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Composite Indicators for Measuring Well-being of Italian Municipalities

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Introduction

Well-being is a complex phenomenon. Multidimensionality is recognized in literature as its main feature. This phenomenon is in some aspects elusive and difficult to monitor, and the definition is the combination of heterogeneous components, which assume different meanings in different contexts. A universally accepted definition of well-being does not exist (yet): each country (or areas) attributes importance to dimensions that for others may not be as relevant, consistent with their culture and social dynamics. Accurate measurement of well-being is a prerequisite for the implementation of effective welfare policies, which, through targeted actions in the most critical areas, are geared to the progressive improvement of living conditions. Until some time ago, such a plurality of components was poorly valued, believing that the only income dimension could represent in an exhaustive way such a complex reality. For many years, GDP (Gross Domestic Product) has been an indisputable landmark for states all over the world, playing the key role in defining, implementing and evaluating the effects of government action. Recently, the international debate has questioned the supremacy of GDP, and initiatives have been launched which, through the involvement of a growing number of countries, aim to develop alternative ways of measuring well-being that assign the same value to its components, Economic, Social and Environmental.

Since well-being, as mentioned above, is a multidimensional phenomenon then it cannot be measured by a single descriptive indicator and that it should be represented by multiple dimensions. It requires, to be measured, the "combination" of different dimensions, to be considered together as components of the phenomenon (Mazziotta and Pareto, 2013). This combination can be obtained by applying methodologies known as composite indicators (Salzman, 2003; Mazziotta and Pareto, 2011; Diamantopoulos et al., 2008).

In this ever-evolving scenario, the Italian experience is represented by the BES (Equitable and Sustainable Well-Being) project that is now considered globally as the most advanced experience of study and analysis. It consists in a dashboard of 134 individual indicators distributed in 12 domains. In the last three BES reports, published in December 2015, 2016 and 2017 by Istat (Italian Institute of Statistics) (Istat, 2015; Istat, 2016; Istat 2017), composite indicators at regional level and over time were calculated for the 9 outcome domains, creating a unique precedent in the official statistics at international level.

Recently, the debate has become from a scientific to a policy scope: parliamentary and local administrators are affirming the necessity to link the Istat well-being indicators to interventions/actions in the socio-economic field, thus constructing an even stronger connection between official statistics and policy evaluation. In fact, the Italian Parliament has finally approved on 2016 July 28 the reform of the Budget Law, in which it is expected that the BES indicators, selected by an *ad hoc* Committee, are included in the Document of Economics and Finance (DEF). The new regulations also provide that by February 15th of each year Parliament receives by the Minister of Economy a report on the evolution of the BES indicators. A Committee for equitable and sustainable well-being indicators is established, chaired by the Minister of Economics and composed by the President of Istat, the Governor of the Bank of Italy and two experts coming from universities or research institutions (Mazziotta, 2017).

The project, from national, is becoming local and already several local authorities, although they not have legislative obligations, are studying the well-being indicators of their territory. With these assumptions, it seems necessary to calculate well-being measures for all Italian municipalities so that administrators and citizens can dispose of them to understand and decide better policies. Since the current statistical surveys do not provide socio-economic indicators disaggregated at municipalities level (Census is the only source, every ten years and it does not collect all the information contained in the BES), it is necessary to use administrative sources, hopefully, collected in informative systems.

The thesis wants to present an experimental statistics conducted on all the municipalities of Italy where nine domains of BES are selected (Population, Health, Education, Labour, Economic well-being, Environment, Economy on the territory, Research and Innovation, Infrastructure and Mobility) and the twenty individual indicators are selected so that they can represent the phenomenon at the municipal level. The individual indicators are calculated starting from administrative sources and then composite indicators are computed in order to have a unidimensional measure. The theoretical framework adopted is represented, therefore, by the conceptual and methodological one developed by Istat and CNEL (National Council of Economy and Labour) for the BES project (Istat, 2015). The structure of the domains and the selection of indicators are derived from the national BES. In each of the domains, some individual indicators are selected so that the starting matrix has 7,998 rows (the municipalities) and a variable numbers of columns (the indicators). A Composite indicator for each domain is calculated and then a unique composite indicator that synthesizes all the composite indicators is computed. Different composite indicators are calculated in order to assess the robustness of the methodologies. The results present interesting reflections also in the key of economic planning.

Therefore, the aim of the thesis is to provide socio-economic indicators for measuring well-being at the municipal level. To achieve this goal it is necessary to define a theoretical framework, to build indicators matrix at the municipal level, to calculate composite indicators in order to obtain a simpler reading and interpretation of the data. The four chapters of the paper are designed to answer these research questions.

The thesis is divide in two parts. The first, Theories and Methods, is composed by two chapters: “Theoretical framework: GDP versus well-being” in which recent well-being theories are presented with a view to supporting GDP; “Composite indicators: theories and methods” in which all the techniques for constructing composite indicators are presented in order to understand how synthesize data and measure multidimensional socio-economic phenomena. The second part, “Application to administrative data”, is composed by two chapters: Administrative data sources in which the data base ARCHIMEDE is described; Well-being of Italian municipalities where a robust composite indicator is applied to the domains and individual indicators in order to have a measure of well-being for all Italian municipalities. The analysis of the results leads to original conclusions in which the application of particular data classification methodologies contributes to the discussion concerning the use of databases from administrative sources for local economic planning based on well-being.

PART I – THEORIES AND METHODS

1. Theoretical framework: GDP versus Well-being

1.1 GDP: definition and uses

The Gross Domestic Product (GDP), still today, represents the fundamental measure of the production of each economic system.

This important index was born during the years of the Great Depression when, following the crisis of 1929, US President Franklin Delano Roosevelt commissioned the Department of Commerce to produce a standardized measuring instrument that would be able to constantly monitor the country's general economic conditions over time.

In 1934, this index was presented to the American Congress by its inventor, Nobel Prize in Economics in 1971, Simon Kuznets. Although it has been its creator to point out its limits, saying that "The well-being of a nation cannot be deduced from a measure of national income", GDP has since become a benchmark for all advanced economies. For this reason, a brief description of its main features is presented below.

GDP is the monetary value of all the finished goods and services produced within a country's borders in a specific time period. Although GDP is usually calculated on an annual basis, it can be calculated on a quarterly basis as well (in the United States, for example, the government releases an annualized GDP estimate for each quarter and also for an entire year). GDP includes all private and public consumption, government outlays, investments, private inventories, paid-in construction costs and the foreign balance of trade (exports are added, imports are subtracted). Put simply, GDP is a broad measurement of a nation's overall economic activity – the godfather of the indicator world.

Intermediate goods are excluded from the calculation to avoid double counting errors. For this reason, only the added value generated at each stage of the production process is considered. In other words, the value of the product is considered net of the cost of intermediate goods. Hence, GDP can also be defined as the sum of added values of all production units in a given time span. GDP is the value of current production, and does not take into account pre-existing exchanges of products.

Two different measures of GDP are considered: nominal GDP and real GDP. Nominal GDP is the value of production at current prices. Real GDP is calculated at constant prices and is used to compare production in different years.

Through this index, it is possible to measure the effective variation in the wealth of a country, depurating the nominal GDP value from the incidence of the inflation rate. For example, an increase in nominal GDP could have been caused by both an increase in the amount of goods and services produced by the country and an increase in the level of prices. Real GDP ensures that this increase is due only to the first component, and not to the second, as the price level remains anchored to a reference year referred to as the "Base year".

Unfortunately, GDP is improperly used not only as a measure of a country's production, but also for the well-being of its inhabitants. Improperly because there are several problems associated with calculating this index. GDP only considers the value of goods and services traded on the market. All the others are ignored. A classic example is domestic work: its value for the calculation of GDP is zero. In addition, for some goods and services, the price is not determined by the market: the value of public services depends on the subjective assessment assigned by the citizens at the expense of the Public Administration, which may be overestimated or underestimated.

While some activities are attributed a positive value to GDP estimates, they are not directed at the production of new goods and services, but are intended to limit some "evils" such as crime. Likewise, GDP should be reduced by the value of all those phenomena whose production has negative externalities. For example, if GDP was a measure of a country's well-being, its value should be lowered by the pollutant produced.

The value of goods and services produced is measured by reference to their price, though it is not always indicative of their quality. To explain this, one can refer to the technology sector: for most products, performance improvements are not accompanied by a corresponding increase in prices. Nevertheless, a comprehensive index should always take into account the improvement of the quality of the goods.

Often GDP per capita is used to measure the amount of goods and services that each citizen may have on average on a given year. This is a completely inappropriate use that does not consider the way resources are distributed within the society. The growth of the GDP per capita value is not a sign of a corresponding increase in well-being levels, if the new wealth produced benefits only a few groups of the population rather than distributing it fairly among the citizens. On the contrary, such phenomena have as their only consequence the growth of inequalities.

In fact, when measuring countries' development using GDP, we also ignore the effects of economic growth on the environment and also the fact that ecosystems provide us with free services that, at a cost, we try to restore. These services - such as the regulation of climate and atmospheric gases, decomposition and absorption of waste, flood control, soil formation, pollination, etc. - are invaluable. No account of these services - which lack a market price, are non-negotiable and not calculated in the GDP - creates a net loss for present and future generations. If we focus attention only on the GDP, we would be blindly looking at the loss of biodiversity, deforestation and their consequent effects on the soil (erosion, geomorphic instability, desertification, salinization, etc.), on the atmosphere (climate regulation at different scales) and on human communities (mass migration due to desertification). Actually, we see that the exponential growth of population and consumption is leading towards an ecological collapse causing rapid mass extinctions (Ciommi et al., 2016).

Around the 70s, various institutions (research centres, public and private institutions) are being set up in Europe and the United States with the aim of studying and deepening the effects of organizing work on individuals. The concepts developed and carried out in those years are those of working conditions, quality of working life (QWL), and, in part, quality of life, outside the strictly productive concept.

In the last decades this indicator has been used also as a metric for the standard of living of people. However, a high level of GDP per capita in a country does not automatically mean that people living there are better off compared with those living in a country with lower GDP per capita. Moreover, the increase in income per person is not associated with the growth of the happiness (Easterlin, 1974) or well-being (Stiglitz et al., 2009).

Moreover, GDP ignores the distributional issues, the contribution of non-market goods and services such as health, education, security and governance. Attention to other aspects of well-being is, therefore, crucial (Stiglitz et al., 2009).

1.2 Beyond GDP: scientific and political context

The issues outlined above and the arrival of the economic crises, that have been exacerbated recently in all the countries of the world, have prompted scholars of all nationalities to question the possibility of developing alternative indicators that are most representative of the state of health and progress of a society, even for the purpose of their use in support of decisions taken by policy makers. Economists, statisticians, sociologists, ecologists and even doctors and psychologists have shown great interest in the subject.

The use of GDP, as an indicator of well-being, has not always been the wrong choice: for many years, income has been an effective measure of progress of the society. If income levels had not increased, there would not have been so much progress in the sectors of health, education and social cohesion. In short, income has been the key to progress for a long time, and a measurement of progress through income could only be considered appropriate. Once satisfied with elementary needs, however, others become the needs of individuals. Progress is evolving along new lines, and income can no longer be the only guide. In fact, the relationship between GDP and happiness is not linear: if income increases happiness increases to an extent less than proportional, and an indicator of well-being based only on that dimension would be completely misleading (Giovannini, 2011).

Researchers of all fields have contributed to the development of new measures that are in line with the complexity and variability of the reality around us. After the first OECD Forum on "Statistics, Knowledge and Politics", which took place in Palermo in 2004 and from which the Global Project on Measuring Society Progress was launched, a second was held in Istanbul in 2007, with a much higher participation, this showed a growing interest in the subject. On that occasion, the Istanbul Declaration was presented, which launched a genuine global movement regarding the issue of progress and the most appropriate methods for its estimation.

This document was signed by the European Commission, the Oecd, the Islamic Conference Organization, the United Nations, the United Nations Development Program and the World Bank, who agreed on the need to go "Beyond conventional economic measures", converting to a multidimensional approach that takes many aspects simultaneously into consideration. The opportunity to have ever-increasing amounts of statistical data relevant to every aspect of human life should have facilitated this process of transition to an assessment of progress, which does not forget the importance of environmental and social factors, as well as those economic.

The Istanbul Declaration brought a first international consensus on the need to undertake a change in this regard. The most important step forward, which should be mentioned in this context, is in February 2008. Joseph Stiglitz, Amartya Sen and Jean-Paul Fitoussi gave birth to the Commission for Measuring Economic Performance and Social Progress (Commission Stiglitz-Sen-Fitoussi) at the request of then-President of the French Republic, Nicolas Sarkozy, with the aim of understanding whether and to what extent GDP could still be considered a reliable indicator of a country's wealth. Twenty-two other world-renowned scholars participated in the Commission, and eight dimensions were identified to be taken into account for accurate assessment:

1. material living conditions;
2. health;
3. education;
4. labour;
5. participation in political life and governance;
6. social relationships;
7. environment;
8. economic and personal insecurity.

The Commission was divided into three subgroups, each of which was tasked with developing a thematic specificity: measurement, quality of life and sustainability. With regard to the first, it is possible to refer to the problem-related issue of calculating the GDP. The second involves the issue of resource allocation, and the inadequacy of GDP capita, which, as we have already pointed out, undeniably represents an ineffective indicator. The third is the most important, since it is a dimension not entirely considered in the determination of GDP.

