful information to policy makers for economic policy actions in order to promote the integration of disabled people in the labour market. In particular, the results of these studies show that in order to promote the integration of disabled people in the labour market, environmental and social capital variables ought to be included as policy instruments within the context of Law

[1] In the Appendix 1 we report some information on the Law 68/99.
[2] These studies were conducted using the non-parametric approach to efficiency measurement, represented by DEA (Data Envelopment Analysis).

68/1999, but with targeted and different interventions depending on the context. In particular, an efficient enforcement of Law 68/99 in some regions will require to invest more in social capital while in other regions will require to take care of the socio-economic environment (Agovino and Rapposelli, 2011; 2012a; 2012b).

The limits of these studies are: the investigation unit (only the province of Bolzano) for the work by Orlando and Patrizio (2006), and the investigation period (only the year 2005) for the works by Agovino and Rapposelli (2011, 2012a, 2012b).

Law 68/99 specifies that regions have the greatest responsibility in its application and, consequently, its successful implementation depends almost exclusively on their actions and ability to efficiently coordinate the various actors involved in the employment of disabled people. However, the socio-economic context where the regions move does not appear to be homogeneous: each region is characterized by different socio-economic conditions, more or less favorable to the employment of disabled people. Hence, also the environmental context, i.e. the socio-economic context where each region is operating, is very significant for the successful implementation of Law 68/99. For example, a high unemployment rate or a hich number of private firms in crisis represent an obstacle to its full implementation. Furthermore, *regional dynamic* is influenced by spatially specific economic and social aspects, such as human resources. and the political and economic environment; in particular, the different performance in the application of Law 68/99 observed among tregions can be explained, in parts, by the spatial concentrations of specific economic activities, particularly in the public and sector service (Schettini et al., 2011).

The aim of this paper is to investigate whether the efficiency of regions in providing employment for disabled people according to Law 68/99 can be affected by the performance of their neighbours. Hence, we propose a two-step analysis focusing on the Italian regions for the years 2000-2009. In the first step, we use the Stochastic Frontier Approach (SFA) in order to evaluate in terms of efficiency the performance of Italian Regions with respect to the number of disabled people placed in employment in accordance with Law 68/99. In the second step, we apply Spatial Markov Chain (SMC) methodology to the efficiency scores in order to obtain probabilities of changing the relative efficiency situations, conditioned on the efficiency levels of the neighborhood (Schettini et al., 2011).

The paper is organized as follows. Section 2 presents the data used, Section 3 reviews the methodology, Section 4 shows the results of the Stochastic Frontier Analysis, Section 5 shows the results of the Spatial Markov Chain Analysis and Section 6 gives the conclusions.

2.DATA

In this study the SF approach is used in order to evaluate the performance of Italian regions with respect to the percentage of disabled people who have been employed in accordance with Law 68/99. In particular, we use a panel with two dimensions: temporal –annual observations from 2000 to 2009; and geographical – 20 regions. In this section, we describe more accurately the variables used in the analysis.

The data required are based on several sources. We use the percentage of employed disabled people as the output. Output data has been obtained from ISFOL (Institute for the Development of Vocational Training for Workers). In **Fig. 1** we can observe for 2000 and 2009 - respectively, the first and the last year of the analysis - that the percentage of employed disabled people is higher in Northern and Central Italy.

According to Law 68/99, both public bodies and private enterprises are potential employers for disabled people. In particular, **Fig. 2** and **3**, which compares the percentages of employed disabled people and employed non-disabled people in different production sectors, show how the public sector, in its different branches[3](Government, Ministry of Education, Department of Health), is the

[3] In particular, the areas of the macro-branch " Government, Ministry of Education, Department of Health " in which people with disabilities are employed are: services of the public administration; education, health and social services; other public, social and personal services; recreational, cultural and sporting activities; other services.

one with more employment opportunities for disabled people (respectively, with 29.2% in 2005 and 40% in 2008), followed by the trade (respectively, with 17.7% in 2005 and 11.3% in 2008) and industry sector (with 16.1% in 2005 and 23.1% in 2008), the transport and communication sector (with 12.2% in 2005 and 7.1% in 2008), and the agricultural sector (with 9.6% in 2005 and 4.1% in 2008)[4]. Consequently, the inputs will be the total employment rate of the service (public and private) (ERSS), industry (ERIS) and agriculture sector (ERAS); employment rates are are interpreted here as a measure of the growth of the sectors and of their ability to provide job opportunities for workers. Input data has been obtained from ISTAT (Italian National Institute of Statistics). Agovino and Rapposelli (2012a) show that the service sector is the one that employs more disabled people; consequently, we will implement twice the efficiency analysis with the stochastic frontier approach: once considering between the input, in addition to the employment rate of agricultural and industry sector, the employment rate of total service sector (the public and private services sectors are not separated), and another time considering the employment rates of the public and private service sectors separately: the employment rates private services sector (trade sector and transport and communication sector) and the employment rate of public services sector (Government, Ministry of Education, Department of Health)[5]; for this analysis ISTAT provides data only for the period 2000-2007.

Insert figure 1

Insert figure 2

Insert figure 3

In addition, we consider a second set of inputs (environmental factors) which could influence the efficiency of the regions analyzed (Charnes et al., 1981; Thanassoulis, 2001). In particular, these inputs are included in the analysis through the **inefficiency function** (see section 3.1). It is

[4] We report only the information for the years 2005 and 2008 because ISFOL does not provide further information for the other years considered in our analysis.

[5] We do not consider the construction, financial brokerage and business service, and other service sectors because they do not hire many disabled people.

important to highlight that a negative sign of the parameters associated to environmental factors has the effect of reducing the inefficiency of the regions in the matching process. In our specific case, the environmental factors identify the socio-economic context where each region operates.

Environmental factors have been obtained from ISTAT. Among these variables we include:

- The mean variation in regional employment over the last four year (i.e. from 1995 to 1999 for the year 2000, from 1996 to 2000 for the year 2001, etc.) as proxy for a structural disequilibrium variable (EC1)[6]. A negative (positive) sign of this variable indicates that the change in employment in the medium run produces positive (negative) effects on, and therefore reduces, the inefficiency of the regions in providing employment for disabled people; in particular, the negative (positive) sign reduces (increases) the inefficiency of the regions in the matching process.
- The variation in regional employment in the last year (i.e. from 1999 to 2000 for the year 2000, from 2000 to 2001 for the year 2001, etc.) as a proxy for a short-time disequilibrium variable (EC2)[7]. A negative (positive) sign of this variable indicates that the change in employment in the short run produce positive (negative) effects on, and therefore reduces, the inefficiency of the regions in providing employment for disabled people;
- The ratio of female to male labour force (FM)[8]. This ratio is an indicator of the health of the labour market; in particular, a negative sign of this variable indicates that the effect connected to female participation is stronger than that of male participation, and this has the effect of reducing the inefficiency of the regions in the process of employment of disabled people. Specifically, a gender analysis shows that female participation is more linked to the dynamics of the labour market; in other words, in the regions where the unemployment rate is high, the female participation is low (Cracolici et al., 2007). An high rate of

[6] We construct this indicator using regional employment rates (see Cracolici et al., 2007).
[7] We construct this indicator using the regional employment rates (see Cracolici et al., 2007).
[8] We consider the ratio between female labour force over total females at working age and male labour force over males at working age (see Cracolici et al., 2007).

unemployment indicates a particularly bad state of the labour market, with heavy consequences for the employment of disabled people. In particular, the regions with a high unemployment rate are characterized by a high number of temporary layoff hours; in this case, Law 68/99 provides that companies with employees in temporary layoffs are not enforced to employ disabled people (Agovino and Rapposelli, 2011).

