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Regional Welfare Systems in Italy: a Cluster Analysis

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Abstract

The reforms of welfare systems, which happened in different countries, have generated more differences at the local authority, thus the improvement of welfare organization has followed specific development methods providing different services for the citizenship living in the same country. The welfare classification research at cross-national level have not considered the heterogeneity of national welfare system, as underlined by Bertin's (2012b) research, based on an Italian case study, which identified that the Italian welfare system could be classify in seven different welfare regimes. Thus, this analysis, using the same data of Bertin's (2012b) analysis and applying a different cluster analysis method (K-mean), attempts to confirm the Bertin's (2012b) classification. The results corroborate some models of welfare systems identified by previous research but other cluster groups suggest that it is useful to conduct deep analysis in order to distinguish some more welfare system features.

Keywords: welfare systems, local welfare, k-mean cluster analysis.

Introduction

Welfare system classification analysis has concentrated mainly on cross-national level and the literature offers a variety of research. In fact, the welfare system was classified adopting specific indicators and using data referring to different timeframes. However, in recent years, the welfare system has been subject to significant reforms that, in some cases, changed the national welfare system features. The causes of these reforms are different, such as the economic crisis that required a review of national social expenditure, new

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kinds of social problems and general social changes that addressed the policy maker agenda and the 'nature' of the welfare system itself. Thus, in some cases, the local authority, as suggested by Craw (2010) and Jensen and Lolle (2013), obtains more autonomy and consequently the development of welfare system has followed different processes which have been generating distinct services in the same country.

Nonetheless, the welfare systems were analysed with different methods. One of these statistical techniques is cluster analysis that has been adopted by many researchers (Gough 2001, Kangas 1994, Wagschal 1999, Pitruzello 1999, Powell and Barrientos 2004, and Kammer, Niehues and Peichl 2012) to classify the welfare system. It allows recognition of groups of cases that are homogeneous within themselves and allows clear boundaries with others. Furthermore, it could indicate the distance between the cluster and the main features of each group. Thus, it is an effective technique to use in order to classify the welfare system.

Furthermore, the cross-national welfare systems classification does not underline the local differences that characterise the national welfare systems instead. Considering that the local diversity is important because it provide different social services, it is interesting to consider also the local authority 'dimension' when the welfare systems are classified. A significant work focusing on an Italian case study is Bertin's (2012b) research that attempts to classify the Italian welfare system using the hierarchical cluster technique, considering the twenty Italian regions as units of analysis.

The Bertin's (2012b) research was followed by another analysis, which focuses mainly on indicators used, while other different attempts of local welfare system classification have been carried out by Maretti (2008), Madama (2010) and Pavolini (2011). Thus this paper, using the same data as Bertin (2012b), but applying a different cluster technique, specifically k-mean cluster analysis, strives to verify the Bertin (2012b) analysis. This analysis does not appear to be a substitution of previous classification, but it would be a beneficial contribution not only to verify, adopting a different method, the heterogeneity of national welfare system, but also to aspire, at the same time, to stimulate the discussion about the classification of welfare systems in order to increase the knowledge of the welfare system organisation.

This essay focuses first on the classification of welfare system at cross-national level, before going on to the regional level of cluster study carried out by Bertin (2012b). In this section, it is also synthesise another analysis of the same indicators used by Bertin (2012b). Then the data and the k-mean cluster analysis method are presented. In the subsequent section the results of k-mean cluster analysis and how the clusters shape are described. Conclusions summarise the cluster welfare systems and compare these clusters with the regional welfare systems identified by Bertin's (2012b) analysis.

1. Cross-national classification of the welfare systems and differences at national level

The seminal work of Esping-Andersen (1990) published with the title 'Three Worlds of Welfare Capitalism', concerning the classification of welfare systems, has furthered the research on categorization of welfare system at cross-national level. Indeed, after his work, many scholars attempted to carry out a cluster analysis of welfare provision, considering the countries as units of analysis, in order to identify some commonalities and differences among the cases. According to Gough (2001) the cluster analysis technique is not widespread in the field of welfare system analysis; in fact, he states in his paper that: "Despite its obvious relevance in confirming or otherwise the existence of 'welfare regimes' it has rarely been applied to cross-national data on social policy: Kangas (1994), Wagschal (1999) and Pitruzello (1999) are two exceptions" (2001: 165).

A synthesis of the research results that attempted to classify the welfare systems is present in the works of Arts and Gelissen (2002; 2010), and as shown by their contributions, current literature offers a variety of welfare system classification models. However, in these analyses, a cluster technique was not always applied. The classification method mentioned by Gough (2001) was applied, for instance, by Powell and Barrientos (2004) and by Fenger (2007), and more recently by Kammer, Niehues and Peichl (2012), who all used both hierarchical and k-mean cluster analysis. Conversely, the welfare classification was also reached through the application of other analysis techniques; for example, the meta-analysis (Ferragina and Seeleib-Kaiser, 2011), the fuzzy set ideal type analysis (Vrooman, 2012), and the nonlinear principal components analysis (Vrooman, 2012).

Furthermore, in the classification welfare systems studies, beside the distinct techniques of analysis, researchers have used different indicators or data collected at different points in time, although they focus as ever on cross-national classification analysis. These 'parameters' sometimes generated different national clusters that not always correspond exactly to other previewed research classifications. Indeed, in some cases, researchers labelled clusters that bracket together the same countries according to previous studies with different labels. Instead, in other cases, it is possible to find that a specific state clusters together, while for others, the same nation has a different grouping. Ferragina and Seeleib-Kaiser (2012), for instance, show a synthesis of these different groupings. This problem could be due not only to the indicators used but also to the classification technique adopted. Thus some Authors, such as Ragin (1994) and Obinger and Wagschal (1998, 2001), identify a hybrid cluster, which is a residual category that usually includes cases that are not clearly distinct from others.