These analyses produced the following twelve recommendations:

1. material well-being should be assessed on the basis of income and consumption, rather than on the basis of production;
2. consideration should be given to the family perspective;
3. along with wealth, income and consumption should also be taken into account;

4. the distribution of income, consumption and wealth should be of greater importance;
5. a good indicator should also refer to activities not directly related to the market;
6. quality of life should be improved by considering also objective conditions and capabilities; the assessment of health, education and environmental conditions should be improved;
7. quality of life indicators should take into account the differences between individuals and social groups, by gender and by generation;
8. through appropriate research and studies, it is important to analyze how changes in a sector of quality of life can influence others;
9. national statistical institutes should produce a composite indicator that combines different components of quality of life;
10. quality of life should be measured both in objective terms and in subjective terms. Statistical institutes should take into account how people evaluate their lives, their level of satisfaction, and their emotional state, so as to enrich the measurement of factors, for some aspects, most significant of income;
11. a set of indicators for the measurement of sustainability should be defined as an indication of the possibility of benefiting in the future of the same level of well-being in the present. The peculiarity of this perspective should require a separate assessment;
12. a set of environmental sustainability indicators should be defined with the aim of monitoring the level of environmental damage.

These guidelines were included in the Stiglitz-Sen-Fitoussi report, which the Commission published in September 2009.

In the same year, on 20 August 2009, the European Commission addressed to the Council and the European Parliament a communication entitled "Not only GDP. Measuring progress in a changing world, with the specific objective of criticizing the ability of GDP to measure dimensions such as environmental sustainability and social inclusion, affirming the need to take these limits into account when using this indicator in analysis and political debates (European Commission, 2009). Overcoming GDP becomes a matter of paramount importance as the effectiveness of measures taken by policy makers also depends on the quality of the indicators they use to support their decisions. The Commission opens up cooperation with all the countries wishing to engage in the project in order to identify shared and applicable international indices.

In order to obtain the most suitable indicators for the measurement of well-being in an ever-changing context, five actions were defined.

First of all, GDP must be completed with environmental and social indicators. The environmental index will have to measure the level of pollution and damage to the environment: therefore, a decrease in this value will be a positive sign of the steps forward in this direction. The index should consider aspects such as climate change and energy consumption, nature and biodiversity, air pollution and its effects on health, water use and pollution, and finally waste generation and the exploitation of resources. The Commission also proposes the possibility of drawing up a further index, which measures this time the quality of the environment and not the damage it produces. As far as social indicators are concerned, measuring the quality of life and the well-being of citizens is indispensable for policy makers to respond more in their own way.

The decision-making process needs accurate, almost real-time, information. Environmental and social data are updated at times that are totally inappropriate to government needs. It is therefore recommended to use tools such as satellites, automatic detection stations and the Internet to ensure the availability of reliable data on environmental conditions. Social data, obtained in most cases by sample surveys, will need to be published in a timely manner, minimizing the time elapsed from the collection phase.

Distributions and inequalities should be subject to more accurate measurements, since, as the Committee reiterates, social and economic cohesion is one of the objectives of the Union and cannot be overlooked. Per capita GDP is a superficial indicator, which gives no information on the disparities between citizens.

The Commission should develop, together with the Member States, an evaluation table for sustainable development, with particular attention to the environmental sustainability thresholds that should in no way be exceeded. For such thresholds, risk areas should be defined so as to alert policy makers before they reach a non-return point.

National accounts should be extended to cover environmental and social issues, pursuing that experiment already attempted by the Commission in 1994, concerning the so-called "green accounting". Since then, Eurostat and Member States have begun to develop methods for calculating environmental accounts.

In 2010, these goals were welcomed by the Conference of Presidents and Directors General of the National Statistical Institutes of Europe with the Memorandum of Sofia, following which a Sponsorship Group was established to "Measure Progress, Well-being and Sustainable Development". This committee should have contributed to identifying more effective ways of using existing statistics to produce indicators that are more responsive to the intended purpose. The final report contained a list of indications that the ESSC, the European Statistical Systems Committee, should have adopted by 2020.

In this context, three domains were considered:

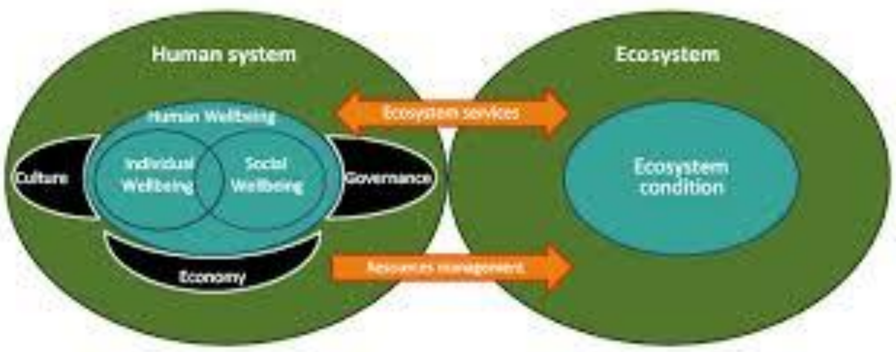
1. the perspective of households and aspects regarding income distribution, consumption and wealth;
2. multidimensional measures of quality of life;
3. environmental sustainability.

1.3 The role of Italian studies

The experiences described are the cornerstone of the path that has been officially launched in Italy since 2010 and has evolved into an inter-institutional colLabouration agreement between Cnel and Istat. The two administrations should "…develop a shared definition of the progress of Italian society, expounding the most important economic, social and environmental areas for the well-being of citizens, by selecting and disseminating a set of indicators of high statistical quality representative of different domains". They should have been expressed in numerical terms so that the non-experts can better understand.

To achieve this goal, an address committee was set up, consisting of members designated by Cnel and Istat and led by two coordinators, one representing Cnel and one representing Istat; a Support Group, which should have been responsible for coordinating the two administrations and supporting the Committee in its work; a Scientific Commission (the author was member of this Commission) that, keeping in mind the international developments, should have developed the most appropriate statistical indicators for our country. This process should have directly involved members of civil society and the scientific community to ensure democratic legitimacy and, at the same time, scientific validity.

The first step is to deepen the concept of Equitable and Sustainable Well-Being, which gives the name to that project. Giving a definition of well-being is an arduous task. This term assumes different meanings with varying times, places, and cultures, and each country should have its own measurement parameters different from those of others. In order to understand the fundamental determinants of well-being, we start from the analysis of the framework published by the Ocse (Hall, J. et al., 2010), which was taken over by Cnel and Istat as a benchmark for their activity.



In this conceptual framework (Istat, 2015), the life of humans takes place in two related systems: the human system and the ecosystem. Through the management of the resources made available by the ecosystem, man is fed by increasing his well-being at individual and social level. Individual well-being is based on attributes such as physical and mental health, understanding of the world in which it lives, its work, while social well-being is focused on relationships between individuals and their degree of trust and mutual cohesion. Humanity could not live in the absence of political and economic institutions that govern its development, and a cultural environment functional to its growth. Unlike what happens to the human system, which, as we have just seen, derives its well-being from a variety of conditions, the health of the ecosystem is measured by a single domain, which sums up the situation of the earth, the waters, the atmosphere, and the biodiversity.

For real well-being, resources must be equally distributed not only among individuals of the same generation, but also between different generations, with a view to future sustainability. From here, the expression Equitable and Sustainable Well-being is more clear, which we can at this point synthetically define as the well-being of today's society, measured in function of that of future generations.

This framework was adapted to the Italian case through extensive consultation, which took place in February 2011 and was part of one of the most important social surveys carried out by Istat: Annual Multipurpose Survey on Aspects of Daily Life. This is a sample survey that Istat has been carrying out annually since 1993, and it is designed to detect the lifestyles of Italian citizens and their degree of satisfaction with the functioning of public services that should improve the quality of their life. Inside the 2011 survey, in the "Daily Life" section, a question was asked for people over the age of 14, with the purpose of understanding what the major well-being dimensions were. A list of 15 conditions was predisposed and respondents were asked to express a significance score from 0 to 10 for each of them.

The interviewed sample, representative of the entire Italian territory, was made up of 45,000 people of different social extraction: a large sample size, which confirms the reliability of the results obtained and represents a unique case on the international scenario. The collected data was used by the Steering Committee for the construction of the Italian theoretical framework, which currently consists of two groups of domains (Istat, 2016). The first group consists of so-called "outcome" domains, the dimensions that directly affect human and environmental well-being. The second includes so-called "contextual" or "instrumental" domains, which, while not having a direct impact on well-being, are functional to its improvement. The domains are 12. The outcome domains include 9 dimensions: health, education and training, work and life-time reconciliation, economic well-being, social relationships, security, subjective well-being, landscape and cultural heritage and the environment.

Health can be considered as the starting point in the definition of individual well-being: absence of health can lead to the inability of the individual to access other dimensions of wellbeing such as work, economic well-being, social relationships and subjective well-being. All aspects of human life are affected by health. Disease can lead to alienation from work, increased spending to address the need for medication, care and assistance, less sociality, and less opportunity to interact with others. This will imply low probability that the individual will be satisfied with his condition. The centrality of this domain also stems from the finding that health conditions accompany the person at all stages of his existence, from his birth to his death. For example, while working conditions affect the individual only once he has entered his workplace, the need to preserve the health and the search of physical and psychic well-being occurs at all ages.

Education qualifies the person: it is his bag of experience, the system of knowledge and skills acquired during his life. Through training, the individual matures his own view of reality, and develops his own attitude towards the world. Education is the key to accessing the political, economic and social life of your country. Ignorance in the sense of lack of education implies a distorted and only partial understanding of the phenomena that affect the community and prevents man from confronting others in a civil and constructive manner and to contribute to the cultural growth of the country. Ignorance, in other words, is synonymous with isolation, neglect, degradation and in any case it is a symptom of the decay of the image of the country.

Labour is more of a source of livelihood for the individual. Participation in the world of work represents the most striking goal of a lifetime, the natural outcome of a course of study and training that the individual has started since his earliest age, the currency with which the country should repay 'the contribution that the individual can give to society in terms of acquired knowledge and skills. Working means to realize oneself, making sense of one's own existence. Work ennobles man, elevating him from his individual condition and becoming part of a collective, makes it useful, putting him in the service of the needs of others, and enriches it through experience and social exchange. As enshrined in our Constitutional Charter, it represents for the person a right and at the same time a duty (Article 4). Our Republic is "Founded on work" (Article 1) And, in the Italian case, it can only represent an indispensable dimension of individual well-being. This domain measures not only the employment levels of the country, but also the quality of work and the ability of individuals to reconcile work and family needs.

Economic well-being has over time become an elusive dimension for many individuals and for many families. The economic crisis has falsified the purchasing power, making in many cases impossible even the same survival. Economic resources are an indispensable tool for achieving adequate standards of living, a fundamental determinant of human dignity. Having an income greatly affects the perception of individual satisfaction with your life: an individual who does not have sufficient economic resources will not be able to buy the goods needed to meet his needs, will not have access to public and private services which improve the quality of life, will have fewer opportunities for social interaction and less opportunities for fun and leisure. In addition to income and capacity of consumption, this domain also takes into account other dimensions, such as wealth and the possession of durable goods.

In an increasingly dynamic society, **social relationships** are a decisive component of wellbeing. They refer to the way in which the individual relates to the other members of society, to his network of contacts, and to the influence that he exerts and receives. Social relationships are an investment: through interaction with others, the individual can profit from his potential, making him known and appreciated in social life and the world of work. Relationships have a direct influence on subjective well-being and perception of the individual's realization.

Security inevitably affects the quality of life. This domain wants to measure the level of crime of the country, which, if too high, can have negative effects on social relations, on subjective well-being and on economic well-being. Law enforcement should protect individuals and should be a tool of defence: when no one respects it, the individual has the perception of being alone, having to be careful of himself, precluding the possibility of establishing relationships with others, increasing spending to protect themselves from crime (immediate example is the railing or armoured doors to defend their home) and, above all, by changing their lifestyle. In many circumstances, victims of crimes have serious psychological damages: they have difficulty re-entering the social context and lead a normal life, they must be supported and guided in this recovery path of their own person. The fear and the perception that law enforcement does not preserve a climate of security and stability in everyday life has significant repercussions on the well-being of the population.

Subjective well-being can be considered as a transversal dimension. It represents a subjective assessment of the individual condition as a whole, based on the analysis of aspects related to other domains, such as health status, job position, economic availability, community of affiliation, the environment in which the individual lives and works, the quality of the services at his disposal, and so on. In short, the subjective data supports the objective data. If the purpose of BES is to detect the well-being of a country, then measurement cannot be ignored by examining the attitudes, perceptions, and feelings of the community. The peculiarity of the BES is the desire to give social legitimacy to indicators that, unlike GDP, must reflect the actual status of living conditions of the population, rather than translate into abstract data and, in many cases, completely meaningless. Of course, the objective aspect cannot be missed, to overcome the possibility of distorted, conditioned and unrealistic evaluations. Objectivity, if not accompanied by social feedback, can become theoretical, close to reality and inadequate to represent phenomena of everyday life.