— The ratio between old and young population (OY)[9]. This ratio is an indicator of the health of the labour market; in particular, a negative sign of this variable indicates that the effect connected to the population over 65 is stronger than the share of the young population, and this has the effect of reducing the inefficiency of regions in the process of employment of disabled people. In other words, we assume that a high share of old people has positive effects on the health of the labor market. In particular, some authors show that regions with a higher share of old people have experienced a lower unemployment rate (Cracolici et al., 2007; Molho, 1995; Lopez et al., 2005; Elhorst, 1995).

The first two factors (EC1 and EC2) are defined in the literature *disequilibrium factors*, while the other two ones are defined *equilibrium factors* (FM and YO) (Cracolici et al., 2007). These factors are used in the study of regional disparities in the labour market (Partridge and Rickman, 1997) and are of particular importance in the study of all aspects of the Italian labour market which is characterized by a strong dualism.

3.METHODS

As mentioned in the introduction, we develop the analysis in two steps. In the first step, we apply the Stochastic Frontier Approach in order to evaluate in terms of efficiency the performance of regions with respect to the percentage of disabled people placed in employment in accordance with Law 68/99. In the second step we apply the Spatial Markov Chain methodology to the regional

[9] We consider the ratio between the population over 65 years and the population of 15-29 years (see Cracolici et al., 2007).

efficiency score obtained from the SFA in order to obtain the probabilities of changing the relative efficiency situation, conditioned on the efficiency levels of theneighbouring regions (Schettini et al., 2011).

3.1 Stochastic Frontier Analysis (SFA)

Following Battese and Coelli (1995), we propose a production[10] function with the following specification[11]:

$$
\begin{aligned}
y_{it} &= \beta_0 + \beta_1 ERAS_{it} + \beta_2 ERIS_{it} + \beta_3 ERSS + \lambda_t + \mu_i + (v_{it} - u_{it}) \\
u_{it} &\sim N^+(m_{it}, \sigma_u^2) \\
m_{it} &= \delta_0 + \delta_1 EC1_{it} + \delta_2 EC2_{it} + \delta_3 FM_{it} + \delta_4 YO_{it}
\end{aligned}
$$

where y_{it} is the percentage of employed disabled people; *ERAS*, *ERIS*, and *ERSS* are respectively the employment rate in the agricultural sector, the employment rate of the industry sector, and the employment rate of the service sector. We also include a time effect λ_t that allows for uniform influence of shocks, and a set of regional dummies with the aim of capturing the unobserved heterogeneity of regions (μ_i). v_{it} is the conventional random noise ($v_{it} \sim iidN(0, \sigma_v^2)$); the inefficiency effect term, u_{it}, is here defined as an explicit function of disequilibrium factors (*EC1, EC2*) and of equilibrium factors (*FM, YO*), which vary over time. Note that in this formulation we directly include as regressors only the three different employment rates.

More in detail, in this panel data frontier model the non-negative technical inefficiency term, u_{it}, is assumed to follow a truncated normal distribution with different means for each regions, depending on the observable variables included. Therefore, the inefficiency effects are assumed to be independently but not identically distributed.

[10] In this paper, we consider the production of a service by the region. In particular, we refer to the service related to the implementation of Law 68/99.

[11] The estimated model is of log-log type, consequently the coefficients are expressed in terms of elasticity.

Modelled in this way the environmental factors (the disequilibrium and equilibrium factors) are interpreted as determinants of inefficiency because they directly explain the inefficiency results of regions.

In this case, differently from the Agovino and Rapposelli's works (2011, 2012a, 2012b) based on non-parametric analysis (DEA) and dealing with a single year (2005), we obtain a measure of the impact of the coefficients associated with the regressors (the SFA is a parametric analysis) and we consider both the temporal and the spatial dimensions (panel analysis).

3.2 Spatial Markov Chains (SMCs)

The SMCs allow us to simultaneously study the spatial and temporal dynamics of a phenomenon (Rey, 2001). The main output of a SMC is a spatial transition matrix that allows to examine the positive or negative influence of the neighbors on the transition of a region between efficiency levels; in particular, it gives the probability for a region to experience upward or downward moves in the distribution in the final period ($t+1$), conditionally to the state of its neighbors in the initial period (t); the transition matrix can thus trace the history of the distribution over time. Specifically, this tool allows to check whether a region with low (high) efficiency score tends to remain in that state if surrounded by other regions with low (high) efficiency score, and in particular whether regions with a low efficiency score negatively affect their neighbors, reducing their efficiency; or whether regions with a high efficiency score positively affect their neighbors, increasing their efficiency; these effects are evaluated considering also the temporal dynamics.

The construction of the *spatial transition matrix* is based on the decomposition of the *traditional transition matrix*; this decomposition allows to obtain the *spatial transition probability*. In particular, the traditional transition matrix is modified so that the transition probabilities of a region in the final period ($t+1$) are conditioned by the average efficiency score of the initial period (t) of neighboring regions. In other words, the spatial transition matrix is a *K-by-K* traditional matrix decomposed into K sub-matrices, where each sub-matrix is a *K-by-K* matrix; in our case, $K = 5$ i.e. the number of possible states.

Formalizing, if we consider the *k-th* matrix between the conditioned matrices, the $p_{ij}(k)$ element of this matrix is the probability that a region in class i in initial period (t) ends up in the class j in the final period ($t+1$), knowing that the average efficiency score of its neighboring regions was in class k in period t.

The estimator of a $p_{ij}(k)$ element of a conditioned transition matrix is defined as follows:

$$\hat{p}_{ij}(k) = \frac{n_{ij}(k)}{n_i(k)}$$

where $n_{ij}(k)$ is the number of regions that are in class i in the period t and in class j in period ($t+1$), knowing that the average efficiency score of their neighbouring regions places them in class k in period t; $n_i(k)$ is the total number of regions that are in class i, knowing that the average efficiency score of their neighbouring regions placeds them in class k at time t, during T=8[12] annual transitions, *i.e.* $n_i(k) = \sum_j n_{ij}(k)$.

The spatial Markov matrix allows to examine the positive or negative influence of the neighbours on the transitions of a region. Indeed, the influence of spatial dependence is reflected in the differences between the initial transition values not conditioned[13], and the various conditional transition values (Le Gallo, 2004). For example, in our case with 5 states ($K=5$), the first state contains the poor efficiency score regions, the third state contains the medium efficiency score and the final state contains the rich efficiency score[14]. Consequently, if $p_{35} > p_{35|1}$, the transition probability of moving upwards of a region with medium efficiency score, excluding the conditioning of its neighbors, is greater than the transition probabilities of moving upwards of a

[12] Our period of analysis consists of 9 years, and so we have $T = 8$ annual transitions.

[13] For reasons of space, we do not report the results of the transition matrix not conditioned; interested readers can request them from the author.

[14] We describe with care the 5 states in Section 5.

region with medium efficiency score conditioned by neighbors with a low efficiency score; an analagour reasoning deals with the probability of moving upwards for regions starting from other levels of efficiency score. Conversely, if $p_{13} > p_{13|5}$, the transition probability of moving upwards of a region with poor efficiency score conditioned by neighbors with a rich high efficiency score is greater than the transition probabilities of moving upwards of a region with poor efficiency score without conditioning.

If the regional context did not matter for transition probabilities, then the conditional probabilities should be equal to the not conditioned initial transition values (Le Gallo, 2004):

$$p_{ij|1} = p_{ij|2} = \ldots = p_{ij|5}$$
$$\forall i = 1,\ldots,5$$
$$\forall j = 1,\ldots,5$$

The significance of space of the importance of considering neighbours is given by the rejection of the null hypothesis of spatial stationarity tests (see Le Gallo, 2004). In our case, we reject the null hypothesis at 5%; consequently, the transition probability of a region depends on the geographical environment.

4.RESULTS OF SFA

In Table 1, we report the results of the efficiency analysis; in particular, we consider two models: a model with the employment rate of the total service sector (the public and private services sectors are not separated) (*first model*), and a second model considering separately the employment rates of the public and private service sectors (*second model*).