The reflections developed previously refer particularly to cross-national comparison; however, the development and the reforms of the welfares systems have produced some differences at sub national level; instead its goals are to improve fairly well being of all citizens and to create some protections against the social risks. In other word, it is fundamental to be cautious to consider a national welfare system as an equally widespread, homogeneous system in all sub administrative country area. Some recent empirical research underlined clearly the heterogeneity of national welfare system. For example, Beatty and Fothergill (2014) show how the implementation of welfare reform in the UK, introduced in 2010, has had a negative influence in some local area more than in others. Jensen and Lolle (2013), analysing the government spending in the provision of care of older people in Denmark, discovered an enormous variation in municipal spending on care of older adults. Another example is the contribution of Craw (2010), who demonstrated the power of local authority in taking decisions concerning the poverty-related issues.

Commencing from the consideration that in some countries such as Italy, the expansion of the welfare system has produced diversity among the local welfare systems; Bertin (2012b) suggests that it is necessary to consider more the local dimension in the classification analysis of social services. This statement is the starting point of his work in an Italian context, in which he classified the national welfare system as units of analysis of the twenty Italian regions.

In his research, Bertin (2012b) used a number of indicators that describe the main features of the welfare system, defined as dimensions: 1) the subject that provides the service; 2) the distribution of services, and 3) the context. Table 1 shows the three main dimensions of the welfare system and the latent indicators, which denote specific welfare system features.

The indicator, 'Mix structured', describes a system in which the services are provided by a variety of subjects, such as public institutions, private companies and non-governmental organizations (NGOs). This system is well organized with a stable framework. The variables that express this system are: 1) Number of cooperatives with a value of production greater than 500,000 euro/Total number of cooperatives; 2) Families who have received at least one free instance of help in looking after children from non live-in help during the last four weeks; 3) Family average monthly expense for heath care

(Euro); 4) Percentage of beds for the elderly in residential public services and 5) Percentage of beds for the elderly in residential non-profit services.

Table 1. Dimensions and indicators identified by Bertin (2012) and used in the cluster analysis

Dimensions	*Indicators*
Subjects who create the service	Mix structured
	Mix towards corporatism
Service diffusion	Diffusion of traditional social services
	Diffusion of innovative social services
Context	Social Cohesion
	Social risks

'Mix towards corporatism' describes a framework in which is noticeable the presence of voluntary organizations; in other words, many social assistance services in this context are carried out by third sector organizations, and the 'provisions' of market services are very limited. This system is identified by the indices: 1) Number of cooperatives/Total resident population; 2) Number of public crèches/Total number of crèches; 3) Percentage of families who have received at least one free help in housework from non live-in help during the last four weeks; 4) Number of voluntary associations/Total resident population; Number of employees and collaborators of cooperatives/Number of resident population, and 5) Number of beds in private hospitals/Total number of beds.

'Diffusion of traditional social services' is composed of variables that describe some traditional services, such as public residential care houses or pension supports. Specifically, the variables that constitute this factor are: 1) Number of elderly guests in the residential care accommodation/population (aged ≥ 65); 2) Number of elderly guests in the public residential care accommodation/population (aged ≥ 65); 3) Municipal social expenditure per capita; 4) Percentage of women (aged ≥ 65) who have had a mammogram without the presence of symptoms or complaints; 5) Number of old-age pensions/Total number of pensions; 6) Percentage of municipalities that have active services for children (e.g. kindergarten, crèche and additional services, and innovative)/Total number of municipalities in the region; 7) Number of days of residential and semi-residential care accommodation/1,000 residents (aged ≥ 65), and 8) Number of invalid pensions/Total number of pensions.

'Diffusion of innovative social services', which concerns some original protection action, is formed only by: 1) Integrated social care services for elderly people, and 2) Potential users and percentage of children who were admitted to the public and private crèches.

'Social Cohesion' dimension describes the 'vitality' of the context, and it is illustrated by six variables which are: 1) Number of voluntary associations/Total resident population; 2) People (aged ≥ 14) who have played at least one social activity (activities free of charge for voluntary associations), in the 12 months preceding the interview; 3) Social capital indicator; 4) Percentage of people (aged ≥ 14) who have engaged in at least one instance of volunteer help to non-cohabiting others, during the last four weeks; 5) Institutional trust, and 6) Percentage of people whose family economic resources have been considered insufficient during the last 12 months.

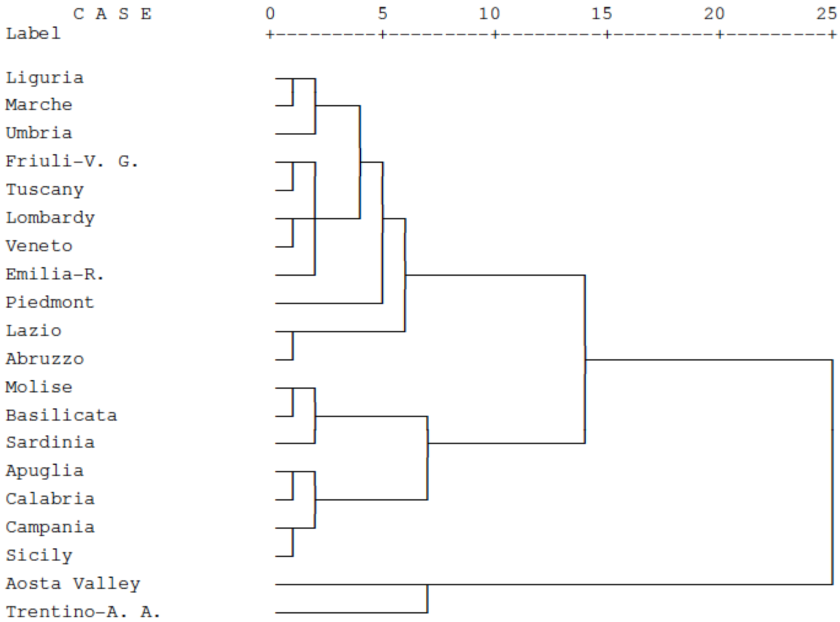
The last index, 'Social risks', sets out the context problems that the welfare system should address. It is represented by: 1) Poor families Index (incidence); 2) Early school leaving rate (young people); 3) Household poverty intensity index; 4) Youth Unemployment Rate; 5) Gini index, and 6) Disability-free life expectancy for males (at 15 years old).