The landscape and the cultural heritage represent the distinctive features of our country. The Article 9 of the Italian Constitution Charter states that the Republic "Protects the countryside and the historical and artistic heritage of the nation". This means that they should be the subject of continuous valorisation. The degradation, the lack of attention, the lack of attention to the variety and the beauty of our territories and our past and our cultural and artistic tradition can negatively affect the well-being of a country whose economy, as many have said, could only live with tourism. Of the 193 countries that have acceded to the UNESCO Convention, Italy is the country with several heritage sites of humanity (currently 51, of which 47 cultural sites and 4 natural sites) and 41 other sites are part of the so-called "Tentative list", advanced by the Italian state to the World Heritage Centre. *“Heritage is our legacy from the past, what we live with today, and what we pass on to future generations. Our cultural and natural heritages are irreplaceable sources of life and inspiration”*. This thought encompasses the essence of this domain, permeating it with obvious references to the theme of sustainability: cultural and natural heritage become "irreplaceable sources of life and inspiration", a legacy of generations passed on to the future, a capital very precious of which we are fortunate heirs.

The environment is the cornerstone of our lives. In the environment, we move every day and from it we draw our livelihood from the air we breathe to the resources that feed the production processes of the industry without stopping. In recent years, the need for an efficient use of natural resources has become an impetus. Many of the non-renewable sources of energy, such as oil, carbon and natural gas, are running out of use. They need very long regeneration times and companies to survive must use alternative sources. The secondary sector is moving more and more towards renewable energy sources such as the sun, wind, water, and so on and in Italy, the share of electricity consumed by renewable sources on gross domestic consumption rose to 33.4%, higher than the European average (27.5%) (Istat, 2016). This domain also detects the environmental impact of productive activities, taking into account aspects such as CO_2 and other pollutants, the problem of waste disposal, the protection of land and sea.

The domains of context are three: policy and institutions, research and innovation, quality of services. Politics and institutions should be the pillars of a country. Institutions should ensure balance and stability, and politics should be at the service of citizens by using public money to provide services that improve the quality of life. This domain takes into account issues such as citizen trust in institutions (parliament, parties, local institutions, etc.) and their degree of participation in the country's political life through the exercise of the right to vote. Being a context dimension, politics and institutions do not represent themselves a determinant of well-being, but they can increase or reduce it by acting on each of the outcome domains described above. Government action, through ministries, laws, regulations, intervenes in areas such as health, education, work, country security and all other factors that contribute to the definition of well-being of the population.

Research and innovation are the engine that drives the progress of a nation. If these two dimensions were not sufficiently valued, the country would risk losing ground in a constantly evolving context, which does not allow any hesitation. Article 9 of the Italian Constitution Charter states that "the Republic promotes the development of culture and scientific and technical research". This implies that it is a primary duty of the State to invest in research, both basic and applied, so that the country can advance in knowledge, making its contribution to this path of scientific and technological evolution involving all people in the world.

The quality of services greatly influences the well-being and quality of life of citizens. This domain involves different dimensions, taking into consideration heterogeneous services such as health services, childcare or mobility.

In the construction of the twelve domains, the Address Committee wanted to exploit all the available statistical information, but only the disaggregated indicators at the regional level, in order to have a better understanding of the phenomena considered. The indicators have been selected by the Scientific Commission taking into account the following general rules (Istat 2015):

- for each domain, a small group of indicators had to be identified that only measured the aspects of greater interest in the determination of individual and social well-being;
- the indicators must have a non-ambiguous polarity with respect to the concept of well-being;
- in order to be able to analyse the evolution of phenomena over time, the indicators with time series available should be preferred;

- each individual indicator should be used within a single domain, avoiding overlapping with others;
- all the individual indicators had to be disaggregated at regional level.

The individual indicators identified were 130. Citizens, institutions, research Centres, associations and companies were directly involved in this process, who were able to fill out an online questionnaire and participate in a blog through the www.misuredelbenessere.it website, developed with the aim of spreading information about the project. Through these initiatives the legitimacy of the indicators was further strengthened.

In the last three BES reports, published in December 2015, 2016 and 2017 by Istat (Istat, 2015; Istat, 2016; Istat, 2017), composite indicators at regional level and over time were calculated for the 9 outcome domains, creating a unique precedent in the official statistics at international level.

Recently, the debate has become from a scientific to a policy scope: parliamentary and local administrators are affirming the necessity to link the Istat well-being indicators to interventions/actions in the socio-economic field, thus constructing an even stronger connection between official statistics and policy evaluation. In fact, the Italian Parliament has finally approved on 2016 July 28 the reform of the Budget Law, in which it is expected that the BES indicators, selected by an *ad hoc* Committee, are included in the Document of Economics and Finance (DEF). The new regulations also provide that by February 15th of each year Parliament receives by the Minister of Economy a report on the evolution of the BES indicators. A Committee for equitable and sustainable well-being indicators is established, chaired by the Minister of Economics and composed by the President of Istat, the Governor of the Bank of Italy and two experts coming from universities or research institutions (Mazziotta, 2017).

"Equitable and Sustainable Well-being" must be part of economic planning from 2018, as envisaged by Law 163/2016 (Amendments to Law N. 196 of 31 December 2009 concerning the content of the budget law in implementation of Article 15 of 243 of 24 December 2012) with 12 indicators provided for in a decree of the Ministry of the Economy (Act of Parliament submitted to Parliament's opinion N. 428). The objective is to complement the Gross Domestic Product (GDP) with a set of indicators that take into account the fundamental variables of well-being which, especially for developed countries, are not correlated to the GDP trend. Italy is the first European country and the first in the G7 to include well-being indicators in economic programming.

The proposed indicators are 12:

1. Adjusted Average income per capita. Relationship between the adjusted gross disposable income of households (consumers and producers) (i.e. inclusive of the value of services provided by public and non-profit institutions), and the total number of people resident in Italy (nominal values in euro). It allows you to estimate the total amount of income available to people resident in Italy, including the value of services;
2. Inequality Index of Available (disposable) Income. The ratio between the total income received by 20% of the population with the highest income and that received by 20% of the lowest income population. The index provides information on the distance in terms of income among the richest and the poorest who, considering equivalent income, takes into account the different family composition (different needs between children and adults, economies of scale realized with coexistence);
3. Absolute Poverty Index. Percentage of people belonging to households with total spending on consumption below the absolute poverty threshold, on the total number of residents. It represents the percentage of people who fail to acquire a predetermined set of goods and services. The thresholds for absolute poverty are differentiated by family size, age classes of components, macro-area and size of the municipality of residence, and reflect territorial differences in the cost of living;
4. Life Expectancy in good health at birth. The average number of years a child born in the reference year can expect to live in good health, assuming that the risks of illness and death at the different ages observed in the same year remain constant over time. The indicator is calculated as the ratio between the cumulated years of good health from birth onwards and survivors. The indicator allows to evaluate the quality of survival, which is particularly relevant in the current phase of the demographic and health transition, characterized by population aging and the spread of chronic-degenerative pathologies;
5. Excess Weight. Standardized proportion of people over the age of 18 and overweight or obese over the total age of 18 and over. The indicator refers to the

World Health Organization (OMS) classification of the Body Mass Index (BMI: ratio between weight, Kg, and height square, in meters), which identifies people overweight (25 <= BMI <30) or obese (BMI => 30). The indicator is standardized using the European standard population by 2013. Excess weight is an important health risk factor. It is associated with cerebral and cardiovascular disease and musculoskeletal, diabetes, hypertension, cancer, liver disease or gallbladder disease;

6. Early exit from the education and training system. Percentage of population aged 18 to 24 years with the highest secondary school diploma), who is not in possession of regional vocational qualifications obtained in courses lasting at least 2 years and does not attend education courses in other training activities. Reducing the proportion of people who abandoned the education and training system early is essential to increasing the level of skills of the population and reducing the risk of social exclusion. The indicator is a target measure of the Europe 2020 strategy, which aims to reduce the drop-out rate below 10% by 2020 at European level (national target: 16%);
7. Lack of participation at work Index. Relationship between the sum of unemployed and inactive "available" (people who have not been looking for work in the last 4 weeks but are available to work), and the sum of work forces (both employed and unemployed) and inactive "available"; the quantities refer to the population between 15 and 74 years. The indicator expresses a measure of unsatisfied work supply wider than the unemployment rate since it also captures that part of the inactive population who declares themselves available to work while not looking for work within the 4 weeks preceding the interview, thus giving account of the phenomena of discouragement and "attendant" behaviours due to the results of past research actions;
8. Relationship between the employment rate of women aged 25-49 with preschool children and women without children. Relationship between the employment rate for women of 25-49 years with at least one pre-schooler (0-5 years) and the employment rate of 25-49 years-old without children per 100. The quality of employment is also measured by the fact that women with young children are able to reconcile paid work with family care work. In this sense, the indicator is an indirect measure of the adequacy of welfare services aimed at reconciling home-work commitments;

9. Predatory Crime Indicator: Number of victims of home burglaries, pick-pocketing and robberies per 1000 inhabitants. The number of victims of home burglaries is calculated by multiplying, for each year, the average family size for the number of home burglaries. The calculation of the indicator is based on the data of the reports of the crimes from the police statistics (source Ministry of the Interior), corrected with the quota average of shadow of the victims of crime, for each type of crime, deduced from the surveys on the citizens' security (2008/2009) carried out by Istat;
10. Efficiency Civil Justice Index (effective average duration in days of ordinary civil court proceedings defined by the courts). The figure takes into account the ordinary and first-degree civil proceedings (litigation + non-litigation) of the SICID area (Sistema Informatica Contenzioso Civile Distrettuale - Computer System District Civil Litigation), net of the activity of the tutelary judge and of the preventive technical assessment in matters of social security. The SICID area includes registers of civil litigation, voluntary jurisdiction and labour litigation. The indicator can be considered an indirect measure of the efficiency of civil justice, an essential condition both for the proper functioning of the economic system and for the trust of citizens in the institutions;
11. CO_2 Emissions and other altering climate gasesTons of CO2 equivalent emitted on an annual basis from agricultural, urban and industrial activities per inhabitant. Emissions of carbon dioxide (CO2), methane (CH4) and nitrous oxide (N2O), expressed in "tons of CO2 equivalent" are included, with weights that reflect the heating potential in relation to carbon dioxide: 1 for CO2 ; 298 for N20; 25 for CH4. The compensatory effect linked to the presence of woods and other plant cover is not considered;
12. Index of Illegal Construction: Number of illegal buildings per 100 buildings authorized by the Municipalities. The indicator expresses a direct measure of the deterioration of the landscape, but can also be read as a proxy of the "rule of law" in the use of the territory, in fact the collective well-being and the cohesion of local communities depend significantly on a correct balance between public and private interests.

Four of the indicators outlined above are already included in the Document of Economy and Finance (DEF) 2017: average adjusted income per capita; income inequality index available; rate of non-attendance at work and CO_2 and other gaseous emissions. The decree will still have to be applied from 2018 onwards. The Budget Committee of the House of Representatives has also suggested, among other observations, to analyse the possibility of introducing a composite indicator in the upcoming revisions of the indicator list.

The project, from national, is getting local and already several local authorities, although they not have legislative obligations, are studying the well-being indicators of their territory. With these assumptions, it seems necessary to calculate well-being measures for all Italian municipalities so that administrators and citizens can dispose of them to understand and decide better policies. Since the current statistical surveys do not provide socio-economic indicators disaggregated at level of municipalities (Census is the only source, every ten years and it does not collect all the information contained in the BES), it is necessary to use administrative sources, hopefully, collected in informative systems.

1.4 GDP is not well-being: an application to real data

As written above, for several years the discussion about the role of Gross Domestic Product (GDP) compared to the measurement of well-being and quality of life of citizens is extensive, continuous and involves experts of different disciplines at the international level. Whereas in the past the debate was focused mainly on developing countries, however, confined to the academic world, in recent years the focus has shifted towards the high-income countries and involving national and international institutions.

Many statistical offices, as well as non-governmental organizations, think tanks and research centres have proposed new indicators that exceed the traditional view of economicist well-being. The assumption, discussed in the literature, that GDP and well-being are positively correlated is disavowed. However, it seems to increase the belief that an increase of one can match the contraction of the other. Or, even better, the two measures explain different aspects of the socio-economic reality by a geographical area or a specific sub-population.

The publication by Italian Institute of Statistics (ISTAT), in December of 2015, of the third report on Equitable and Sustainable Well-being (BES) has marked a unique case in international official statistics since methods, known in the literature as composite indices (OECD, 2008) in order to synthesize the individual indicators for each pillar (Mazziotta and Pareto, 2013; Mazziotta and Pareto, 2016) have been used. The goal is to measure the well-being as a multidimensional phenomenon and interpretation of a latent factor making it, therefore, one-dimensional and visible. The resolution of the complexity represented by a "classical" dashboard opens the way to new statistical analysis to compare among them the composite indices of each domain by understanding the reciprocal influences (correlations) as well as the relations between these composite indices and the GDP. The aim of the section 2 of the paper is to analyse the mutual influence among composite indicators of the domains and measure how much the GDP fails to explain the latent factor well-being, based not on economic theories but using statistical models in order to quantify precisely the percentage of this divergence.

In fact, the correlation matrix among the composite indicators of the BES domains is presented below; furthermore, it should be noted that the factors generated from the Principal Components Analysis, applied to the composite indices of the BES, placed in relation to GDP, showing its partial informative capacity to explain wellbeing.

The well-being composite indicators used in this section are selected from BES 2015 report (Istat, 2015). In particular, these are the composite indicators of the nine dimensions of BES (Health, Education and Training, Labour, Well-being, Social relationships, Security, Subjective well-being, Landscape and cultural heritage, Environment), calculated at the Italian regional level, to which some complementary indicators were added.