The Likelihood ratio (LR) test, rejecting the null hypothesis in both cases, confirms the presence of technical inefficiency (for critical values of the test see Kodde and Palm (1986)). In addition, the significance of the parameter γ, i.e. the ratio between the variance of the inefficiency term $\sigma^2{}_u$ and the sum of the total variance $\sigma_v^2 + \sigma_u^2 = \sigma^2$, shows that 35% (first model) and 15% (second model), of the change in the percentage of disabled people employed among Italian regions is due to differences in their technical inefficiencies.

With regard to the **first model**, we observe that an increase in the employment rate in all three production sectors leads to an increase in the employment of disabled people; it is interesting to note that the parameter associated with the employment rate of the agriculture sector is the one with the greatest impact, followed by the industrial and service sector ones. With regard to the factors that determine the inefficiency of the matching process between demand and supply of employment of disabled people, we observe that the FM variable is not significant, on the contrary, the OY variable is significant and with a negative sign. The negative sign indicates a reduction in the inefficiency of Italian regions in the process of employment of disabled people. In other words, the performance of the regions in the process of employment of disabled people is more sensitive to the relative variation of the population over 65 years of age; therefore, regions with a high share of old people have experienced an healthier labour market (a lower unemployment rate)[15]. Moreover, the regions performance are explained by the short-run change in employment. The negative and significant coefficient of the variable EC2 implies that the performance of regions in the process of employment of disabled people depends strongly and positively on the change in employment in the last previous year. In contrast, the variation of employment in the medium run (EC1) does not produce any effect on the performance of the regions. In other words, the effect of the change in employment is dissipated over the years – as the coefficient of EC1 shows – and produces effects only in the short run, as confirmed by the coefficient of EC2 (Cracolici et al., 2007).

By examining the **second model** we can note that the coefficients associated with the employment rate of the agricultural and the industrial sectors continue to be positive and significant, therefore increased employment rates in these sectors will lead to an increase in the employment of disabled people. With regard to the disaggregation of the employment rate of the services sector, we observe

[15] In Appendix 2 we report the motivation of the sign of the variable YO.

that: an increase in the employment rate in the trade sector has no effect on the employment rate of disabled people; on the contrary, an increase in the employment rate of the public sector and in the transport and communication sectors will increase the employment rate of disabled people; in particular, we note that an increase in the employment rate in the transport e communication sectors has the greatest impact on the employment rate of people with disabilities. Concerning the **inefficiency factors**, we observe that the coefficient associated with the variable FM, in this case, is significant and has a negative sign. The negative sign is certainly due to a stronger female rather than male participation[16]; in other words, the performance of regions in the process of employment of disabled people is more sensitive to the relative variation of the female participation; therefore, regions with a high female participation rate have experienced a healthier labour market (a lower unemployment rate). The OY variable is significant and presents a negative sign; the negative sign indicates a reduction of the inefficiency of Italian regions in the process of employment of disabled people. Moreover, in this case as well the variation of employment in the medium run (EC1) does not produce any effect on the performance of regions; while the short-run change in employment (EC2) - since is significant and has a negative sign- has a positive effect on the performance of the regions in the process of employment of disabled people.

Information-theoretic criteria such as Akaike's Information Criteria (AIC) (Akaike, 1973) and Bayesian Information Criteria (BIC) (Schwarz, 1978) are increasingly being used to address model selection problems; in particular, a model that minimize AIC and BIC criteria is selected. In our case, the first model minimizes the AIC, BIC criteria and maximizes the Log-likelihood criteria. The first model achieves the best compromise between to data fit and parsimony.

The major conclusion that we can draw from our estimates, considering the first model, is that the three sectors are important in the process of employment of disabled people; in addition, the performance of regions in the process of employment of disabled people is explained in terms of

[16] For an analysis of the negative sign of the FM see the same Appendix 2 used for the YO variable.

both disequilibrium and equilibrium factors. The efficiency of Italian regions, in the process of employment of disabled people, is mainly explained by a disequilibrium factor (short-run change in employment) and weakly by equilibrium factors such as the share of the population over 65 years. Consequently, the most recent changes occurring in the labour market have the largest impact on the ability of regions to achieve an efficient matching process (EC2); in addition, a healthier labour market, with a lower unemployment rate (see OY variable), promotes a more efficient implementation of Law 68/99 by regions.

In order to clarify the effect of the OY variable, we show in **Figure 4** a scatter plot of regionsalefficiency scores (vertical axis) with respect to OY (horizontal axis), for the years 2000-2009. In particular, we observe that a healthier labour market (high values of OY) match higher efficiency scores; consequently, a healthy labour market will favor regions in improving their performance in the matching process between demand and supply for the employment of disabled people; this result is in line with Agovino and Rapposelli (2012a, 2012b).

We can observe (**Fig. 5**) an uneven distribution of annual average efficiency scores; in particular, we observe two clusters, which we shall formally analyse in the next section: a first cluster of regions in Central and Northern Italy, characterized by a high annual average efficiency score; a second cluster of regions of Southern Italy, characterized by a low annual average efficiency score. In summary, the regions of Central and Northern Italy are more efficient in the matching process between demand and supply of jobs for disabled people.

Insert table 1

Insert figure 4

Insert figure 5

We conclude this section with the implementation of Moran's scatter plot[17] (Anselin, 1993) of regional annual average efficiency scores. Moran's I coefficient of spatial autocorrelation is strongly linked to Spatial Markov Chain analysisThe Moran's scatter plot is an intermediate step of our analysis before implementing the SMC analysis. In particular, Moran's I coefficient is defined as follows:

$$I = \frac{\sum_i \sum_j W_{ij} (X_i - \mu)(X_j - \mu)}{\sum_j (X_j - \mu)^2}$$

Xi and *Xj* indicate the variable describing the phenomenon under investigation respectively observed in region *i* and in region *j*, μ is the average value in the sample, and W_{ij} is the standardized matrix of spatial contiguity, which specifies the criteria for defining contiguity; in this analysis we have used a *queen first order contiguity matrix*[18] (Anselin, 1988). This index allows us to establish the relationship existing between a phenomenon observed in a given region *j* and the same phenomenon observed in contiguous regions. Moran scatterplot (**Figure 6**) shows the Moran's I coefficient as the slope of the regression line in the scatter plot, where the spatial lag of the annual average efficiency scores is on the vertical axis and the annual average efficiency scores is on the horizontal axis (both variables standardized). **Figure 6** shows a high positive value of the Moran's

[17] The Moran scatter plot provides a tool for visual exploration of spatial autocorrelation (Anselin 1996, 2002). The four different quadrants of the scatterplot identify four types of local spatial association between a region and its neighbors:

- (HH) a region with a high efficiency score surrounded by neighbors with a high efficiency score (quadrant I);
- (LH) a region with a low efficiency score surrounded by neighbors with a high efficiency score (quadrant II);
- (LL) a region with a low efficiency score surrounded by neighbors with a low efficiency score (quadrant III);
- (HL) a region with a high efficiency score surrounded by neighbors with a low efficiency score (quadrant IV).

Quadrants I and III pertain to positive forms of spatial dependence while quadrants II and IV represent negative spatial dependence (Rey and Montouri, 1999).

[18] We obtain the same results using a rook and a bishop contiguity matrix.

I coefficient (0.6719)[19]; this indicates positive spatial correlation for the annual average efficiency scores[20].

This result highlights a spatial relationship among Italian regions in terms of efficiency scores *in the matching process between demand and supply of jobs for disabled people;* in particular, **Figure 6** shows **spatial spillovers** between contiguous regions. According to these results, it will be interesting to verify if more (less) efficient regions are able to influence less (more) efficient regions, determining, in this way, an improvement (deterioration) of the performance of these regions in the process of employment of disabled people[21].

This hypothesis will be tested in the next section by implementing the SMC analysis.