The factor scores of the these six indicators were analysed with a hierarchical cluster analysis in Bertin's (2012b) research, and the results, which are illustrated in the dendogram in Figure 1, grant Bertin (2012b) to identify different models; thus, he was able to state that the Italian welfare system might be characterised by seven dissimilar welfare systems, and these clusters have been labelled according to their features. The table 2 illustrates the seven groups according to regions[1].

The main features of each welfare system could be represented as follows: 'Generalized social system mixed with a corporative system' describes a system in which the social services are provided mainly by public and corporative actors. These services are widespread in all local areas of the regions that compose this cluster. Low levels of social risks and high levels of social cohesion also characterize this cluster. In the cluster, generalized and generous, the local services are also widespread, but in this case, the main providers of welfare services are public and private actors. Although in this cluster there is a high level of social cohesion, there is also a slightly higher level of social risks.

[1] For a detailed description of the cluster see Bertin (2012b).

Figure 1. Hierarchical cluster analysis



From Bertin (2012b), p. 64

Table 2. The group of welfare state systems present in Bertin (2012) classification

Welfare systems labels	*Regions*
1. Generalized social system mixed with a corporative system	Aosta Valley and Trentino-Alto Adige/Südtirol
2. Generalized and generous system	Friuli-Venezia Giulia, Tuscany, Lombardy, Veneto and Emilia-Romagna
3. Structured mixed	Liguria, Marche and Umbria
4. Consolidated system but less innovative	Piedmont
5. Residual and not diversified	Abruzzo and Lazio
6. Residual with some corporative input	Basilicata, Molise and Sardinia
7. Minimal system with high social risks	Apulia, Calabria, Campania and Sicily

Where social cohesion and risks are not extensive is in the cluster called 'Structured mixed', but it does not offer elevated quality of social provisions, and it is changing towards a corporatist system. 'Consolidated system but less innovative' cluster has a low level of social cohesion and social risks, but it has also limited services on the territories, and it shows a deficiency of corporatist organization. In 'Residual and not diversified' model, the services are mainly traditional and less innovative, even though it is possible to identify some processes of modernization. The main subjects that produce services are public and private. Another particularity of this group is that both social cohesion and social risks are low. 'Residual with some corporative input' shows a limited offer of all kinds of services - public, private and third sector - and they are not widespread in all areas of regions. Moreover, the innovation is limited, while the cohesion contributes to increase the cooperation. 'Minimal system with high social risks' is the cluster with inadequate services; for example, there are scarce public actors that provide services and also the cooperative services are minimal. Social cohesion is not widespread, and there are huge quantities of social risks.

The data used in Bertin's (2012b) research have been re-analysed by Pastore and Tonellato (2013). Following, for instance, Ahlquist and Breunig (2012), McLachlan and Basford (1988), McLachlan and Peel (2000) and Fraley and Raftery (2002) 'theory', they applied a cluster analysis model, based on the probability theory, to each dimension identified by Bertin (2012b). This method assumes that the observed data are created by a limited number of 'mixture' of probability distributions in which each component represents a different group or cluster. Although it presents some advantages (Ahlquist and Breunig 2012), such as to be able to adapt numerous cluster profiles, which are not readily implemented in other methods, or to offer a variety of statistical tools that can aid the choice of cluster method, it has also some inconveniences (Ahlquist and Breunig 2012; Fraley and Raftery 2002); for example, it does not produce significant results with a large dataset and when the groups are not clearly distinct. Nevertheless, its application has risen inside the Social Sciences, especially as a direct result of the statistical researchers, because it reduces the probability that the idea of researcher in selection of variables influence the outputs. The objective of Pastore and Tonellato (2013), in applying this procedure, was not to identify another different welfare system classification, but simply to underline the strength of this approach to analyse the same data.

The conclusions achieved could be synthesised as follows: first of all, there is a region, the Trentino-Alto Adige/Südtirol, that is difficult to identify within some clusters because it forms a cluster in itself. According to the Authors, this could be due to administrative, historical or geographical reasons. Moreover, the inclusion of this region on the database might considerably influence the results.

Secondly, some variables, such as the number of beds in private hospitals/total number of beds; families who have received at least one free instance of help in looking after children from non live-in help during the last four weeks, and the number of public crèches/total number of crèches which Bertin (2012b) used in his research, when analysed separately, do not allow for discrimination of the welfare systems.

Focusing on the context dimension, the analysis has shown only two clusters: one composed of Centre-Nord Regions (Abruzzo, Aosta Valley, Emilia-Romagna, Friuli-Venezia Giulia, Liguria, Lazio, Lazio, Lombardy, Marche, Molise, Piedmont, Tuscany, Umbria and Veneto) and the other with southern regions (Apulia, Basilicata, Calabria and Campania), including the two islands (Sicily and Sardinia). Moreover, in this case the Trentino-Alto Adige/Südtirol is an 'outlier'.

The analysis of the diffusion services has identified only four discriminating variables: number of days of residential and semi-residential care accommodation/1,000 residents (aged $\geq$ 65); integrated social care services for elderly people; percentage of women (aged $\geq$ 65) who have had a mammogram without the presence of symptoms or complaints and number of elderly guests in the public residential care accommodation/population (aged $\geq$ 65). The resulting influence on the cluster formation contributes to divide the Italian regions in three groups. One cluster includes Abruzzo, Basilicata, Calabria, Campania, Lazio, Liguria, Marche, Molise, Piedmont, Apulia, Sardinia, Sicily, Tuscany and Umbria. Another cluster is formed only by Aosta Valley, and the Emilia Romagna, Friuli-Venezia Giulia, Lombardy and Veneto regions constitute yet a different cluster.

These results lead the Authors to suggest that it is beneficial, when the objective is to identify a classification, to select accurately the variables, and this process should not only be done with consideration of the specific theoretical knowledge of the researcher, but also should include empirical evidence, because different variables could identify diverse classifications. These two 'factors', the researcher knowledge and the statistical methods, should be considered together.