In table 1.4.1, the list of the indicators, with labels and years of reference, is presented. For a detailed description of the indicators, please refer to ISTAT volume (2015).

Table 1.4.1 - Well-being composite indicators in Italy (source: Istat, 2015)

Label	Well-being indicator	Year
HEA	Composite indicator of health	2013
EDU	Composite indicator of education and training	2014
QOW	Composite indicator of quality of work	2014
EMP	Normalized employment rate	2014
INC	Composite indicator of income and inequality	2014
HAR	Composite indicator of economic hardship	2014
REL	Composite indicator of social relationships	2014
SAF	Composite indicator of safety	2014
HOM	Normalized homicide rate	2014
LSI	Life satisfaction index	2014
LAN	Composite indicator for landscape and cultural heritage	2011
ENV	Composite indicator of environment	2012

In table 1.4.2 the correlation matrix of the 12 composite indicators and GDP is reported (year 2014).

Table 1.4.2 - Correlation among well-being composite indicators and GDP

Well-being indicator	HEA	EDU	QOW	EMP	INC	HAR	REL	SAF	HOM	LSI	LAN	ENV
HEA	1.000	0.842	0.911	0.917	0.906	0.876	0.902	-0.232	0.457	0.871	0.803	0.559
EDU	0.842	1.000	0.807	0.850	0.841	0.832	0.829	-0.119	0.190	0.826	0.763	0.540
QOW	0.911	0.807	1.000	0.963	0.963	0.913	0.842	-0.201	0.452	0.791	0.784	0.538
EMP	0.917	0.850	0.963	1.000	0.969	0.908	0.884	-0.229	0.413	0.821	0.809	0.494
INC	0.906	0.841	0.963	0.969	1.000	0.916	0.887	-0.172	0.452	0.858	0.799	0.555
HAR	0.876	0.832	0.913	0.908	0.916	1.000	0.845	-0.185	0.404	0.785	0.700	0.478
REL	0.902	0.829	0.842	0.884	0.887	0.845	1.000	-0.084	0.427	0.927	0.865	0.639
SAF	-0.232	-0.119	-0.201	-0.229	-0.172	-0.185	-0.084	1.000	-0.048	0.020	-0.129	0.178
HOM	0.457	0.190	0.452	0.413	0.452	0.404	0.427	-0.048	1.000	0.418	0.228	0.428
LSI	0.871	0.826	0.791	0.821	0.858	0.785	0.927	0.020	0.418	1.000	0.775	0.696
LAN	0.803	0.763	0.784	0.809	0.799	0.700	0.865	-0.129	0.228	0.775	1.000	0.532
ENV	0.559	0.540	0.538	0.494	0.555	0.478	0.639	0.178	0.428	0.696	0.532	1.000
GDP	0.889	0.748	0.889	0.928	0.899	0.834	0.873	-0.221	0.554	0.847	0.733	0.577

As you can see, the majority of composite indices are positively correlated with each other (HEA, EDU, QOW, EMP, INC, HAR, HOM, LSI, LAN, ENV), and the values are very high ($r \geq 0{,}550$). The composite indicator of environment (ENV) and the rate of homicides (HOM) are positively correlated with this set of indicators, but with different intensity: ENV ($0{,}700 \geq r \geq 0{,}450$) and HOM ($0{,}450 \geq r \geq 0{,}200$).

The composite indicator of security, instead, shows a slight negative correlation with the other composite indices ($0{,}200 \geq r \geq -0{,}250$).

Regarding the correlations of the 12 composite indicators with GDP, the highest correlation is observed with employment rate (EMP), followed by the composite indicator of income and inequality (INC), the composite indicator of quality and satisfaction work (QOV) and the composite indicator of health (HEA).

The composite indicators less concordant with the GDP are the rate of homicides (HOM), with $r = 0.554$, and the composite indicator of environment (ENV), with $r = 0.577$; while the composite indicator of security is the most discordant (SAF) since it shows a negative correlation with GDP ($r = -0.221$).

These results confirm that if, on the one hand, the main well-being composite indicators can be 'explained' by the GDP, some of them, such as those relating to security and the environment, are almost completely 'unconnected' from this measure.

The results of the previous section suggest the application of PCA (Principal Components Analysis) on the matrix composed by the 12 composite indicators.

As known, PCA is a multivariate technique that, starting from a set of original indicators, allows to obtain new indicators (principal components or factors) with the following features: i) decreasing importance; ii) orthogonal; iii) linear combination of the starting indicators. This allows to describe the statistical units with a lower number of new indicators, maximizing the proportion of ‘explained variance' (Dunteman, 1989).

In figure 1.4.1 the scree-plot and the PCA are presented.

From the scree-plot examination, an elbow is evident at the second factor and this means that most of the variability of Italian regions (80.77%) can be explained by the first two factors. The third factor explains 7.63% of the remaining variance, but having an eigenvalue of less than 1 ($\lambda = 0.914$) may be insignificant. By projecting the original variables in the plane of the first two main components, the circle of correlations is obtained, where each composite indicator is represented by a point with coordinates equal to the two coefficients of correlation with the first and second factors. Note that the first factor is strongly correlated to 9 composite indicators on 12, while the second represents only the composite indicator of safety (SAF). Finally, the standardized homicide rate (HOM) and the environmental composite indicator (ENV) are to be placed in an intermediate position between the two axes, partially correlating with both factors.

Figure 1.4.1 - Scree-plot and correlation circle of PCA

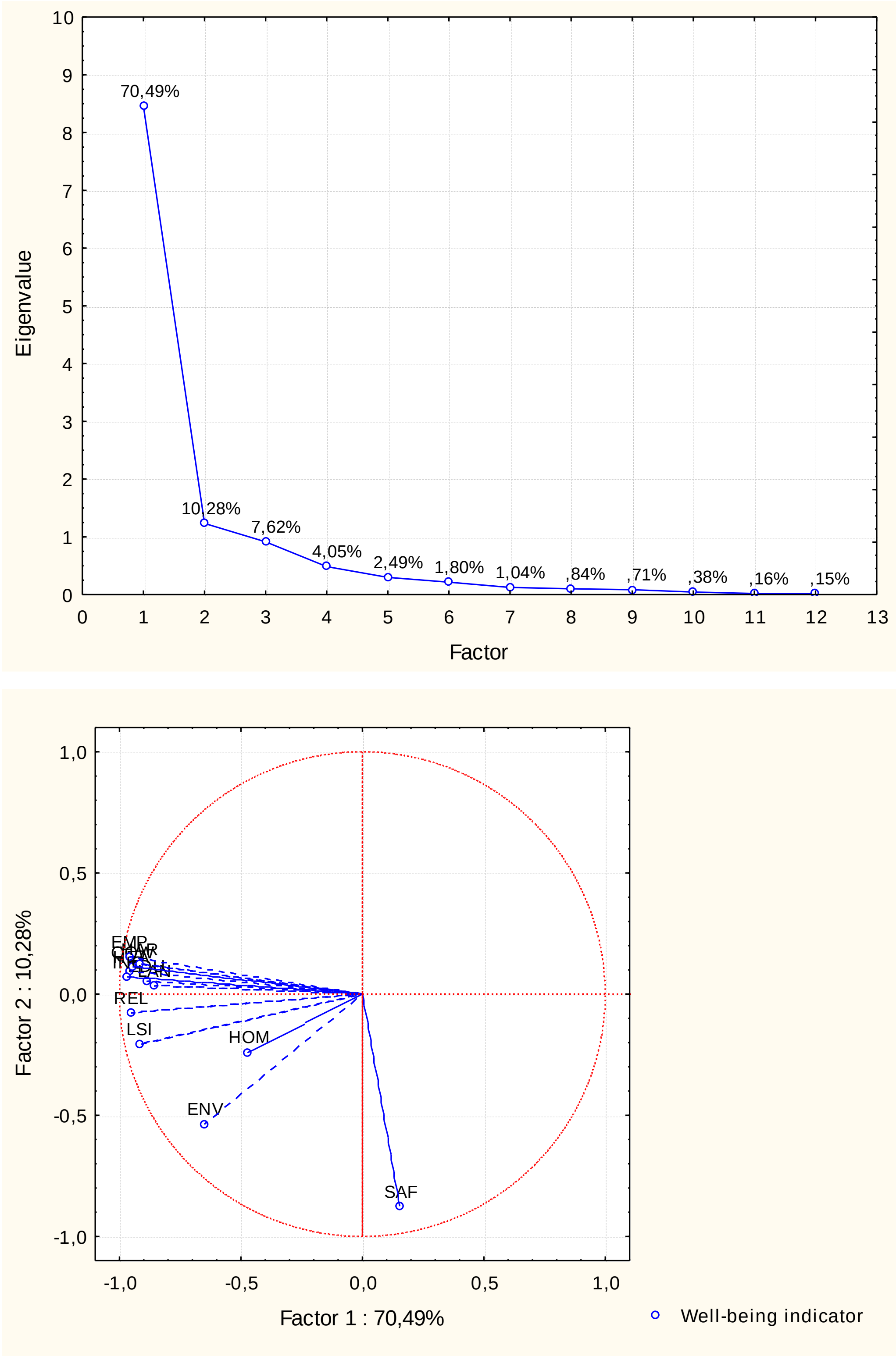
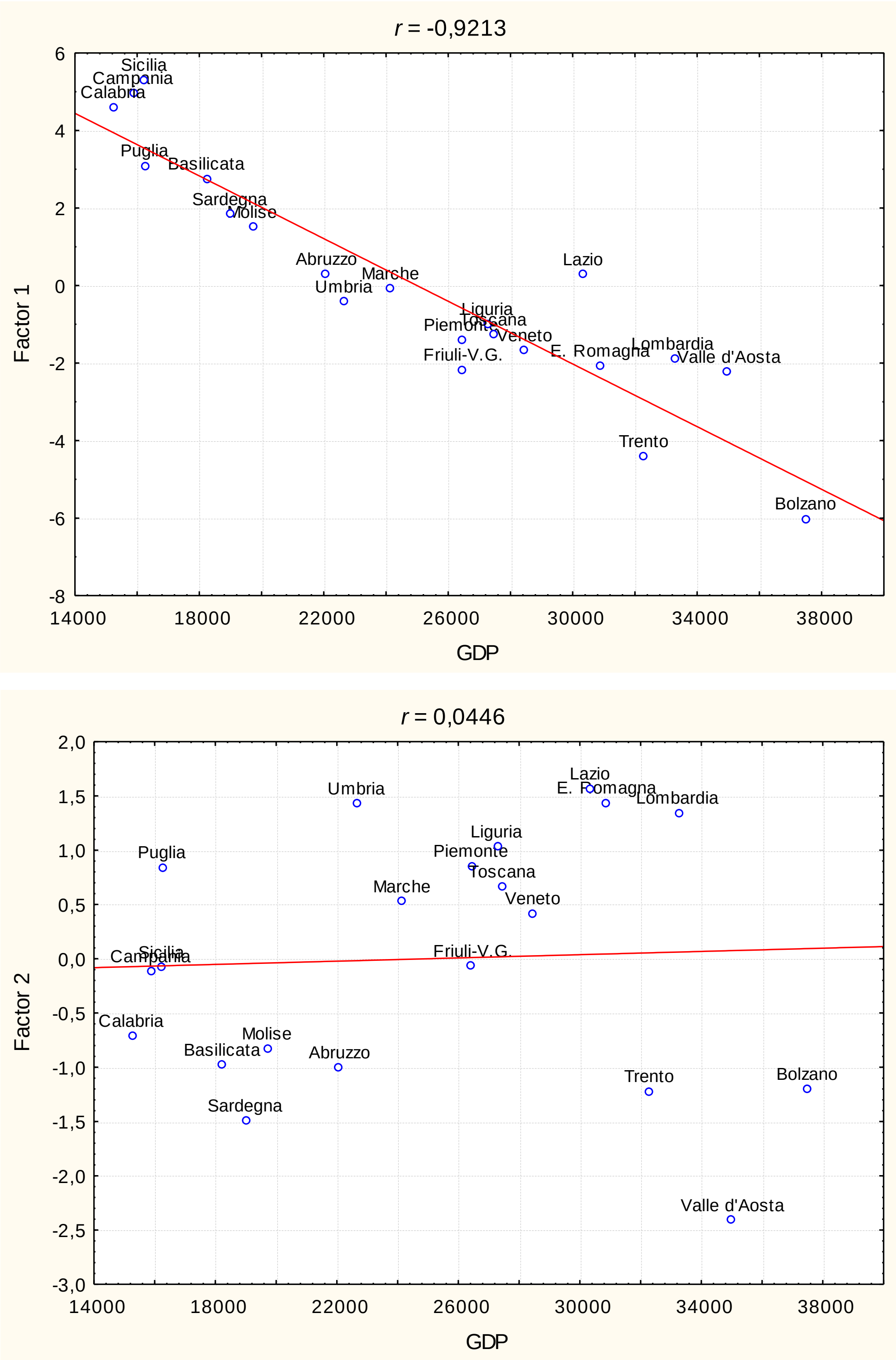


Figure 1.4.2 shows graphical representations of the relationship between GDP and the first two factors of the PCA.