Insert figure 6

5.RESULTS OF THE SPATIAL MARKOV CHAIN

The transition spatial Markov matrix is calculated using the efficiency scores estimated in the previous section. In this methodology, the transition of efficiency states is considered between two consecutives periods of time; in our analysis we have eight possible transitions in the period 2000-2009 (e.g., 2000-2001, 2001-2003, …, 2008-2009)[22], and for each pair of years we calculate the number of cases for each state. In our analysis, we have 20 regions (*n*), 8 years (*t-1*) from 2000 to 2009 (except for 2002 which is not available) and 5 (*K*) states; consequently, it is possible to obtain, at most, (20*5*8) = 800 cases of transitions[23].

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[19] The null hypothesis of the Moran's I test is spatial independence. According to the results, we reject the null hypothesis at the 1% level and conclude that the annual average of the regions' efficiency scores presents spatial autocorrelation.

[20] The Moran's I test, implemented on efficiency scores for each year of the analysis, always rejects the null hypothesis of spatial independence. For reasons of space we do not show them; interested readers can request them from the author.

[21] We obtain the same results for the efficiency scores of the second model. For reasons of space we do not show them; interested readers can request them from the author.

[22] We do not have nine possible transitions because data for the year 2002 are not available.

[23] With *n* regions, *K* states, and *t* years, there are *(t-1)*K*n* possible cases of transitions.

In this exercise, we report the results of SMC as in Rey (2001); in particular, we define five feasible states (*K=5*) based on the value of the variable (efficiency score) with respect to the mean (M) (Schettini et al., 2011). In this case, we have a state with a:

- poor efficiency score (P), for an efficiency score *lower* than the mean to 3/4 than a standard deviation;
- low efficiency score (L), for an efficiency score *lower* than the mean to 1/4 than a standard deviation;
- medium efficiency score (M), for an efficiency score *close* to the mean;
- upper efficiency score (U), for an efficiency score *higher* than the mean to one standard deviation;
- rich efficiency score (R), for an efficiency score *higher* than the mean to 1½ standard deviation;

In summary, the five states are set in the followin*g order*: P<L<M<U<R.

The results of conditioning the transition probabilities on the spatial lag[24] of a given region are reported in table 2; in particular, in column 4 we show the number of cases in each situation. For example, line 8 indicates the probability of transition of a region that started in *t* with M efficiency, to move to the other classes of efficiency in the following year (*t+1*), given that it is surrounded by L neighbors. Considering the pairs of consecutive years, there are 3 cases (line 9 column 4) of regions in that situation. The same reasoning can be applied to the other lines.

Lines 1-5 represent regions embedded in neighborhoods with a poor efficiency score (P); lines 6-10 represent regions embedded in neighborhoods with a low efficiency score (L); lines 11-15 represent regions embedded in neighborhoods with a medium efficiency score (M); lines 16-20 represent regions embedded in neighborhoods with an upper efficiency score; finally, lines 21-25 represent

[24] Where the spatial lag is the average efficiency score of neighboring regions. The spatial lag is a weighted average, where the weights are represented by the elements of the contiguity matrix.

regions embedded in neighborhoods with a rich efficiency score. It 's interesting to note that the shaded cells contain the highest values of the lines (the cells of the main diagonal); this result reveals the presence of inertia. In other words, the probability of a region to stay in the same class of efficiency is relatively high; in some cases this probability is over 90%.

Considering the regions with an efficiency score below the mean (P and L), we observe that the probability of remaining below the mean is:

- high for L regions embedded in neighborhoods with a poor efficiency score (P); in particular, it is equal to 100% (sum of the cells until to L, line 2). The same probability is equal to zero for the P regions; in this case, there was never an instance of a P region being surrounded by P neighbors (line 1) (Rey, 2001);
- high for both P and L regions embedded in neighborhoods with a low efficiency score (L): 100% for P regions (sum of the cells until L, line 6) and almost 90% for L regions (sum of the cells until L, line 7);
- high for both P and L regions embedded in neighborhoods with a medium efficiency score (M); 100% for P regions (sum of the cells until L, line 11) and 80% for L regions (sum of the cells until L, line 12);
- high for L regions embedded in neighborhoods with upper efficiency score (U); in this case, regions L have a 75% chance of staying below the mean efficiency score (sum the cells until L, line 17); in contrast, they have a probability of 25% of improving if they are surrounded by U regions (the cell in correspondence of U, line 17). P regions have a probability equal to zero because they are never surrounded by U neighbors (line 16).
- Finally, it is interesting to note that both P and L regions are never surrounded by R neighbors (lines 21 and 22).

Now we consider the regions that started off with higher levels of efficiency (in the year *t*), the regions with an efficiency score above the mean (U and R), but embedded in regions that were generally underperforming (P and L) (lines 4, 5, 9, 10); in this case, we observe what is the probability of remaining above the mean or fall below the average. In particular, we observe that:

- The P regions have no effect on the U and R regions, because there was never an instance of U and R regions being surrounded by P neighbors (lines 4 and 5); this result is also confirmed in the case of neighboring regions with a low efficiency score (lines 9 and 10).

In the case in which these regions, that start with a high efficiency score, are surrounded by regions with a good performance in the process of employment of disabled people (U and R regions) (lines 19, 20, 24 and 25), we observe that:

- U regions if surrounded by other U regions have the same probability to improve and worsen their performance, and it is very low (1.4%) (line 19); on the contrary, R regions surrounded by U regions have a high probability of worsen their performance (57.1%) (line 20).
- R regions have no effect on U regions, because there was never an instance of U regions being surrounded by R neighbors (lines 24); on the contrary, R regions surrounded by other R regions have a high probability of worsen their performance by 50% (line 25).

Finally, if regions U and R are surrounded by regions M we observe that: regions U have a probability of 16.7% of worsen their performance (line 14); R regions are not affected by regions M (line 15).

In summary, we observe that regions with a poor and low efficiency score are closely linked: P regions affect L regions and vice versa; this influence is negative because it worsens the performance of the regions. Regions with a low efficiency score if surrounded by U regions improve their efficiency in promoting the employment f disabled people. Moreover, regions with poor and low efficiency scores are never influenced by the ones with rich efficiency scores. Regions with a poor and low efficiency scores do not affect the ones with upper and rich efficiency scores; U regions (negatively) affect R regions, but not vice versa; regions with rich efficiency score affect themselves.

Figure 7 shows a higher variability in the efficiency score of the regions in Northern and Central Italy than the ones of Southern Italy. The regions in Central and Northern Italy show an improvement in their performance over the years; the South is quite stable with very low efficiency scores, with the exception of Abruzzo and Molise. From figure 7, it is clear that regions with a high efficiency score (U and R regions), located in the North of Italy, cannot affect regions with a low efficiency score (P and L regions), located in the South of Italy, due to the presence of regions with a mean efficiency score (M regions); these regions are located in Central Italy dividing northern regions from southern regions and not allowing the contact. In summary, these results show a dualism between North and South Italy in terms of efficiency in the employment process of disabled people.

Insert table 2

Insert figure 7

In **Tables 3** and **4** we report the information extracted from the results presented in Table 2. In particular, **Table 3** shows the probability of a region to stay in the same class of efficiency, independently of its neighborhood (Schettini et al., 2011); in this case, we observe that this probability is very low for all classes; the highest is for regions classified as U-efficient (34%), followed by regions classified as M-efficient (34%).

In **Table 4**, following Schettini et al. (2011), we count all the cases of *getting better* and *worse* (respectively the second and the fifth row in Tables 4). In particular, we consider the cases of regions that *could improve* their performance in the employment of disabled people (regions that in period (*t+1*) remain in the initial state or end up in a worse state) (column A in table 4), and we consider the regions that *got better* in their performance (regions that in period (*t+1*) move to a better class) (column B in table 4). Dividing the two values, we obtain an "**improvement index**" as a measure of the degree of improvement of the regional performance in the matching process (column B/A in table 4); the same method is applied to the worsen cases (in this case, we refer to a "**deterioration index**" as a measure of the degree of deterioration of the regional performance in the matching process; see the fourth and the fifth row in table 4).