Thus, the final target of this paper, as done by Pastore and Tonellato (2013), is not to find a different classification of the Italian welfare systems, but to test if the clusters identified by Bertin (2012b) are harmonized. To achieve this goal, the k-mean cluster analysis was applied to the three core dimensions of the welfare system, using six indicators.

2. Data and analysis method

This essay draws its data from the classification welfare system research carried out by Bertin (2012b*)*. The sources of the statistic information are the databases of the Welfare Ministry and the Ministry of Education. The data used cover a period between 2005 and 2010, and due to the heterogeneous databases, only the more recent variables were considered. The twenty Italian regions are classified as the unit of analysis.

There are three principal analyses in Bertin's (2012b) research: first, a semantic analysis second, a factorial analysis and than a cluster analysis. The semantic was adopted to vet which variables might describe the three main features of welfare system. Then, the factor analysis was applied to identify some latent dimension upon each of the three principal characters of welfare systems, and subsequently, the six factors were identified and labelled (see table 1). Finally, these factor values were used as indicators in the cluster analysis.

Cluster analysis is a statistical technique that classifies the observations, which share the same characteristics in homogenous clusters or groups, while the cases that compose a cluster are very dissimilar to the objects that belonging to other groups. There are different cluster approaches: hierarchical methods, partitioning methods (or k-means) and two-step clustering.

Hierarchical cluster analysis (HCA) - the approach that was used in Bertin's (2012b) research - is a specific cluster method that begins to consider each observation as an individual cluster; then, the algorithm proceeds one step at a time, merging other cases that are similar, until all observations are clustered together. When two or more cases are merged in a group, they remain joined without the possibility to change cluster, and these steps are efficiently displayed in a dendogram, which is an intelligible method to represent the clusters. In this procedure, the number of clusters is not predefined, and it is the researcher that decides on the distance measure to identify the clusters.

In this study, following the Gough (2001) idea, the same six indicators used by Bertin (2012b), have been analysed with k-means cluster analysis (KCA).

In KCA, the number of clusters, indicated by 'k', is predefined, and the algorithm of KCA considers the within-cluster variation as a measure to structure homogenous groups; in other words, the logic of this approach is to segment the data in a manner that the within-cluster variation[2] is marginal. To achieve these objectives, the clustering process starts by randomly assigning observations to a number of clusters, and successively, the objects are reassigned to other groups to minimize the within-cluster variation. If the reallocation of an object to a different cluster decreases the within-cluster

[2] The within-cluster variation is basically the (squared) distance from each observation to the centre of the associated cluster.

variation, this object is reassigned to that cluster, and if there are not other opportunities, for example to reduce the within-cluster variation or it has run for the number of iterations specified, the clustering stop. Thus, in the KMC, the observations do not remain in the same cluster as in the HCA where there is a hierarchy, but they could change collocation in order to find the more near collocation to the centre.

KCA offers some measures, such as distance, final cluster centres and distance between cluster centres that support the researcher in interpreting the classification. The distance measures how far each case is from the cluster empirical centre: the higher the value, the farther it is from the centre of the cluster. Final cluster centres denote the contribution of each variable to discriminating between the clusters; thus, some variables could have a positive effect in certain clusters and negative in others. Additionally, the higher the value, the greater the variable effects on the cluster fit will be[3]. This information helps the researcher to interpret the influence of the variable on each cluster. The variables contribution to discrimination among the clusters is indicated by the F statistic, which comes from the analysis of variance (ANOVA). Finally, the distance between cluster centres indicates the degree of similarity or dissimilarity between the identified clusters.

Although KCA appears a valuable technique, it presents some problems in its application. One of these is that the number of clusters needs to be initially specified by the researcher. This probably makes the KCA less suitable than other cluster approaches. To avoid this difficulty, HCA is commonly applied to help the researcher to recognize a possible number of clusters; thereafter, it is used as parameter in the KCA.

The KCA was adopted in this research because it permits the recombination of cases and clusters over repeated iterations; thus, it is a technique that attempts to find the better solution. Furthermore, it offers a suitable range of information to help the researcher to interpret the results. Finally, the Bertin's (2012b) classification, which identifies seven different welfare systems, offers operative information to select the value of K.

3. The different welfare systems in Italy

In this research, a number of KCA with a range of values from k=2 to K=7 were carried out in order to identify the validity of Bertin (2012b) classification, and the typologies produced by the various K-means analyses

[3] This value usually helps the research to interpret the cluster and to label it: the final cluster centres table gives the mean abundance of each species in each of the clusters.

are presented in the following tables; to simplify the reading, the results are added together, referring to the number of cluster. The value of K=2 was considered as the first number of clusters, and this small number allow us to identify how they are formed.

The KCA with k=2 (Table 3 colon K=2) shows that the central northern regions (excepted the Lazio) are separated from the other regions of South Italy, including the islands (Sardinia and Sicily). However, these two groups are not homogeneous: as show by the distance values, in both clusters there are some regions that are a great distance from the centre of the group. This is the case in the majority of regions in cluster one; for example, Lazio and Basilicata have a distance value away from the centre more than two, and the other regions more than one.

The second cluster presents the same problem of the cluster one and in this cluster some regions are further from the cluster centre than in cluster one. Trentino-Alto Adige/Südtirol and Aosta Valley, which are 3.923 and 3.467, respectively, are farther from the middle of the group. On the other hand, Tuscany and Friuli-Venezia Giulia are the regions nearest the cluster centre.

The values in table 4 specify which indicators influence clusters. The social risks index has a positive influence only on group one, while in cluster two is the opposite, wherein all indices have positive effects, while the social risks indicator is negative. The factor that has the higher positive impact is that which describes the mix structure organisation.

The indices that contribute the most in discriminating between the two clusters (table 5) is the mix structured variable, while the mix towards corporatism is not significant.

These two groups are well demarcated, as shown by the values in the distance between the final cluster centre table (table 6), classifying the welfare regimes into 'two Italies', recalling a common Italian stereotype: northern Italy is characterized by some services, while southern regions are marked with social risks.