Figure 1.4.2 - Relationships among the first two factors of PCA and GDP



The correlation between GDP and the first factor is very high (r = 0.9213), confirming that a large part of the information on the well-being of the regions can be derived from GDP. It is interesting to note, however, that the first factor explains about

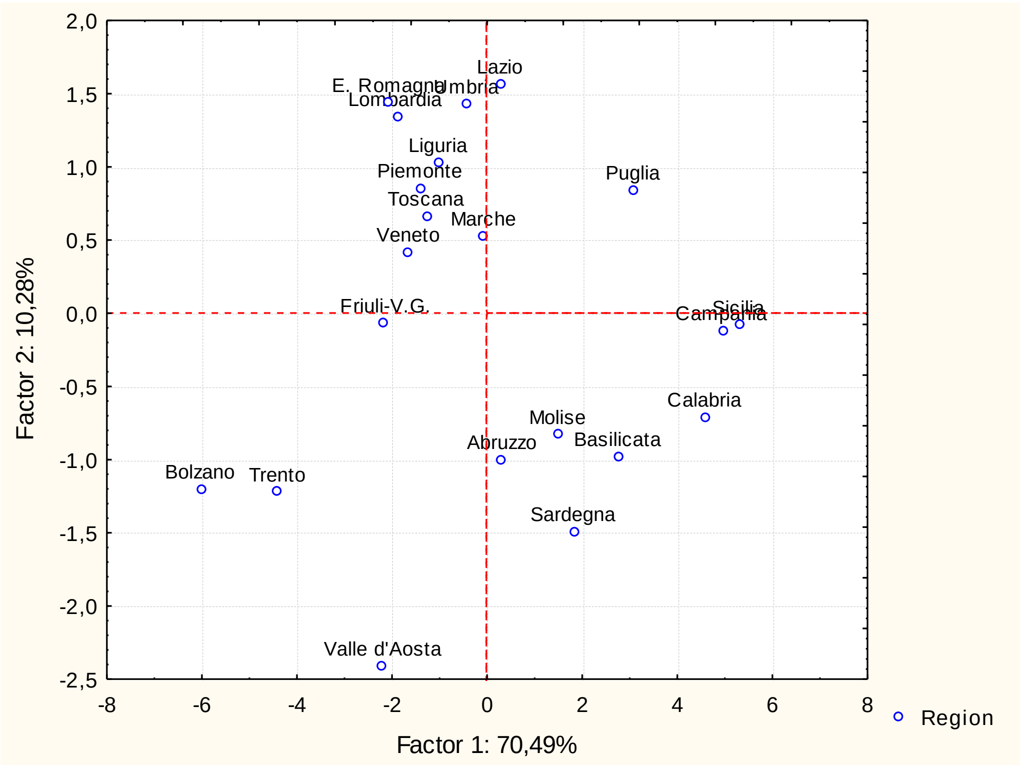
70% of the total variance. As a result, GDP does not 'capture' the remaining 30% of the information. In fact, the second factor in the PCA, which represents security (SAF) and, in part, the environment (ENV), is totally uncorrelated to GDP (r = 0.0446).

Note that the first factor cannot be used as a composite indicator of well-being at least for two reasons. Firstly, it summarize a set of indicators only because they are correlated among themselves, but not because they are functions of a common latent variable. Secondly, it ignores some important indicators, such as SAF. In fact, it accounts for only 70% of the information about the well-being.

The Italian BES project is developed also to measure the phenomenon at level of provinces and, from this point of view, the analysis presented in this paper is more interesting respect to the regions since the number of units is greater.

The aim of this case study is to: compute well-being composite indicators of the Italian provinces; analyse the correlations among the composite indicators of the domains; analyse the quota of GDP that does not explain the latent factor well-being, using multivariate model: in this way it is possible to quantify exactly the percentage of this discrepancy.

Figure 1.4.3 - First plane of PCA



In the table 1.4.3, the 41 individual indicators distributed for the 11 domains are presented.

Table 1.4.3 – Well-being individual indicators al level of Italian provinces

Label	Composite indicator	Individual indicator	Polarity
D_1	Health	Life expectancy at birth (M)	+
		Life expectancy at birth (F)	+
		Avoidable mortality	-
D_2	Education and training	Young people leaving school early	-
		People of working age with no higher education	-
		Competence level alphabetic students	+
		Level of digital competence of students	+
		People of working age in lifelong learning	+
D_3	Work and life balance	Rate of non-attendance at work (15-74 years)	-
		Gender difference in the rate of non-participation (F-M)	-
		Employment rate (20-64)	+
		Gender differences in the employment rate (M-F)	-
		Youth employment rate (15-29 years)	+
		Rate risk for serious accidents at work	-
D_4	Economic well-being	Estimated gross disposable income per household	+
		Average amount of family assets	+
		Gender differences in the average wage employees (M-F)	-
		Differences of generation in the average wage employees	-
D_5	Social relationship	Dissemination of non-profit institutions	+
		Volunteers for 100 residents aged 14 and over	+
D_6	Politics and institutions	Turnout in the European elections	+
		Turnout in provincial elections	+
		Percentage of women in municipalities	+
		Percentage of young people (<40 years old) in municipalities	+
D_7	Security	Violent crimes reported	-
D_8	Landscape and cultural heritage	Consistency of the historic urban fabric in good condition	+
		Density of urban parks and green of historical interest	+
		Museums accessible	+
D_9	Environment	Availability of urban green	+
		Overruns limits air pollution - PM10 (Maximum)	-
		Energy produced from renewable sources	+
		Municipal waste landfilled	-
D_{10}	Research and innovation	Propensity to patent (applications)	+
		Flows of new graduates in S & T residents (total)	+
		Specialization in knowledge-intensive sectors	+
D_{11}	Quality of service	Electricity outages without notice	-
		Children 0-2 years old receiving services for children	+
		Separate collection of municipal waste	+
		Index of overcrowding of prisons	-
		Emigration hospital in another region	-
		Density of urban networks of local transport	+

The methodology adopted for constructing composite indicators is the same of 2015 BES Report by Istat, that is the Adjusted Mazziotta-Pareto Index (AMPI) (for details, see Chapter 2). The composite indicators of each domains D_i (i=1, …,11) is computed, under the hypothesis of no-substitutability of the components and AMPI is chosen with negative penalty. Similarly, the global well-being index is obtained, applying AMPI with negative penalty, synthesizing the 11 composite indicators. In this way, it is possible to construct both a ranking of the Italian provinces for each of the 11 well-being domains and a general ranking ("one number" for each province).

Composite indices were created with a formative model by applying the same method as used in 2015 BES Report for Italian regions, namely the Adjusted Mazziotta-Pareto Index (AMPI). Specifically, for each pillar P_i (i=1, …, 11), a composite indicator was computed, under the hypothesis of non-substitutability of the components, and the formula of the AMPI with negative penalty was used (Mazziotta and Pareto, 2016). Similarly, a global well-being index was obtained, by aggregating the 11 composite indices. In this way, we obtained both a ranking of Italian provinces for each dimension of well-being and a general ranking ('one number' for each province). The individual indicators used try to emulate the theoretical framework of the national BES even if, in some cases, it is impossible have exactly the same measure since many sample surveys estimate parameters only at the regional level (Istat, 2015).

Table 1.4.4 Correlation among well-being composite indices and GDP

Composite indicator	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
D1	1.000	0.499	0.619	0.436	0.448	0.496	0.162	0.547	-0.060	0.585	0.594
D2	0.499	1.000	0.639	0.300	0.387	0.410	0.079	0.480	-0.149	0.542	0.439
D3	0.619	0.639	1.000	0.492	0.668	0.547	0.058	0.722	-0.139	0.725	0.810
D4	0.436	0.300	0.492	1.000	0.520	0.403	0.153	0.530	0.113	0.249	0.445
D5	0.448	0.387	0.668	0.520	1.000	0.244	0.317	0.694	0.343	0.365	0.584
D6	0.496	0.410	0.547	0.403	0.244	1.000	-0.035	0.443	-0.195	0.511	0.426
D7	0.162	0.079	0.058	0.153	0.317	-0.035	1.000	0.090	0.332	0.045	-0.030
D8	0.547	0.480	0.722	0.530	0.694	0.443	0.090	1.000	0.149	0.404	0.598
D9	-0.060	-0.149	-0.139	0.113	0.343	-0.195	0.332	0.149	1.000	-0.322	-0.213
D10	0.585	0.542	0.725	0.249	0.365	0.511	0.045	0.404	-0.322	1.000	0.676
D11	0.594	0.439	0.810	0.445	0.584	0.426	-0.030	0.598	-0.213	0.676	1.000
GDP	0.630	0.632	0.848	0.302	0.550	0.472	-0.115	0.549	-0.257	0.738	0.748

In the figure 1.4.4, the correlations among the composite indicators of the 11 domains are presented. As known, there is a good level of correlation among the composite indicators excepted for the domains 7 (Security) and 9 (Environment). This means that the domains of well-being Health, Education, Labour, Economic well-being, Social Relations, Politics and Institutions, Landscape and Cultural Heritage, Research and Innovation, Quality of Services are, with different intensity, positively correlated among themselves. In fact, the most of the composite indices (D_1-D_6, D_8, D_{10} and D_{11}) are positively inter-correlated ($0.244 \leq r \leq 0.810$), excepted for D_7 (Security) and D_9 (Environment) that are negatively correlated with some of them. This means that the dimensions of well-being concerning Health, Education and training, Work and life balance, Economic well-being, Social relationship, Politics and institutions, Landscape and cultural heritage, Research and innovation, Quality of service are, with different intensity, concordant among themselves. Only Security and Environment are, in some cases, discordant from the others dimensions. D_7 and D_9 are also negatively correlated with the GDP per capita; whereas the other composite indices are all positively correlated with it ($0.302 \leq r \leq 0.848$).