In addition, we consider all the cases of regions whose neighbors were classified in better classes of efficiency (column C in table 4) and, among these, count the cases of regions that improve their situation (column D in table 4); at this point, we calculate *the probability of moving to better classes of efficiency*, given that the region is surrounded by higher efficiency neighbors (column D/C in table 4); the same method is applied to the worsen cases (see the fourth and the fifth row in table 4).[25]

The calculations in **Table 4** show that:

— *the improvement index is higher than the deterioration index:* 11 versus 6 cases. In particular, we observe 11 cases of regions that did improve their performance in the employment of disabled people for each100 cases of regions that could have improved their performance; on the contrary, we observe, in the case of the deterioration index, 6 cases of regions that worsen their performance in the employment of disabled people for each 100 cases of regions whose performance could deteriorate;

[25] In this case we will have a probability and not an index because the ratio between numerator and denominator is equal to: the ratio of the number of actual occurrences to the total number of possible occurrences.

- if a region is surrounded by neighbors with better efficiency, it has a *probability* of 29% to improve its performance. This *probability* is about three times higher than the one obtained when neighboring regions are not considered;
- if a region is surrounded by neighbors with worse efficiency, it has a *probability* of 20% to worsen its performance. This *probability* is three times higher than the one obtained when the neighbouring regions are not considered; in practice, the presence of bad neighbors triples the chance of reducing the efficiency.
- the *probability* of a region to improve its efficiency, if surrounded by good neighbors (29%), is higher than the *probability* of a region to worsen it if surrounded by bad neighbors (20%); the difference between the two *probabilities* is about 10%. In this case, we can conclude that the **pull effect** (i.e., the effect of good neighbors in improving efficiency) is higher than the **drag effect** (i.e., the effect of bad neighbors in reducing efficiency) (see Schettini et al., 2011).

The results of this analysis have shown the importance of good neighbors in promoting an improvement in the performance of the regions in the *integration process of disabled people in the labour market.* The probability of this effect is very small and the reasons for this result are already highlighted in the discussion of **Figure 7**. The effects produced by bad neighbors should not be underestimated, especially when they are concentrated in one area of the country and have a time-space persistence. This persistence if not mitigated by policy-makers would result in an enlargement of the dualism between the North and the South of Italy. This effect is evident from the results of the local Moran test (Anselin, 1995) which allows to identify the presence of spatial clusters (see **Table 5**).

The local Moran test (Anselin, 1995) can be used to identify local clusters (regions where adjacent areas have similar values) or spatial outliers (areas distinct from their neighbors). In particular, the Local Moran statistic decomposes the Moran's I into contributions for each location, I_i. The sum of I_i for all observations is proportional to Moran's I, an indicator of a global pattern. Thus, there can be two interpretations of Local Moran statistics, i.e. considering them as indicators of local spatial clusters and as a diagnostic for outliers in global spatial patterns. In Table 5 we report the results from the application of the Local Moran statistics to the efficiency scores in each of the years; in the third column there is the number of years for which the local Moran statistic provides indications of clustering using a pseudo- significance level of p=0.05; we also report the number of years for which the statistic is significant in each of the four quadrant of the Moran's scatter plot (columns 4-7). The results show that:

- 100% of significant local indicators fall in either quadrants I and III of the Moran's scatter plot, reflecting HH and LL clustering respectively;
- two strong regional clusters emerge and seem to be persistent in the 7 years of the analysis. The first is the North-Central Italy cluster of high efficiency score regions including Piemonte, Liguria, Emilia Romagna, Toscana, Umbria and Marche, each of which appears in quadrant I when its local Moran is significant. The second cluster is the Southern Italy cluster consisting of the low efficiency score regions including Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna, each of which appears in quadrant III when its local Moran is significant.

The effect of a persistent dualism on the regional performance in *the process of integration of the disabled people in the labour market* is a problem that must be seriously considered by policy makers; especially when regions with a low efficiency score are surrounded by neighbors with poor efficiency score (Southern Italy cluster); in this case the probability of worsening their performance is equal to 20%. Furthermore, labour market policies in regions where the unemployment rate is very high (unhealthy labour market) (see figure 4) could *promote the integration of disabled people* *in the labour market;* consequently, this could increase the efficiency of the regions in the application of Law 68/99.

Insert table 3
Insert table4
Insert table 5

6. CONCLUSIONS

In this paper we have evaluated the performance of 20 Italian regions over the 2002-2009 period with respect to the application of Law 68/99 by means of the stochastic frontier approach.

In this first stage of analysis, we have identified two regional clusters: a cluster formed by the regions of Central and Northern Italy, characterized by a high annual average efficiency score; a second cluster formed by the regions of Southern Italy, characterized by a low annual average efficiency score. In summary, the regions of Central and Northern Italy are more efficient in the *matching process between demand and supply of jobs for disabled people*. In addition, we verify that labour market policies in regions where the unemployment rate is very high (South Italy) could promote *the integration of disabled people in the labour market*; consequently, this could increase the efficiency of the regions in the application of Law 68/99.

In the second step of the analysis, we have analyzed through the SMC approach how the efficiency of a region can be affected by the efficiency score of its neighbours.The results of this analysis have shown the importance of good neighbors in promoting an *improvement in the performance of the regions in the process of labour integration of disabled people.* In particular, the probability of a region to improve its efficiency, if surrounded by good neighbors (29%), is higher than the probability of a region to worsen it if surrounded by bad neighbors (20%).

However, the effects produced by bad neighbors should not be underestimated, especially when they are concentrated in an area of the country and have a time-space persistence. This persistence ,if not mitigated by policy-makers, would result in an widening of the dualism between the North and the South of Italy. The effect of a persistent dualism on the performance of the regions with respect to the application of Law 68/99 is a problem that must be seriously considered by policy makers; especially when the regions with a low efficiency score are surrounded by neighbors with poor efficiency score (Southern Italy cluster).

We propose for the future to extend this analysis to the British and American administrative data in order to evaluate their performance in the promotion of laws in favor of disabled persons (respectively the *American with Disabilities Act* in the U.S. and the *Disability Discrimination Act* in the U.K.).

APPENDIX 1

Law 68/99 (from now on Law 68/99): some clarifications

Law 68/99 is addressed to: "the working-age people suffering from physical, mental or sensory and intellectual disabilities, resulting in a reduced capacity to work for more than 45 percent…", "Disabled from work with a degree of incapacity of more than 33 percent…", "the blind or the deaf-mute…", "war invalids, civil war invalids and disabled with disabilities ascribed from the first to the eighth category…".

The prerequisite to take advantage of the benefits provided by Law 68/99 is the inclusion in the compulsory employment lists, that are held by the Employment Services of the provincial governments. Employment services usually enroll the applicant in the lists of compulsory employment conditionally to further assessment of disability by health care bodies. Next to the entering, the disabled person is then able to join the job opportunities that come to the Employment Service from both public bodies and private companies, by filling out the form reservation.

The inclusion of people with particularly serious handicap may be facilitated by an ad hoc employment situation, i.e. social cooperatives of type B in order to allow them to learn about the assigned task.

Law 68/99 provides that private employers can sign a contract with these cooperatives, in order to temporarily employ the disabled person in the same social cooperatives, to which employers agree to assign work orders. This special three sided employment contract represents the novelty introduced by this law.

APPENDIX 2

As OY is a combined variable, it may be interesting to discover whether the effect is mainly connected to young or old people. To this end, we decompose the coefficient of the variable in the following way[26]:

$$\hat{\beta}_{OY} = \frac{\partial Ln(ERDP)}{\partial Ln(OP/YP)}$$

$$\frac{1}{\hat{\beta}_{OY}} = \frac{\partial Ln(OP/YP)}{\partial Ln(ERDP)} = \frac{\partial}{\partial Ln(ERDP)}(LnOP - LnYP)$$

where we denote by ERDP the employment rate of disabled people, OP the old people and with YP the young people.