Even though the cluster boundaries are significantly manifest, the two clusters are not homogeneous; thus, to increase the K value of KCA with K=3 (or more) could identify new groups.

Table 3 k-means cluster analysis, k values from 2 to 7 (see Appendix)

The analysis with k=3 identified a new group composed of the regions that were far from the centre in cluster two in K=2 analysis. Thus, Trentino-Alto Adige/Südtirol and Aosta Valley now form a new group. Moreover, in this case, the Lazio region is incorporated into cluster two, with the northern regions. However, in this case, although the distance value is changed, all the three clusters present low levels of homogeneity, since the distance value is more than 1 for the majority of regions. In the first cluster (K=3), the region, Apulia, is near the centre, while in the second is Friuli-Venezia Giulia and Tuscany. The traditional services diffusion, social cohesion, mix toward corporatism, mix structured and social risk indices have a positive effect on cluster three, while innovative service diffusion has a negative impact. The discrimination effects of the factors between cluster one and two are the same as in the analysis with K=2, but the intensity of these effects has changed.

Five of all six dimensions adopted to describe welfare systems are highly significant in discrimination among the three clusters, and they are the traditional services diffusion, mix structured, innovative service diffusion, social risks and social cohesion. These three clusters are well demarcated, as show by the distance between the cluster centres.

Table 4 Final cluster centres (Z-score) (see Appendix)

Observing the dendogram (figure 1), if the cluster is cut at the distance value of 10, three main clusters are identified. Comparing these with the result of KCA (K=3) and focusing on the group composed of fewer number of regions, it is possible to state that the results of the two different cluster techniques are similar: the regions, Trentino-Alto Adige/Südtirol and Aosta Valley, formed a group by themselves. The first cluster in the dendogram is composed of Liguria, Marche, Umbria, Lombardy, Veneto, Friuli Venezia Giulia, Tuscany, Emilia Romagna, Piedmont, Lazio and Abruzzo. The KCA (K=3) finds the same output, except in the case of Abruzzo, which is considered in another 'model'. However, as it is noticeable from the dendogram of HCA, Abruzzo and Lazio are not very close to the other regions and this is confirmed with the KCA (K=3) because their distance value from the cluster centre is high. Then, the first cluster in the dendogram corresponds, except in the case of Abruzzo, to the second group of KCA findings. Nevertheless, as it is possible to see on the dendogram, these similarities between the two diverse methods result inside the first two clusters. There are some regions that are closer than others, such as Molise, Basilicata and Sardinia, and this is confirmed also from the distance centre values. It is possible to affirm that cluster suffers from heterogeneity; thus, it is interesting to analyse the K=4 in order to identify the stability of classification.

The results achieved with KCA (K=4) are more interesting because some clusters identified by Bertin's (2012b) research start to take shape. In this case, the southern regions, which in the previous analysis (whit K=3) were combined together, now are divided into two clusters; one formed by Apulia, Calabria, Campania, Sicily, and the other by Basilicata, Molise, Sardinia. These two clusters correspond exactly to clusters identified by Bertin (2012b). These two groups are homogeneous because the distance from the centre is less than 1; and these clusters, which have achieved a near collocation to the centre, will stay together for future analyses (K=5; K=6 and K=7). From the same analysis (K=4), the cluster composed of Trentino-Alto Adige/Südtirol and Aosta Valley is confirmed, but it is still heterogeneous according to the distance values. Thereafter, there is a consistent cluster formed of some northern and central regions; this cluster now includes the region, Abruzzo, which before was integrated into the cluster formed of southern regions. This is not a closer cluster because instead, there are some regions, such as Friuli-Venezia Giulia, Marche and Tuscany that are closer to others; for instance, for Abruzzo and Lazio, the distance value from the centre is high. This condition is also clearly visible in the dendogram.

Tab. 5 ANOVA

Variable labels	*F stat*					
	K = 2	*K = 3*	*K = 4*	*K = 5*	*K = 6*	*K = 7*
Mix structured	71.990***	30.311***	17.546***	12.700***	11.585***	29.427***
Mix towards corporatism	1.347	3.022†	12.721***	26.899***	13.061***	17.137***
Traditional services diffusion	16.883**	54.706***	25.815***	18.185***	14.169***	22.445***
Innovative service diffusion	8.599**	22.414***	12.910***	12.510***	15.642***	8.745**
Social cohesion	7.556*	15.092***	10.861***	8.438**	21.985***	29.718***
Social risks	12.161**	20.112***	27.412***	28.100***	16.295***	19.282***

† $p \leq 0.10$; * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

The influence variables on the clusters are show in table 4, at the lines corresponding to K=4. Interesting is the analysis of clusters one and two, which coincide exactly with Bertin's (2012b) classification. The Author labelled cluster one as 'Minimal system with high social risks' because it is characterised by high levels of social risks; while cluster two as 'Residual with some corporative input', because it has some signal that indicates a corporative organisation system, but there is not a mix of 'subjects' that offer services, and their diffusion and innovation are limited. From this analysis, it is possible to confirm Bertin's main findings. In fact, in cluster one, the only variable that has a positive effect is the social risks factor, and the only two factors that have the same effects on the cluster two are mixed with corporatism (which contribute to label the cluster) and social risks, whereas others influence negatively. The effect that the variables have on the cluster formed by Trentino-Alto Adige/Südtirol and Aosta Valley is the same as in the analysis with K=3 since there are not interchangeable. The influence of the factors in cluster three is uniform as in preview analysis, but it has changed the intensity due to the fact that Abruzzo is now joined with the cluster formed by central northern regions.

The social risks and traditional services diffusion factors contribute the most to discrimination among the clusters. Significant is also the effect of the mix structure dimension.

The boundaries of the clusters are well demarcated. In particular, cluster four (composed of Trentino-Alto Adige/Südtirol and Aosta Valley) is very far from cluster one (formed of Apuglia, Calabria, Campania, Sicily) and cluster two (Basilicata, Molise, Sardinia).