Figure 1.4.4 – Correlations among the 11 composite indicators

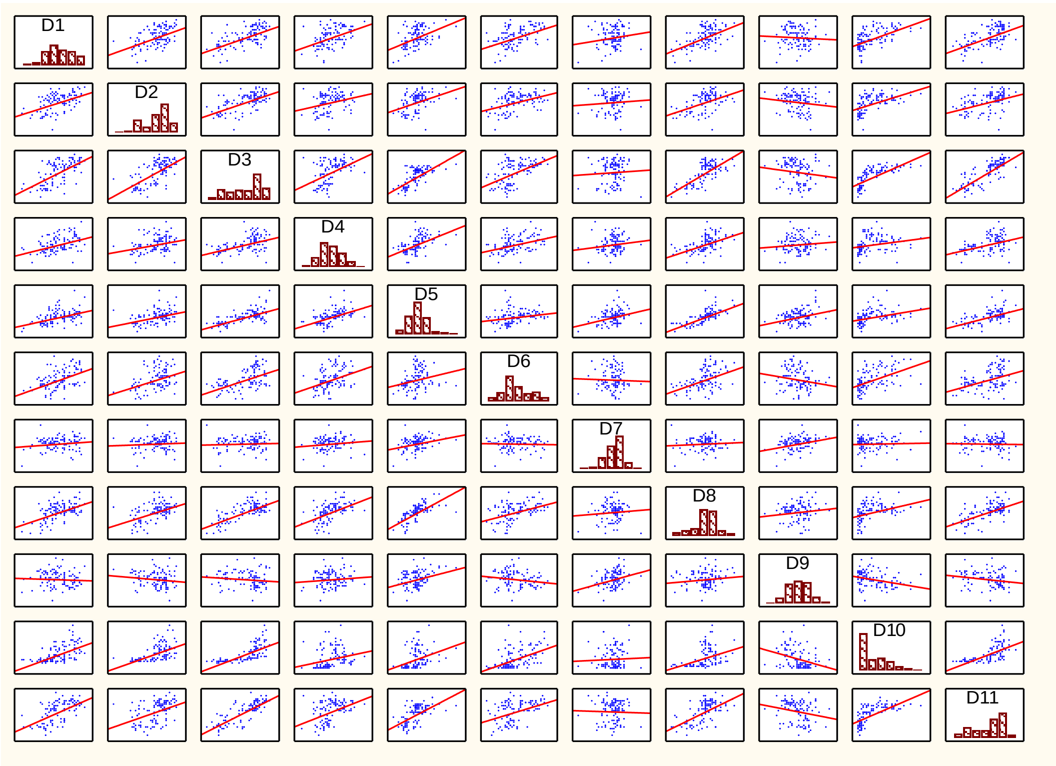
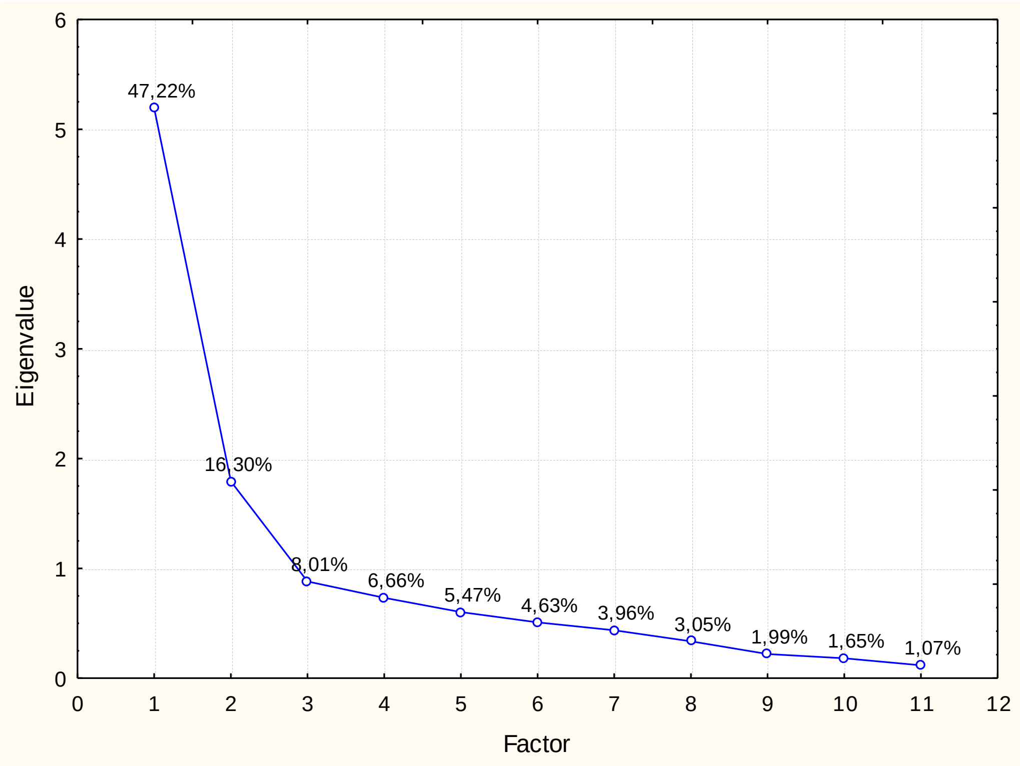
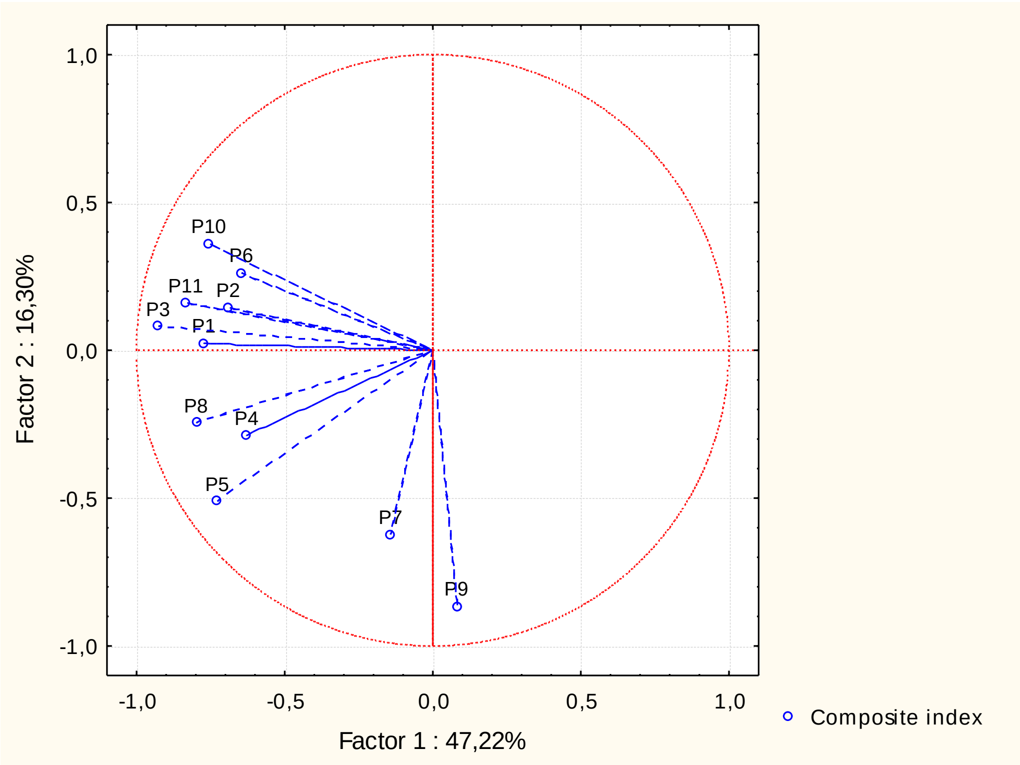


Figure 1.4.5 - Scree-plot and correlation circle of PCA





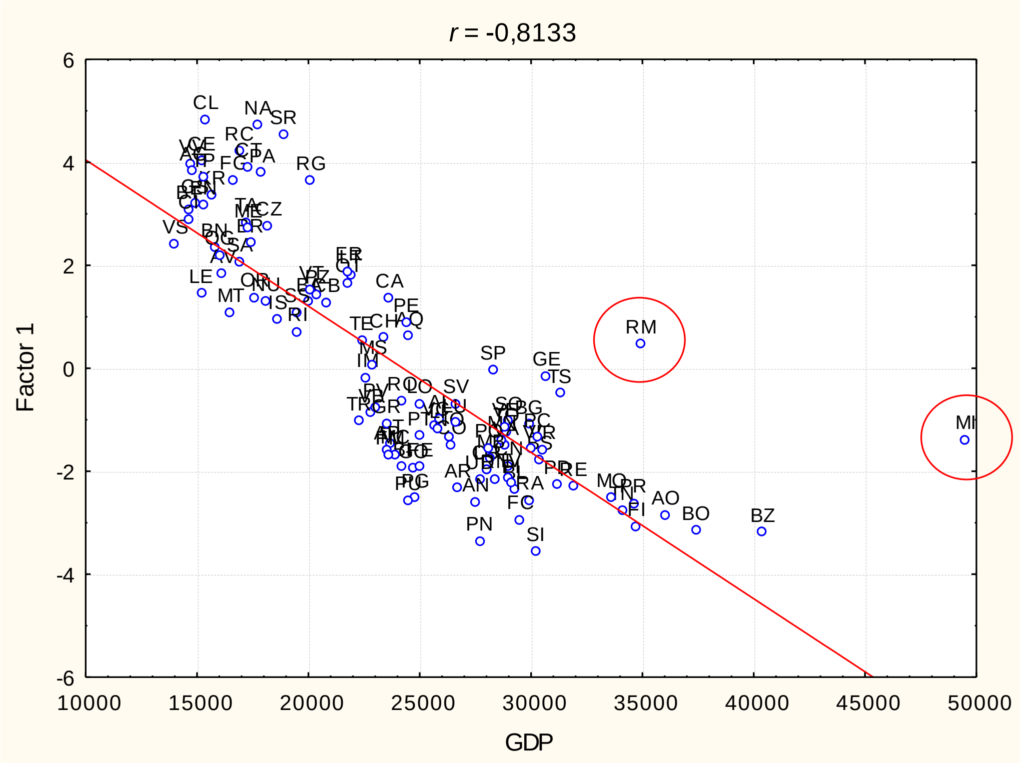
From the two graphs, we see that the first factor of PCA for Italian provinces accounts for 47,22% of the total variance and it is positively correlated with P_1-P_6, P_8, P_{10} and P_{11}. By contrast, the second factor accounts for 16.30% of the total variance and it is positively correlated, above all, with P_7 and P_9. So, the first plane of PCA accounts for about 63.5% of the variability of Italian provinces.

The scatterplots of the first two factors versus the GDP per capita are given in Figure 1.4.6.

Similarly to the case of Italian regions, the first factor is strongly correlated (in absolute values) with the GDP per capita (r = -0.8133), despite the presence of two outliers, such as Rome (RM) and Milan (MI). On the contrary, the second factor is weakly correlated with it (r = 0.2646). However, the amount of total variance 'explained' from GDP per capita seems very lower for Italian provinces, as the variance accounted for by the first factor is less than 50%.

The projection of the provinces on the first plane of PCA is displayed in Figure 1.4.7, where the polarization between northern provinces (to the left along the *x*-axis) and southern provinces (to the right along the *x*-axis) is reproduced. The higher the value of the first factor, the lower the GDP per capita of the province. Note that three big provinces such as Rome (RM), Milan (MI) and Naples (NA) are placed at the top of the map, away from the rest of the group.

Figure 1.4.6 - Relationships between GDP per capita and the first two factors of PCA plans



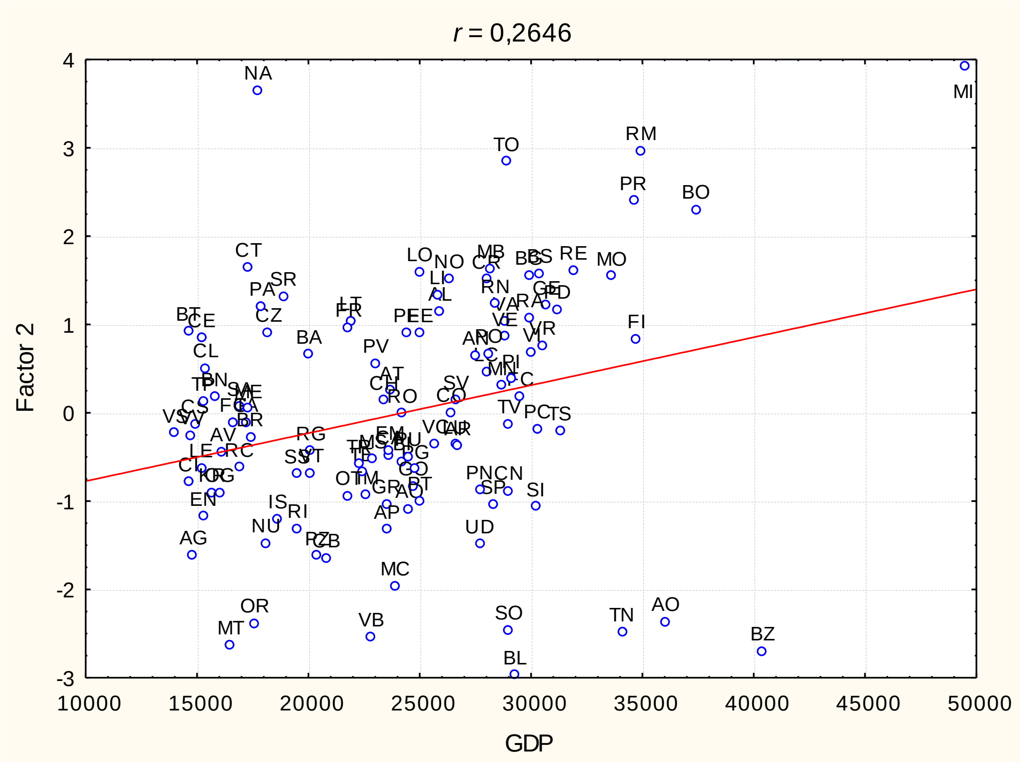


Figure 1.4.7 – First plane of PCA

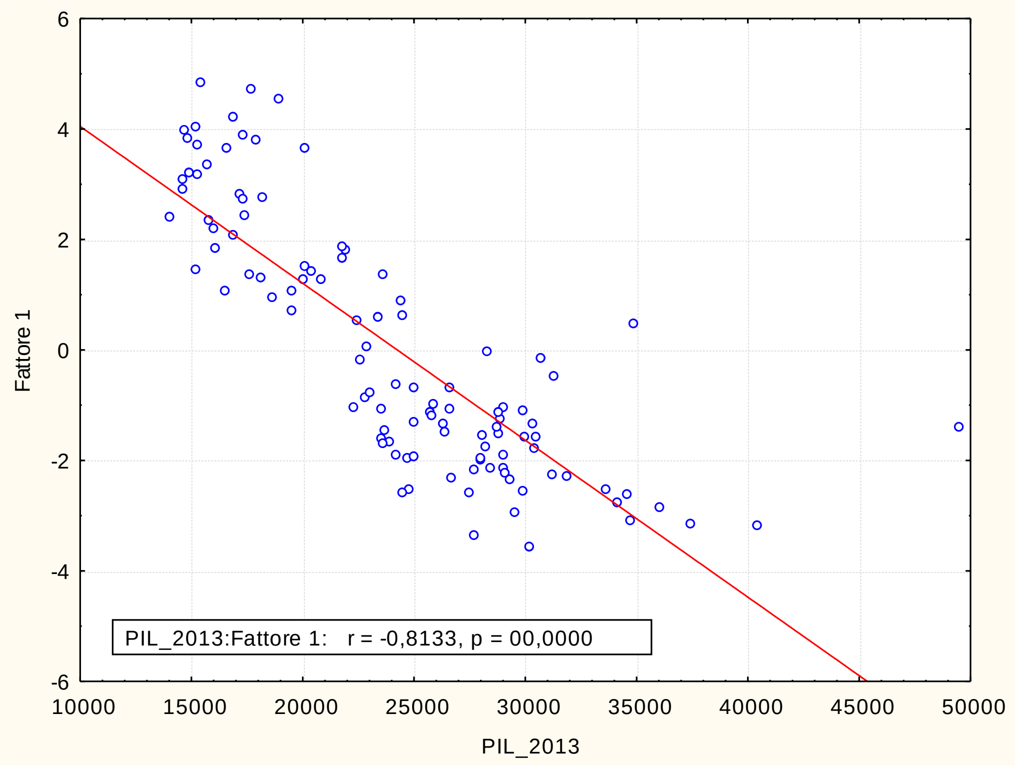
After calculating the global well-being composite indicator (BES), it was correlated with the GDP per capita (r = -0.7637). The relationship between this two measures is shown in Figure 1.4.8 and it is very similar to the relationship between GDP per capita e first factor of PCA (Figure 5a). However, in this case, also Naples (NA) can be considered an outlier, although it has different characteristics from Rome (RM) and Milan (MI). This means that the BES index is able to ‘capture’ some aspects of the well-being that the first factor of PCA ignores. In fact, Naples has a very low GDP per capita and a low level of well-being, Rome has a medium-high GDP per capita and a medium-low level of well-being, Milan has a high GDP per capita but a level of well-being equal to the national average. Therefore, they cannot match the performances of provinces such as Trento (TN), Bolzano (BZ) and Aosta (AO), which traditionally have a very high level of well-being.