Now we define the elasticity of the employment rate of disabled people with respect to the variable YP and OP respectively as:

$$\beta_Y = \frac{\partial Ln(ERDP)}{\partial LnYP}$$

$$\beta_O = \frac{\partial Ln(ERDP)}{\partial LnOP}$$

[26] The same decomposition is valid for the variable FM (see Cracolici et al., 2007).

so we have:

$$\frac{1}{\hat{\beta}_{OY}} = \frac{1}{\beta_O} - \frac{1}{\beta_Y}$$

and consequently:

$$\hat{\beta}_{OY} = \frac{\beta_O * \beta_Y}{\beta_Y - \beta_O}$$

Since we are thinking in terms of inefficiency, we can conclude that:

$\hat{\beta}_{OY} > 0$ if $\beta_Y > \beta_O$; the positive sign results in an increase of the inefficiency of the regions in their application of Law 68/99.

on the contrary, we have $\hat{\beta}_{OY} < 0$ if $\beta_Y < \beta_O$; in this case, the negative sign results in a reduction of the inefficiency of the regions in their application of Law 68/99.

REFERENCES

Acemoglu D., Angrist J.D. (2001) Consequences of employment protection? The case of the Americans with disabilities act, Journal of Political Economy, 109, 915-957.

Agovino M., Rapposelli A. (2011) Inclusion of disabled people in the Italian labour market: an efficiency analysis of Law 68/99 at regional level, Quality & Quantity, doi: 10.1007/S11135-011-9610-2.

Agovino M., Rapposelli A. (2012a) Employment of disabled people according to Law 68/99. A multidimensional analysis at regional level, Rivista Internazionale di Scienze Sociali, vol. 1/2012.

Agovino M., Rapposelli A. (2012b) Employment of disabled people in the private sector. An analysis at the level of Italian Provinces according to article 13 of Law 68/99 (submitted).

Akaike H. (1973) Information Theory and an Extension of the Maximum Likelihood Principle. In: B.N. Petrov and F. Csaki (eds.) 2nd International Symposium on Information Theory: 267-81 Budapest: Akademiai Kiado.

Anselin L. (1996) The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association. In M. Fischer, H. Scholten, and D. Unwin (eds.), Spatial Analytical Perspectives on GIS. London: Taylor and Francis, pp. 111-125.

Anselin L.(1988) Spatial econometrics: Methods and models. Boston: Kluwer Academic Publishers.

Anselin L.(1993) The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association. Paper presented at the GISDATA Specialist Meeting on GIS and Spatial Analysis, Amsterdam,The Netherlands, December 1-5 (West Virginia University, Regional Research Institute, Research Paper 9330)

Anselin L. (1995) Local indicators of spatial association – LISA. Geogr. Analysis, 27, 93-115.

Anselin, L. (2002) Exploring Spatial Data with DynESDA2. CSISS and Spatial Analysis Laboratory University of Illinois, Urbana-Champaign. September 12, 2002.

Battese G.E., Coelli T.J. (1995) A model for tecnica inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20(2), 325-32.

Bell D., Heitmuller A. (2005) The disability discrimination act in the UK: helping or hindering employment amongst the disabled? IZA DP, n. 1476.

Charnes, A., Cooper, W.W., Rhodes, E. (1981) Evaluating program and managerial efficiency: an application of Data Envelopment Analysis to program follow through. Manag. Sci. 27, 668-697.

Cracolici M., Cuffaro M., Nijkamp P. (2007) Geographical Distribution of Unemployment: an Analysis of Provincial Differences in Italy. Growth and Change a Journal of Urban and Regional Policy- Volume 38. Issue 4, pp.649-670.

Elhorst J.P. (1995) Unemployment Disparities between Regions in the European Union. In Convergence and Divergence among European Regions edited by H.W. Armstrong and R.W. Vickerman. London: Pion.

Jones M.K., Latreille P.L., Sloane P.J. (2003) Disability, gender and the labour market, IZA DP, n. 936.

Jones M.K., Latreille P.L., Sloane P.J. (2007) Disability and work: a review of the British evidence, Estudios de Economia Applicada, 25-2, 473-498.

Jones M.K., Sloane P.J. (2009) Disability and skill mismatch, IZA DP, n. 4430.

Kodde D.A., Palm F. C. (1986) Wald Criteria for Jointly Testing Equality and Inequality Restrictions. Econometrica, 54(5): 1243-48.

Le Gallo J. (2004) Space-time analysis of GDP disparities among European regions: A Markov chains approach. International Regional Science Review 27(2): 138-163.

López-Bazo E., del Barro T., Artis M. (2005) Geographical Distribution of Unemployment in Spain. Regional Studies 39(3): 305–318.

Ministry of Employment (2004-2005) Terza relazione al parlamento sullo stato di attuazione della legge 12 marzo 1999, n. 68, Norme per il diritto al lavoro dei disabili. Roma.

Ministry of Employment (2008-2009) Quinta relazione al parlamento sullo stato di attuazione della legge 12 marzo 1999, n. 68, Norme per il diritto al lavoro dei disabili. Roma.

Molho I. (1995) Spatial Autocorrelation in British Unemployment. Journal of Regional Science 35: 641– 658.

Orlando N., Patrizio M. (2006) Il collocamento mirato dei disabili: l'applicazione della legge 68/1999 nella Provincia di Bolzano. In: Parodi G. (Eds.) Aspetti socioeconomici della disabilità, ARACNE editrice, Roma, 179-216.

Patridge M.D., Rickman D.S. (1997) The Dispersion of US State Unemployment Rates: The Role of Market and Non-market Equilibrium Factors. Regional Studies 31(6), 503–606.

Rey S. (2001) Spatial empirics for economic growth and convergence. Geographical Analysis 33 (3): 195-214.

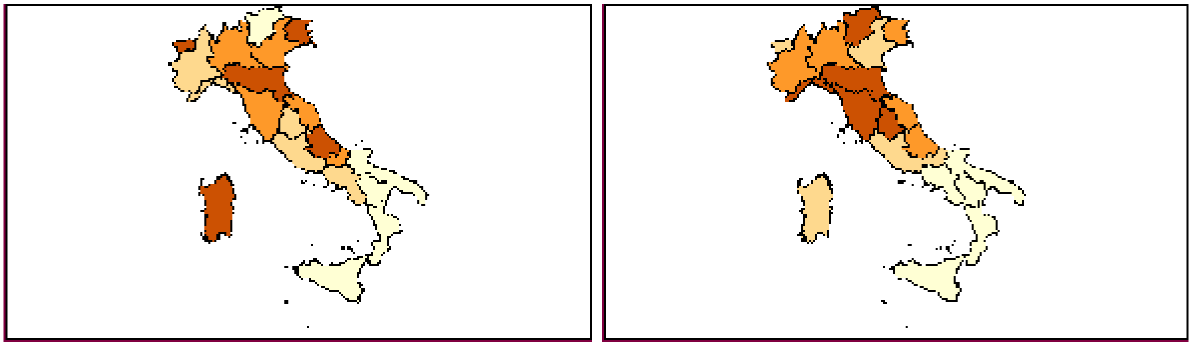
Schettini D., Azzoni C.R., Paez A. (2011) Neighborhood and efficiency in manufacturing in Brazilian regions: a spatial markov chain analysis, International Regional Science Review, 34 (4), 397-418.

Stock W.A., Beegle K. (2004) Employment Protections for Older Workers: Do Disability Discrimination Laws Matter? Contemporary Economic Policy, Western Economic Association International, vol. 22(1), 111-126.

Schwarz G (1978). Estimating the Dimension of a Model. Annals of Statistics 6: 461–464.