The cluster analysis with K=5 identifies the same clusters that, in the previous analysis, showed 'stability', which in this case corresponds to the cluster number two, four and five (table 3 columns refer K=5). The group that was subsequently composed of central northern regions is now divided into two clusters, and these regions now form a new group in the KCA (K=4), presented with highest distance from the centre, such as Piedmont, Lazio, Abruzzo and Lombardy. These two new groups are not homogeneous. Indeed, the region distance values from the cluster centre of the first cluster are more than 1, and also in the cluster three; with the exception of Friuli-Venezia Giulia, Marche and Tuscany, the other regions are not close. To sum up, these two clusters are not homogeneous.

In cluster one, the variables that have a positive impact are mix structured, traditional services diffusion and innovative service diffusion; while mix towards corporatism, social cohesion and social risks affect it negatively. However, in cluster three, all variables, except social risks, have a positive influence. The indices which contribute most to discrimination of the group are social risks and mix toward corporatism. The majority number of clusters is well separated, as illustrated by the value of the final distance from the cluster centre, but the boundary between clusters one and three is not delineated; in effect, these two groups have a low value of distance from final cluster centre, and this is due also to the homogeneity problems. Therefore it is important to remember that in the KCA (K=4), these regions join together in only one cluster.

Tab. 6 Distance between final cluster centre (See Appendix)

The heterogeneity of the cluster gradually attenuates as the numbers of K increase from 2, but it is still substantial for k=6. From the KCA (K=6), some clusters that were identified in advance and which are stable, such as the cluster composed of Apulia, Calabria, Campania and Sicily, or that are formed by Basilicata, Molise and Sardinia, now are identifiable again. However, in this case, two particular changes are evident. First, the cluster that before was formed by Trentino-Alto Adige/Südtirol and Aosta Valley is now divided into two different groups, and consequentially, these two regions form two distinct clusters by themselves. Second, the Lombardy region that in KCA (K=5) was inserted into a cluster with Abruzzo, Lazio and Piedmont is now assimilated into the other regions, as it was in K= 4.

Thus, now it is possible to identify two new clusters formed by only one region (Trentino-Alto Adige/Südtirol and Aosta Valley) and a cluster composed of Abruzzo, Lazio and Piedmont, while the other clusters are stable. Despite this reallocation, this last cluster, as well as the cluster number six, is not homogeneous due to the high distance value of Piedmont from the centre.

In cluster one, the variables that have a negative impact are: mix towards corporatism, traditional services diffusion, social cohesion and social risks; while in cluster two and four, it is only the diffusion of innovation, but with different intensity, which is negative. In cluster six the social risks dimension has a negative impact as in the previous analyses, but in this case, there is a change in the effect intensity. For the other clusters, the effect is unchanged.

All the effects of the six variables are significant in discriminating among the clusters, and the variable that contributes the most to distinction is social cohesion. The boundaries of the clusters are well demarcated, but this it is not true for clusters one and six. In effect, all the regions that in the KCA are classified in cluster one and six, according to the dendogram, could be considered as a unique cluster.

The KCA with K=7 corresponds to the number of clusters identified by HCA carried out by Bertin (2012b). The KCA method generates seven clusters, and three of these correspond exactly to Bertin's classification.

The group that coincides with previous research is cluster one, composed of Basilicata, Molise and Sardinia; cluster six, formed of Abruzzo and Lazio, and cluster seven that categorizes Apulia, Calabria, Campania and Sicily. These clusters are homogeneous, considering that their distance from the cluster centre is less than 1; thus, it is possible to affirm that the regions that form a cluster have analogous systems of welfare.

The reflection concerning the other clusters is more complicated, but it does not deviate far from Bertin's (2012b) conclusion. Starting from the consideration of the two autonomous regions that form a cluster by themselves, Bertin (2012b) considers them as a unique cluster, while the KCA (K=7) divides these two regions into different clusters. Observing the dendogram, which shows that these are not very close, but have more similarity compared to other regions, it is possible to affirm that, although these regions are considered in different groups, their similarity is greater than other regions. It could be confirmed by the KCA (K=5) that these two regions were added to the same cluster.

Considering the other regions, the cluster adopted in this research divides some of the central northern regions into two groups; one (cluster three) formed of Lombardy, Piedmont, Tuscany and Veneto, and another (cluster five) composed of Emilia Romagna, Friuli-Venezia Giulia, Liguria, Marche and Umbria.

The HCA, the same classification assumed by Bertin (2012b), identified the Piedmont welfare system as a cluster 'per se'. The distance score of the Piedmont from the cluster centre is more than 1, according the KCA; thus this group is not homogeneous. The other regions present in this cluster correspond with Bertin's (2012b) classification, but there are also Friuli-Venezia Giulia and Emilia-Romagna that, according to the KCA, are in cluster five with Liguria, Marche and Umbria. However, cluster five is also not homogeneous because Emilia-Romagna has a distance score more than 1, as has Umbria. Thus, these cluster are not very close.

However, from the dendogram, if we consider a distance less than 5, these regions form a unique cluster, and the boundary of these clusters is not clear, as confirmed by the distance between the final cluster centres.

Conclusions

The purpose of this study was to test the classification of the Italian welfare system, carried out by Bertin (2012b), who applied a different cluster analysis technique. Considering the cluster analysis as an adequate and consolidate descriptive method to compare clusters, the KCA was used to asses the 'robustness' of the previous Italian classification of welfare system, according to Bertin (2012b), who identified different clusters of 'social services'.

Initially, some considerations about the classification of the welfare systems were developed, and they emphasized that many classification analyses focused on cross-national classification. However, the development of the welfare system and its reforms has underlined that the national welfare system could not be homogeneous in all sub-administrative area of each country. Thus, it is more valuable to consider the sub-national dimension. Generally speaking, this was also the 'input' that animated Bertin (2012b) to carry out his research, based on the Italian case study, in which the application of HCA to identify seven different welfare systems was adopted.