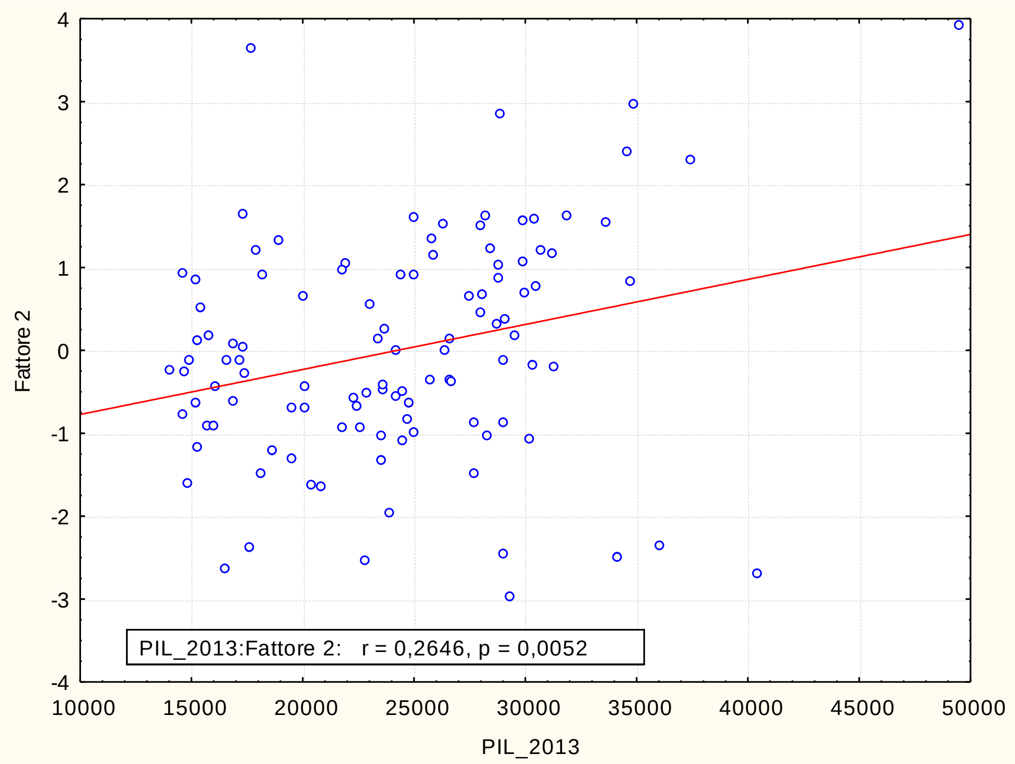
In this case too, PCA can be an useful tool for understanding the phenomenon, analysing correlations and visualizing data, but a composite indicator of well-being, such as the BES index, must be created following a formative approach.

After calculating the composite indicator of the 11 composite indicators related to 11 domains, the provinces were located on a Cartesian plane with GDP and the global composite indicator of well-being. The coefficient of correlation is equal to 0.76 and also in this case the provinces of North (on the top of the figure) are separated from those of the South. Rome, Naples and Milan are outliers even if with different characteristics. Naples has a low GDP per capita and well-being, Rome has a medium-high GDP per capita and a medium-low level of well-being, Milan has high GDP per capita and the well-being is on the national average. However, all three cannot match the performance of provinces such as Trento (TN), Bolzano (BZ) and Aosta (AO), which traditionally have a very high level of well-being.

Figure 1.4.8 – Relationship between GDP per capita and Well-being composite indicator

Figure 1.4.9 – Correlations among the first two factors of PCA and GDP





The two figures presented above are very important since in the first the relationship between GDP and the first factor of the PCA is very strong (r=-0.81) and it means that there is correlation. In the other figure the relationship between the second factor and

GDP is very weak (r=0.26). Since the first factor explains about 47% of the variability than we can conclude that GDP cannot represent well-being or at least it can only explain a limited part of it.

Several socio-economic approaches, over the years, have supported the ineffectiveness of GDP as a measure of well-being by finding in the multidimensionality the most convincing answer from a theoretical point of view (Rinaldi and Zelli, 2014). The publication of Italian BES composite indicators at regional level has seemed an institutional and methodological opportunity for trying to quantify how (from a quantitative point of view) GDP cannot explain well-being as a latent factor. The PCA shows that, at regional level, this share is about 30%; It seems necessary to emphasize that, from a strictly methodological point of view, by shifting to a greater territorial detail (provincial level), the unexplained variance from GDP may be even higher by 30%. In fact in the section 2.4, the application made (using PCA) to the Italian provinces has shown that 50% of the phenomenon well-being is not explained by GDP. Theoretical approach is accompanied by the methodological one in which, through statistical models, it is possible to quantify the misalignment (not complete) between the multidimensional approach of well-being and the one-dimensional GDP.

Obviously, this belief must not be a point of arrival, but a starting point for continuing the activity of defining well-being from a theoretical point of view and measuring the various components (dimensions) that best represent it. Recent experimental studies to build well-being indicators at the municipal level, starting from administrative archives gathered in information systems, are paving the way for a research path that seems to be particularly appreciated by national and local (political) institutions. The ability to measure social and economic performance at such a disaggregated level of detail is a fundamental tool for policy makers who want to address the actions more effectively on the territory.

Statistical methodology and official statistics, more than under other circumstances, have been introduced to the service of communities (not only scientific) in order to measure and improve the citizens' well-being.

2. Composite Indicators: theories and methods

2.1 Manage the complexity

International interest in well-being research has significantly increased in recent years due to the boost of the “Beyond GDP” initiative and the Stiglitz, Sen and Fitoussi report (2009). Policy makers and researchers have become more and more aware of the fact that the well-being is relevant for countries at all levels of development, and that the GDP (Gross Domestic Product) per capita cannot alone explain this concept (Boarini *et al.,* 2014; OECD, 2015). In fact, human well-being is determined by a wide range of factors that are not captured by GDP, such as health, education, environmental quality, meaningful work, leisure time, and so on (Sen, 1985). Furthermore, the GDP is positively correlated with some of these factors (e.g. health and education), while in other cases the relationship is weak, if not negative. For example, some indicators of environmental performance (e.g., carbon dioxide [CO_2] emissions) tend to worsen with increased GDP (Nahman *et al.* 2016).

In well-being research, we often distinguish between objective and subjective well-being. Objective well-being concerns observable factors such as richness, health, and tangible goods. Subjective well-being concerns psychological experiences (Michalos 2014). Hence, the objective approach looks at ‘harder’ data, such as income per capita or gross enrolment ratios, while the subjective approach considers ‘softer’ matters, such as an individual’s satisfaction with income and his perceived adequacy of educational opportunities (Bleys 2012). As a result, objective well-being can be assessed in terms of indicators of *outcome*; whereas subjective well-being is often measured as ‘happiness’ or ‘life satisfaction’ by response scales in questionnaires surveys (Van Beuningen *et al.* 2014).

Well-being indicators are often analysed by multivariate statistical technique, such as Principal Components Analysis (PCA), in order to summarize the data. However, a fundamental distinction must be made between reducing dimensionality and constructing composite indicators.

Reducing dimensionality is a purely mathematical operation that consists in summarizing a set of individual indicators, so that most of the information in the data is preserved. Many techniques have been developed for this purpose, but PCA is one of the oldest and most widely used (Hotelling 1933). The idea is simple: reduce the dimensionality of a dataset, while preserving as much 'variability' as possible. This translates into finding new variables that are linear functions of the original ones, that successively maximize variance and that are uncorrelated with each other. Finding such new variables reduces to solving an eigenvalue/eigenvector problem, and the results depend on the dataset, rather than being pre-defined basis functions. Because the new variables are defined by the dataset at hand, and not *a priori*, PCA can be considered an adaptive data analysis tool (Jolliffe and Cadima 2016).

Constructing a composite indicator (or composite indicator) is a conceptual as well as mathematical operation that consists in summarizing (or aggregating as it is termed) a set of individual indicators, on the basis of a well-defined measurement model. Therefore, a composite indicator is formed when individual indicators are compiled into a single index, on the basis of an underlying model of the multi-dimensional concept that is being measured (OECD 2004). Constructing a composite indicator is a complex task. The steps involve several alternatives and possibilities that affect the quality and reliability of the results (Booysen 2002). The main problems, in this approach, concern the choice of theoretical framework, the selection of the more representative indicators and their treatment in order to compare and aggregate them (Salzman 2003; Mazziotta and Pareto 2017).

Obviously, a composite indicator can be obtained by reducing dimensionality, but not necessarily reducing dimensionality provides a composite indicator.

2.2 Formative versus Reflective model

As known, a model of measurement can be conceived through two different conceptual approaches: reflective or formative (Jarvis *et al.* 2003; Diamantopoulos *et al*. 2008).

The most popular approach is the reflective model, according to which individual indicators denote effects (or manifestations) of an underlying latent variable. Therefore, causality is from the concept to the indicators and a change in the phenomenon causes variation in all its measures. In this model, the concept exists independently of awareness or interpretation by the researcher, even if it is not directly measurable.

Specifically, the latent variable R represents the common cause shared by all indicators X_i reflecting the concept, with each indicator corresponding to a linear function of the underlying variable plus a measurement error:

$$X_i = \lambda_i R + \varepsilon_i \qquad (1)$$

where X_i is the indicator i, λ_i is a coefficient (loading) capturing the effect of R on X_i. and ε_i is the measurement error for the indicator i. Measurement errors are assumed to be independent and unrelated to the latent variable.

A fundamental characteristic of reflective models is that individual indicators are interchangeable (the removal of one of the indicators does not change the essential nature of the underlying concept) and correlations between indicators are explained by the measurement model (all indicators must be inter-correlated).

Another important issue concerns the polarity of the individual indicators. The ‘polarity’ of a individual indicator is the sign of the relation between the indicator and the concept to be measured. For example, in the case of well-being, “Life expectancy” has positive polarity, whereas “Unemployment rate” has negative polarity.

In a reflective model, individual indicators with equal polarities must be positively correlated, whereas individual indicators with opposite polarities must be negatively correlated.

A typical example of reflective model is the measurement of the intelligence of a person. In that case, it is the ‘intelligence level’ that determines the answers to a questionnaire for measuring attitude, and not vice versa. Hence, if the intelligence of a person increased, this would be matched by an increase of correct answers to all questions (Simonetto 2012).

The second approach is the formative model, according to which individual indicators are causes of an underlying latent variable, rather than its effects. Therefore, causality is from the indicators to the concept and a change in the phenomenon does not necessarily imply variations in all its measures. In this model, the concept is defined by, or is a function of, the observed variables.

The specification of the formative model is:

$$R = \sum_i \lambda_i X_i + \zeta \qquad (2)$$

where λ_i is a coefficient capturing the effect of X_i on R, and ζ is an error term.

In this case, indicators are not interchangeable (omitting an indicator is omitting a part of the underlying concept) and correlations between indicators (r_{ij}, $i \neq j$) are not explained by the measurement model (high correlations between indicators are possible, but not generally expected). So, in a formative model, polarities and correlations are independent and individual indicators can have positive, negative or zero correlations.

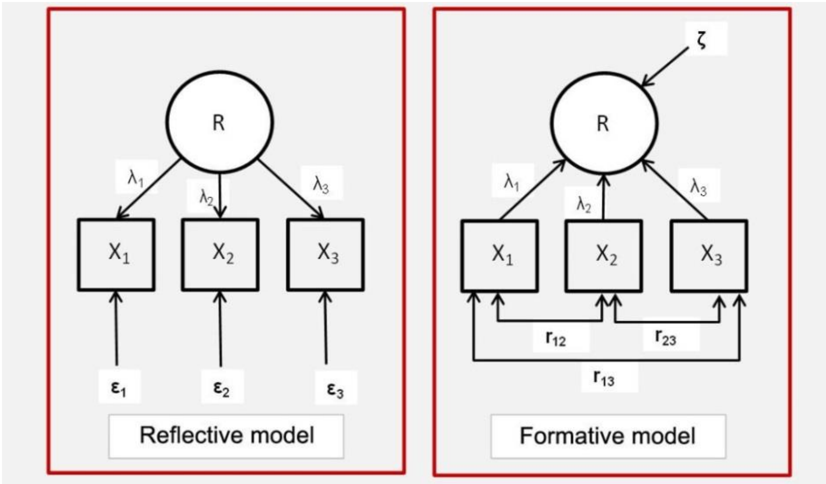
A typical example of formative model is the measurement of the well-being of the people. It depends on health, income, occupation, services, environment, etc., and not vice versa. So, if any one of these factors improved, the well-being of the people would increase (even if the other factors did not change). However, if the well-being of the people increased, this would not necessarily be accompanied by an improvement in all factors.