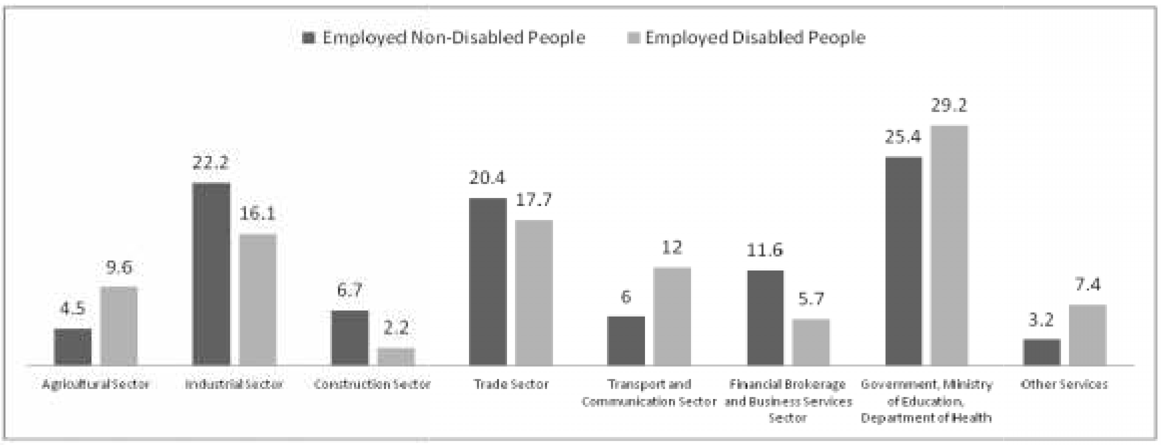
Thanassoulis, E. (2001) Introduction to the theory and application of data envelopment analysis: a foundation text with integrated software. Kluwer, Norwell.

Fig. 1 Percentage of employed disabled people, 2000 and 2009



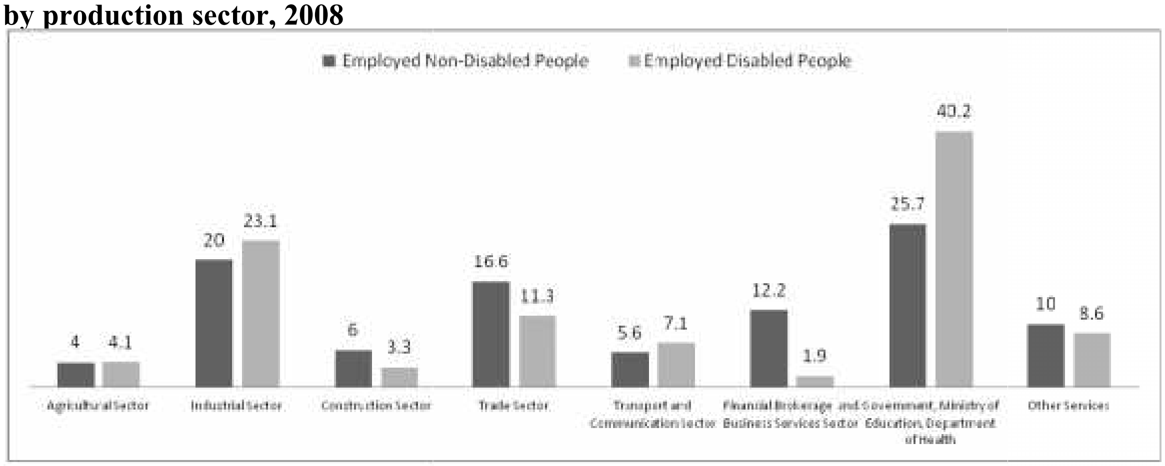
(2000) **(2009)**

Fig. 2 Percentage of employed disabled people and employed non-disabled people. Percentage by production sector, 2005



Source: Ministry of Employment (2004-2005)

Fig. 3 Percentage of employed disabled people and employed non-disabled people. Percentage by production sector, 2008



Source: Ministry of Employment (2008-2009)

Table 1:results of the Stochastic Frontier Analysis

		Coefficients of first model	Coefficients of second model
Frontier Function	Constant	0.1870***	-0.2253**
		(4.63)	(-2.56)
	Employment Rate of Agricultural Sector	0.0052**	0.0246***
		(2.14)	(3.17)
	Employment Rate of Industry Sector	0.0024***	0.0090***
		(5.06)	(3.13)
	Employment Rate of Sector Sector	0.0022***	
		(5.44)	
	— *Government, Ministry of Education, Department of Health*		0.0093*
			(1.91)
	— *Trade*		-0.0119
			(-0.92)
	— *Transport e communication*		0.0332*
			(1.84)
	— *regional dummies*	yes	yes
	— *time effect*	yes	yes
Inefficiency Function	Constant	105.0517***	37.2157***
		(14.15)	(14.37)
	FM	-6.3242	-10.4996**
		(-1.31)	(4.54)
	OY	-20.3952***	-11.7493***
		(-5.93)	(-2.63)
	EC1	-30.2775	4.6875
		(-0.44)	(0.09)
	EC2	-170.5013***	-54.5660**
		(-4.87)	(-2.12)
	σ^2	0.0082***	0.0057***
		(10.0389)	(10.1064)
	γ	0.3499***	0.1535***
		(10.4378)	(8.6684)
	LR test of $\sigma_u^2 = 0$	371.2250***	503.1071***
	Log-likelihood	473.6333	183.7672
	Mean efficiency	0.6319	0.6412
	AIC	-925.2666	-339.5344
	BIC	-890.144	-298.3514

***, **, *: 1%, 5%, 10%; (): t statistics.

Fig. 4 Regional efficiency scores with respect to OY, first model (years 2000-2009)

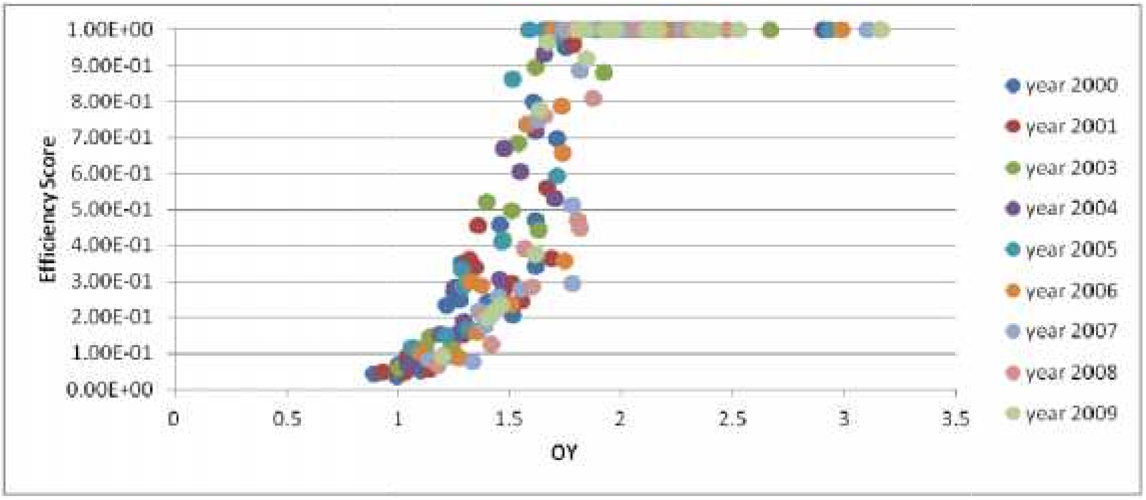


Fig. 5 Annual average efficiency scores, first model

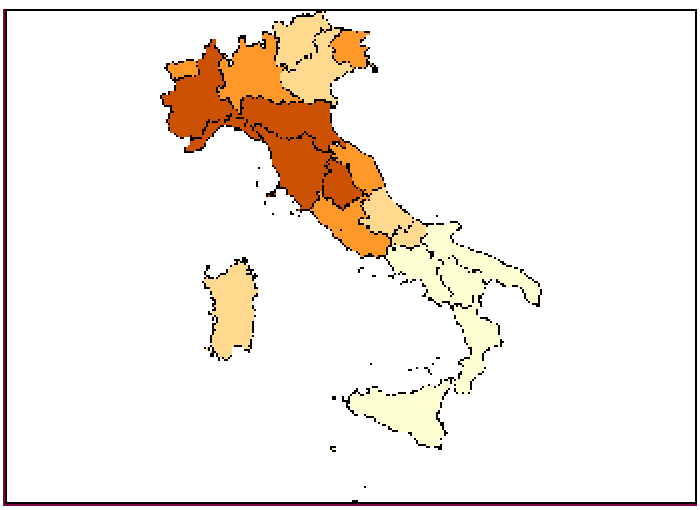


Fig. 6 Moran's scatter plot of annual average efficiency scoresof regions, first model