The results achieved confirm exactly three welfare regimes identified by previous Bertin's (2012b) research. They are the clusters formed by Abruzzo and Lazio regions; the cluster composed of Basilicata, Molise and Sardinia and the group that join together the regions Apulia, Calabria, Campania and Sicily. These clusters were labelled 'Residual and not diversified', 'Residual with some corporative input', and 'Minimal system with high social risks', respectively, according to the feature that the welfare regimes showed.

Moreover, the features of these welfare regimes, which were founded by Bertin (2012b), are confirmed by this analysis. In fact, the final cluster centre values, which indicate the influential factors, represent the same attributes identified by Bertin (2012b). Additionally, these three of the seven welfare systems identified appear to be homogeneous; they are totally demarcated from the other models; for example, from the Trentino-Alto Adige/Südtirol and Aosta Valley welfare organisation.

Conversely, these results are less clear concerning the remainder welfare models. For example, Bertin (2012b) considers the regions Trentino-Alto Adige/Südtirol and Aosta Valley as a unique cluster, because this analysis underlines their different welfare. However, the welfare system of Trentino-Alto Adige/Südtirol and Aosta Valley could be grouped together if we consider a smaller number of clusters (K=5 instead K=7), so only in this case might they be identified as a unique cluster, although the distance value underlines that they are not totally homogeneous. The analysis of the dendogram, concerning these two cases, also describes that the 'fusion' point, the position in which they join together, is much farther than considered by Bertin (2012b) in order to classify the other clusters. Although the analyses are contradictory concerning these two welfare models, it is possible to state that the Trentino-Alto Adige/Südtirol and Aosta Valley welfare system appears particularly different from the characteristics of the other regions. This emerged as a consideration in K=3; in other words, when great differences between the welfare systems were identified. However, considering the same level of difference used to classify the others welfare system, these two model appear distinct. This could be due to some specific features; in fact, considering the variables used to identify a single dimension (Bertin 2012b), Trentino-Alto Adige/Südtirol has a significantly higher number of associations than Aosta Valley, which instead shows many more public crèches.

The other 'problem' concerns the clusters formed by the northern and central regions. The cluster identified by Bertin (2012b) is different from those characterised here. According to HCA, Bertin (2012b) considered Liguria, Marche and Umbria as composed by a structured mixed welfare system, while Friuli-Venezia Giulia, Tuscany, Lombardy, Veneto and Emilia-Romagna has a generalized and generous welfare, and Piedmont has a specific welfare system. KCA identified that the welfare system of Piedmont is similar to that of Lombardy, Tuscany and Veneto. Nevertheless, Piedmont is far from the cluster centre, so its welfare system is moderately different from the other cases, and this aspect is underlined in the dendogram.

The Welfare systems of Liguria, Marche and Umbria are similar according to the HCA, but KCA adds the Emilia Romagna and Friuli Venezia Giulia welfare models to this cluster. On the other hand, the case of Emilia Romagna and Umbria are not close to the cluster centre. Likewise, the Lombardy, Tuscany and Veneto (over the Piedmont, which have already discuss) show a different model of welfare. However, considering K=6, all these regions, excluding Piedmont, are included in one group, meaning that their welfare show few differences, and this is confirmed also from the dendogram because the horizontal lines, which describe comparisons are not extensive. However, these few differences could initiate new questions that could be related; for example, the quality of the services provided, but other methods should be used for analysis.

In this case, there are some differences, but it is also important to consider that cluster analysis is an exploratory rather than inferential technique, so there is not a statistical base from which to chose a particular cluster solution over another, as state by Ahlquist and Breunig, 'The choice of both the number of clusters to focus on and the substantive interpretations assigned to them is solely the responsibility of the analyst' (2012, p. 96). Furthermore, the different algorithms used affect the cluster results; thus, it is better to try to apply different cluster methods before adopting one classification.

In order to develop the classification of welfare systems, it is also important to reflect on the indicator used, as suggested by Pastore and Tonellato (2013), because in some cases, a high level of correlation between them could not generate clear results.

Finally, it is also necessary to consider that the welfare system nowadays is in continual change, due to the contingent economic situation and the new demand for services; it is necessary to regard the welfare system has a dynamic organisation, and to judge the national welfare system as a heterogeneous system, as show by this analysis.

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Appendix: tables.

Table 3 k-means cluster analysis, k values from 2 to 7

K = 2			*K =3*			*K =4*			*K =5*			*K =6*			*K =7*		
Clusters	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*
1	Abruzzo	1.477	1	Abruzzo	1.736	1	Apuglia	0.798	1	Abruzzo	1.370	1	Abruzzo	0.983	1	Basilicata	0.759
1	Apuglia	0.652	1	Apuglia	0.642	1	Calabria	0.591	1	Lazio	1.218	1	Lazio	0.853	1	Molise	0.581
1	Basilicata	2.045	1	Basilicata	1.924	1	Campania	0.856	1	Lombardy	1.571	1	Piedmont	1.592	1	Sardinia	0.783
1	Calabria	1.119	1	Calabria	1.143	1	Sicily	0.789	1	Piedmont	1.301						
1	Campania	1.790	1	Campania	1.814							2	Aosta Valley	0.000	2	Aosta Valley	0.000
1	Lazio	2.179	1	Molise	1.381	2	Basilicata	0.759	2	Apuglia	0.798						
1	Molise	1.445	1	Sardinia	1.434	2	Molise	0.581	2	Calabria	0.591	3	Apuglia	0.798	3	Lombardy	0.680
1	Sardinia	1.631	1	Sicily	1.328	2	Sardinia	0.783	2	Campania	0.856	3	Calabria	0.591	3	Piedmont	1.164
1	Sicily	1.431							2	Sicily	0.789	3	Campania	0.856	3	Tuscany	0.928
			2	Emilia-R.	1.362	3	Abruzzo	1.741				3	Sicily	0.789	3	Veneto	0.888
2	Aosta Valley	3.467	2	Friuli-V. G.	0.694	3	Emilia-R.	1.469	3	Emilia-R.	1.115						
2	Emilia-R.	1.695	2	Lazio	1.911	3	Friuli-V. G.	0.840	3	Friuli-V. G.	0.608	4	Trentino-A. A.	0.000	4	Trentino-A. A.	0.000
2	Friuli-V. G.	0.984	2	Liguria	1.252	3	Lazio	1.759	3	Liguria	1.030						
2	Liguria	1.243	2	Lombardy	1.398	3	Liguria	1.219	3	Marche	0.825	5	Basilicata	0.759	5	Emilia-R.	1.180
2	Lombardy	1.464	2	Marche	0.906	3	Lombardy	1.480	3	Tuscany	0.843	5	Molise	0.581	5	Friuli-V. G.	0.829
2	Marche	1.305	2	Piedmont	1.706	3	Marche	0.816	3	Umbria	1.245	5	Sardinia	0.783	5	Liguria	0.858
2	Piedmont	1.696	2	Tuscany	0.700	3	Piedmont	1.707	3	Veneto	1.337				5	Marche	0.695