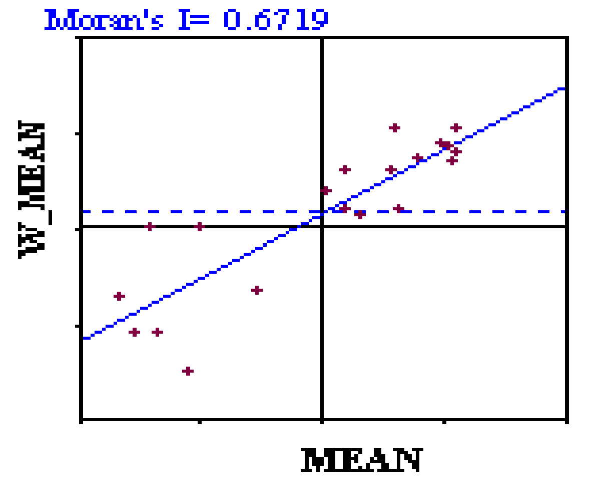


Table 2: SMC matrix, first model

Line	*t*	*Neighborhood condition*	*num. Cases*	***(t+1)* P**	***L***	***M***	***U***	***R***
1	P	P	0	0	0	0	0	0
2	L		9	0	**1**	0	0	0
3	M		0	0	0	0	0	0
4	U		0	0	0	0	0	0
5	R		0	0	0	0	0	0
6	P	L	14	**0.786**	0.214	0	0	0
7	L		18	0.056	**0.833**	0.111	0	0
8	M		3	0	0	**0.667**	0.333	0
9	U		0	0	0	0	0	0
10	R		0	0	0	0	0	0
11	P	M	3	**0.667**	0.333	0	0	0
12	L		5	0	**0.8**	0.2	0	0
13	M		5	0	0.2	**0.4**	**0.4**	0
14	U		6	0	0	0.167	**0.833**	0
15	R		0	0	0	0	0	0
16	P	U	0	0	0	0	0	0
17	L		4	0	**0.75**	0	0.25	0
18	M		11	0	0	**0.636**	0.364	0
19	U		71	0	0	0.014	**0.972**	0.014
20	R		7	0	0	0	**0.571**	0.429
21	P	R	0	0	0	0	0	0
22	L		0	0	0	0	0	0
23	M		1	0	0	0	**1**	0
24	U		0	0	0	0	0	0
25	R		2	0	0	0	**0.5**	**0.5**

Note: the largest value in each row is presented in boldface. Shaded cells indicate permanence in the same situation between years.

Fig. 7 Regions efficiency scores, first model (years 2000-2009)

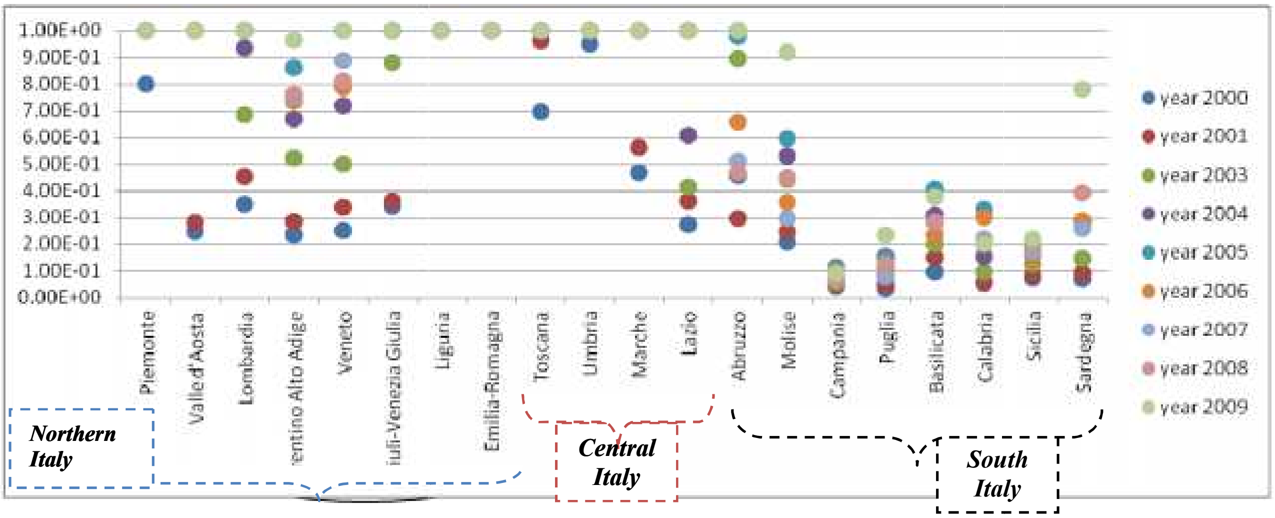


Table 3: probability of staying in the same class of efficiency

probability	P	L	M	U	R
	0.1094	0.0622	0.3406	0.361	0.1858

Table 4: summary of SMC analysis

	Cases of regions that could get better	Cases of regions that got better	Improvement Index	Cases of regions with better neighbors	Cases of regions with better neighbors and that got better	Probability of getting better with better neighbors
Getting better	***A***	***B***	***(B/A)*100***	***C***	***D***	***D/C***
	143	**16**	**11%**	**38**	**11**	**0.2894**
	Cases of regions that could get worse	Cases of regions that got worse	Deterioration Index	Cases of regions with worse neighbors	Cases of regions with worse neighbors and that got worse	Probability of getting worse with worse neighbors
Getting worse	***A***	***B***	***(B/A)*100***	***C***	***D***	***D/C***
	150	**9**	**6%**	**25**	**5**	**0.2**

Table 5: Summary of local measures of spatial association: efficiency scores, first model (years 2000-2009)

Macro Area	*REGIONS*	*p<0.05*	*Q1*	*Q2*	*Q3*	*Q4*
Northern Italy	Piemonte	9	**9**	0	0	0
Northern Italy	Valle d'Aosta	0	0	0	0	0
Northern Italy	Lombardia	0	0	0	0	0
Northern Italy	Trentino Alto Adige	0	0	0	0	0
Northern Italy	Veneto	0	0	0	0	0
Northern Italy	Friuli-Venezia Giulia	0	0	0	0	0
Northern Italy	Liguria	9	**9**	0	0	0
Northern Italy	Emilia-Romagna	9	**9**	0	0	0
Central Italy	Toscana	8	**8**	0	0	0
Central Italy	Umbria	4	**4**	0	0	0
Central Italy	Marche	3	**3**	0	0	0
Central Italy	Lazio	0	0	0	0	0
South Italy	Abruzzo	0	0	0	0	0
South Italy	Molise	0	0	0	0	0
South Italy	Campania	9	0	0	**9**	0
South Italy	Puglia	9	0	0	**9**	0
South Italy	Basilicata	9	0	0	**9**	0
South Italy	Calabria	7	0	0	**7**	0
South Italy	Sicilia	4	0	0	**4**	0
South Italy	Sardegna	0	0	0	0	0

$p<0.05$ Number of years local statistic is significant at 0.05.
Q1 Number of years for which the local statistic is in quadrant 1 of Moran's scatterplot
Q2 Number of years l for which the local statistic is in quadrant 2 of Moran's scatterplot
Q3 Number of years for which the local statistic is in quadrant 3 of Moran's scatterplot
Q4 Number of years for which the local statistic is in quadrant 4 of Moran's scatterplot