K = 2			*K =3*			*K =4*			*K =5*			*K =6*			*K =7*		
Clusters	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*	*Clusters*	*Regions*	*Distances*
2	Trentino-A. A.	3.923	2	Umbria	1.477	3	Tuscany	0.737				6	Emilia-R.	1.102	5	Umbria	1.015
2	Tuscany	0.486	2	Veneto	1.227	3	Umbria	1.440	4	Aosta Valley	1.338	6	Friuli-V. G.	0.535			
2	Umbria	2.061				3	Veneto	1.375	4	Trentino-A. A.	1.338	6	Liguria	1.177	6	Abruzzo	0.462
2	Veneto	1.436	3	Aosta Valley	1.338							6	Lombardy	1.481	6	Lazio	0.462
			3	Trentino-A. A.	1.338	4	Aosta Valley	1.338	5	Basilicata	0.759	6	Marche	0.954			
						4	Trentino-A. A.	1.338	5	Molise	0.581	6	Tuscany	0.731	7	Apuglia	0.798
									5	Sardinia	0.783	6	Umbria	1.415	7	Calabria	0.591
												6	Veneto	1.176	7	Campania	0.856
															7	Sicily	0.789

Table 4 Final cluster centres (Z-score)

	Cluster	Mix structured	Mix towards corporatism	Traditional services diffusion	Innovative service diffusion	Social cohesion	Social risks
		Variable labels					
K = 2	1	-0.96	-0.28	-0.75	-0.61	-0.59	0.68
	2	0.79	0.23	0.61	0.50	0.48	-0.56
K = 3	1	-1.05	-0.17	-0.79	-0.72	-0.53	0.88
	2	0.68	-0.16	0.16	0.82	-0.03	-0.81
	3	0.81	1.50	2.36	-1.21	2.23	0.56
K = 4	1	-1.06	-1.07	-0.81	-0.92	-0.82	1.29
	2	-1.28	1.14	-0.79	-0.65	-0.02	0.79
	3	0.59	-0.19	0.08	0.73	-0.10	-0.78
	4	0.81	1.50	2.36	-1.21	2.23	0.56
K = 5	1	0.46	-0.92	0.05	0.30	-0.36	-0.42
	2	-1.06	-1.07	-0.81	-0.92	-0.82	1.29
	3	0.66	0.22	0.10	0.98	0.04	-1.00
	4	0.81	1.50	2.36	-1.21	2.23	0.56
	5	-1.28	1.14	-0.79	-0.65	-0.02	0.79
K = 6	1	0.26	-0.91	-0.09	0.01	-0.70	-0.51
	2	0.43	1.76	2.37	-1.73	1.08	0.50
	3	-1.06	-1.07	-0.81	-0.92	-0.82	1.29
	4	1.18	1.23	2.36	-0.70	3.37	0.61
	5	-1.28	1.14	-0.79	-0.65	-0.02	0.79
	6	0.71	0.08	0.14	1.00	0.12	-0.89
K = 7	1	-1.28	1.14	-0.79	-0.65	-0.02	0.79

	Variable labels					
Cluster	Mix structured	Mix towards corporatism	Traditional services diffusion	Innovative service diffusion	Social cohesion	Social risks
2	0.43	1.76	2.37	-1.73	1.08	0.50
3	1.15	-0.61	0.50	0.76	0.35	-0.41
4	1.18	1.23	2.36	-0.70	3.37	0.61
5	0.49	0.40	0.00	0.98	-0.12	-1.13
6	- 0.29	- 0.85	- 0.57	0.05	- 0.97	- 0.68
7	- 1.06	- 1.07	- 0.81	- 0.92	- 0.82	1.29

Tab. 6 Distance between final cluster centre

K	*Clusters*	*Clusters* 1	2	3	4	5	6	7
K = 2	1		3.020					
	2	3.020						
K = 3	1		3.063	4.914				
	2	3.063		4.326				
	3	4.914	4.326					
K = 4	1		2.431	3.438	5.485			
	2	2.431		3.228	4.458			
	3	3.438	3.228		4.375			
	4	5.485	4.458	4.375				
K = 5	1		2.774	1.514	4.607	3.233		
	2	2.774		3.875	5.485	2.431		
	3	1.514	3.875		4.335	3.352		
	4	4.607	5.485	4.335		4.458		
	5	3.233	2.431	3.352	4.458			
K = 6	1		4.525	2.533	5.462	3.110	1.741	
	2	4.525		5.027	2.676	3.973	4.265	
	3	2.533	5.027		6.202	2.431	3.831	
	4	5.462	2.676	6.202		5.248	4.708	
	5	3.110	3.973	2.431	5.248		3.395	
	6	1.741	4.265	3.831	4.708	3.395		
K= 7	1		3.973	3.770	5.248	3.263	2.921	2.431
	2	3.973		4.148	2.676	4.348	4.974	5.027
	3	3.770	4.148		4.375	1.583	2.367	3.727

K	*Clusters*	*Clusters*						
		1	2	3	4	5	6	7
	4	5.248	2.676	4.375		4.977	6.014	6.202
	5	3.263	4.348	1.583	4.977		2.072	3.897
	6	2.921	4.974	2.367	6.014	2.072		2.354
	7	2.431	5.027	3.727	6.202	3.897	2.354	