Note that (1) is a simple regression equation where the individual indicator is the dependent variable and the latent variable is the explanatory variable; whereas (2) represents a multiple regression equation where the latent variable is the dependent variable and the indicators are the explanatory variables[1]. Hence, the correct interpretation of the relationships between indicators and latent variable allows the procedure aimed at aggregating individual indicators to be correctly identified (Maggino 2017).

In Figure 2.2.1, the two different approaches are graphically represented.

[1] Because the formative measurement model is based on a multiple regression, the stability of the coefficients λ_i is affected by the strength of the indicator intercorrelations. So, individual indicators should have little or no correlation among themselves in order to avoid multicollinearity (Diamantopoulos and Winklhofer 2001).

Figure 2.2.1 Alternative measurement models



Traditionally, the reflective model is applied in the development of scaling models for subjective measurement (e.g. scale construction), whereas the formative model is commonly used in the construction of composite indices based on both objective and subjective indicators (Maggino and Zumbo 2012). Hence, although the reflective view dominates the psychological and management sciences, the formative view is common in economics and sociology (Coltman *et al*., 2008).

2.3 How to construct a composite indicator

In recent years, the debate on the measurement of multidimensional phenomena has caused, within the worldwide scientific Community of developed countries, a renewed interest. It is common awareness that a number of socio-economic phenomena cannot be measured by a single descriptive indicator and that, instead, they should be represented with a multiplicity of aspects or dimensions. Phenomena such as development, progress, poverty, social inequality, well-being, quality of life, etc., require, to be measured, the ‘combination’ of different dimensions, to be considered together as components of the phenomenon (Mazziotta and Pareto, 2013). In fact, the complex and multidimensional nature of these phenomena requires the definition of intermediate objectives whose achievement can be observed and measured by individual indicators. The mathematical combination (or aggregation as it is termed) of a set of indicators that represent the different dimensions of a phenomenon to be measured can be obtained by applying methodologies known as composite indicators (Saisana and Tarantola, 2002; Salzman, 2003; OECD, 2008).

As known, building a composite indicator is a delicate task and full of pitfalls: from the obstacles regarding the availability of data and the choice of individual indicators, to their treatment in order to compare (normalization) and aggregate them (weighting and aggregation). Despite the problems mentioned, the composite indices are widely used by several international organizations for measuring economic, environmental and social phenomena and, therefore, they provide an extremely relevant tool and in the course of evolution (OECD, 2008).

Many scientists dispute the use of composite indices that lead to the determination of a single value for each geographic area, preferring the so-called dashboard (as in the case of monitoring the state of health of a vehicle: oil level, gasoline, water temperature, etc.). In the case of dashboard, it is possible to identify various dimensions of the phenomenon, all relevant, without which, they are further aggregated. From the statistical point of view, it is an incontrovertible choice but from the standpoint of political and media is a heavy limitation. The easy-disclosure in the media and the immediate understanding by the user are certainly the strengths of a unique index. Obviously, both approaches have strengths and weaknesses. The dashboard manages complexity not using synthetic measures so that certainly it defects from the communication point of view. In this case the question without answer is: "Is well-being increased or decreased?". The composite indicator manages also the complexity but it reduces the dimensions in space with an evident loss of information; however, the composite indicator allows a single measure that is more communicative. A composite indicator, before the theoretical and methodological aspects, has a problem: is it possible to measure well-being with a formula? The answer is probably yes if a paradigm of work is strictly respected (see next paragraphs). In literature, for example, many attempts to measure well-being do not respect a paradigm of work and arrive to unreliable and questionable conclusions. This aspect causes the failure of many alternative measures to GDP.

2.3.1 Mission "Replace GDP"

The debate presented above has convinced scientists that the economic measure for excellence (GDP) is not able to represent the well-being or the progress of a society, much less to express the quality of life of a geographical area or a community. This debate has produced worldwide a considerable literature with more than a hundred alternative indices, published by government organizations (and others), academia and business press, but despite this, it seems that the popularity of GDP has not been minimally scratched.

In fact, the GDP is based on very solid theoretical bases, while many alternative indices are poor from the stage of definition of the phenomenon; in many circumstances, not having a shared socio-economic theory behind, taking into account dozens of indicators so that all possible aspects are considered (and then no one).

A clear difference in the approaches is between dashboard and composite indicator. Obviously both approaches have strengths and weaknesses. The dashboard manages complexity not using synthetic measures so that certainly it defects from the communication point of view. In this case the question without answer is: "Is well-being increased or decreased? The composite indicator manages also the complexity but it reduces the dimensions in space with an evident loss of information; however, the composite indicator allows a single measure that is more communicative. A composite indicator, before the theoretical and methodological aspects, has a problem: is it possible to measure well-being with a formula? The answer is probably yes if the paradigm of work is strictly respected. In literature, many attempts to measure well-being do not respect a paradigm of work and arrive to unreliable and questionable conclusions. This aspect causes the failure of many alternative measures to GDP.

The publication, in September 2009 of the report by the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz Commission), set up by the former French President Nicolas Sarkozy, was crucial for developing several studies about "Beyond GDP" scenarios. The Commission's aim is to identify the limits of GDP as an indicator of economic performance and societal progress, to consider what additional information might be required for the production of more relevant indicators of social progress, to assess the feasibility of alternative measurement tools, and to discuss how to present the statistical information in an appropriate way (Giovannini and Rondinella, 2012).

In truth, even before the Stiglitz Commission, several attempts to measure phenomena “close to” well-being (progress, quality of life, happiness, etc.) have been made and published by scientists and prestigious institutions. These attempts can be divided in 4 groups and some of these studies are presented below. The first proposes to adjust the GDP: MEW – Measure of Economic Well-being (Nordaus and Tobin, 1972), ISEW – Index of Sustainable Economic Welfare (Daly and Cobb, 1989), GPI – Genuine Progress Indicator. Another group of studies takes into account aspects such as social and environmental activities or directly the level of (perceived) satisfaction of individuals: HLE - Happy Life Expectancy (Veenhoven, 1996) and HPI - Happy Planet Index. A third group includes measures that represent a composite indicator including GDP: the best known among these are HDI - Human Development Index (UNDP, 1990, 2001, 2010), BLI - Better Life Index (OECD, 2011) and GNH - Gross National Happiness. Finally, the fourth approach argues that it is preferable to measure different dimensions with a set of indicators (dashboard) rather than to get a single synthetic measure (Rinaldi and Zelli, 2014), for example the Millennium Development Goals (MDGs) by UNDP. For a detailed review of composite indicators see Bandura (2008).

In the Italian panorama, the first report on “Equitable and Sustainable Well-being” (BES) by the Committee composed by Istat (Italian National Institute of Statistics) and CNEL (Italian Council for Economics and Labour) was published in March 2013. It consists in a dashboard of 134 individual indicators divided in 12 domains. The third BES report, published in December 2015, presents a composite indicator for each domain of well-being (Istat, 2015). Also in Italy, since 2003, the “Campaign Sbilanciamoci!” has published the Index of the Regional Quality of Development (QUARS) with the aim of providing a multidimensional measure of the development of Italian regions, based on 41 individual indicators divided in 7 domains and synthesized by a simple arithmetic mean (Gnesi et al., 2010). One of the indices with greater media coverage in Italy is the measure of the Quality of Life (QoL) which, every year, the economic newspaper “Il Sole 24ore” publishes at the provincial level. It is based on 36 individual indicators divided in 6 domains and synthesized by a simple arithmetic mean.

2.3.2 The use (good and bad) of the composite indicators

The construction of a composite indicator is a good solution but a paradigm of work must be strictly followed. It is a complex task whose phases involve several alternatives and possibilities that affect the quality and reliability of the results. The main problems, in this approach, concern the choice of theoretical framework, the availability of the data (in space and over time), the selection of the more representative indicators and their treatment in order to compare and aggregate them.

The paradigm of work is based on the following steps (OECD, 2008; Mazziotta and Pareto, 2013; Maggino, 2006; Maggino, 2017):

1. defining the phenomenon to be measured. The definition of the concept should give a clear sense of what is being measured by the composite indicator. It should refer to a theoretical framework, linking various sub-groups and underlying indicators;
2. selecting a group of individual indicators. Ideally, indicators should be selected according to their relevance, analytical soundness, timeliness, accessibility, etc. (Maggino, 2014). It is necessary to consider that socio-economic phenomena, as well- being, follow a *formative approach* according to which the latent factor (well-being) depends on the indicators that “explain” it and not vice versa (Diamantopoulos et al., 2008);
3. normalizing the individual indicators. This step aims to make the indicators comparable and to define the polarity. Normalization is required prior to any data aggregation as the indicators in a data set often have different measurement units. We want to normalize the indicators so that an increase in the normalized indicators corresponds to an increase in composite indicator;
4. aggregating the normalized indicators. It is the combination of all components to form one or more composite indices (mathematical functions). Different aggregation methods are possible and the choice must be conditioned by the nature of the indicators into the *formative approach*;
5. validating the composite indicator. This step aims to assess the robustness of the composite indicator, in terms of capacity to produce correct and stable measures, and its discriminant capacity.

It is important to emphasize that the theoretical part is not separate from the statistical-methodological one: then, the choice of the individual indicators is not independent from the choice of the aggregation method. Unfortunately, many methods in the literature do not comply with this restriction and, for example, they use the factor analysis as a method of synthesis into a formative model.

No universal method exists for composite indices construction. In each case their construction is much determined by the particular application, including formal elements and incorporates some expert knowledge on the phenomenon. Nevertheless, the advantages of composite indices are clear, and they can be summarized in unidimensional measurement of the phenomenon, easy interpretation with respect to a battery of many individual indicators and simplification of the data analysis.

A basic rule to keep in mind is "garbage in garbage out" that is, if the original matrix contains garbage then the composite indicator produces garbage. If a phenomenon is poorly defined, then he will certainly be poorly measured. Despite this, the reverse is not true. If the phenomenon is well defined and the matrix is composed of elementary indicators of good quality, then it is not always true that the composite indicator is valid. It depends on the statistical methodology used which must be “well-matched” with the theoretical framework on which is based the phenomenon to be measured.

2.3.3 The “perfect” composite indicator does not exist

As mentioned in the previous section, no universal method exists for composite indices construction. The best composite indicator is the one that respects the objectives required by the researcher or the commitment. The paradigm of work requires that some questions should be asked before starting work. The responses influence the path to be followed in order to obtain the best possible solution of composite indicator. All the answers can influence both the choice of the individual indicators and the methodology to normalize and synthesize them.

- do you need territorial comparisons? If yes, the individual indicators chosen must be available for the required territorial disaggregation and this may affect the use or not of some measures;
- do you need comparisons over time? If yes, the individual indicators chosen

must be available for the required time series and above all only some normalization methods allow performing effectively and correctly by statistical points of view comparisons over time between composite indices;

- are the individual indicators non-substitutable? Alternatively, is the compensation between the indicators admitted? Usually, in the measurement of socio-economic phenomena, the formative approach is required and then the compensation is not admitted. Therefore, if the individual indicators are non-substitutable the choice of the aggregation method must be taken based on this factor. In this case, the arithmetic mean and the linear models are not eligible. For example, the HDI and the HPI are characterized by indicators non-substitutable and the aggregation methods (power mean, respectively, of order 0 and 3) do not allow compensation between them;
- what is the audience to which the analysis is targeted? The client and recipient of the composite indicator should influence the choice of the statistical synthesis method of the individual indicators. The simplicity of calculation, the immediate use and easy interpretation of output results are conditions essential when the study is addressed to a broad audience not accustomed to technicalities: the reader should immediately understand both the methodology used and the meaning of the obtained results. If the study is addressed towards an academic audience then the methodology can certainly be more complex and the results have “shades of reading”. In all cases, the transparency of method and calculation must be respected because otherwise the composite indicator is a fraud;
- is the method robust? The first rule for constructing a good composite indicator is the compliance with the aims of the study. However other rules must be respected: the index should be robust i.e. it must incorporate the changes but not be too influenced by outliers. The method must be stable (but not too much) to the variations of the input matrix. It is very important to choose the most robust method through sensitivity analysis (influence analysis or others similar techniques).

The answers to these questions should guide the research toward the most effective method for reducing the multidimensionality of the phenomenon. It is not possible to ignore either one of these questions because the risk of altering the reality is very high.

In particular, the attention has to be focused on the search of the most suitable method depending on the following factors: type of indicators (substitutable/non-substitutable), type of aggregation (simple/complex), type of comparisons to be made (relative/absolute), type of weights of the indicators (subjective /objective) as described in the next paragraphs.

2.3.4 The steps characterizing the composite indicators construction

We have seen that the main steps for constructing a composite indicator are the following (Salzman, 2003; OECD, 2008; Mazziotta and Pareto, 2013)[2]: (1) Defining the phenomenon to be measured, (2) Selecting a group of individual indicators, (3) Normalizing the individual indicators, (4) Aggregating the normalized indicators, and (5) Validating the composite indicator.

2.3.4.1 The definition of the phenomenon

The definition of the phenomenon should give a clear sense of what is being measured by the composite indicator. It should refer to a theoretical framework, linking various sub-groups and underlying indicators. A fundamental issue, often overlooked in composite indicator construction, is the identification of the model measurement, in order to specify the relationship between the phenomenon to be measured (latent variable) and its measures (individual indicators). In this respect, if causality is from the phenomenon to the indicators we have a reflective measurement model; if causality is from the indicators to the concept we have a formative model (Diamantopoulos, 2008).

The reflective measurement model is most widely used in psychological and management sciences. Typical examples of reflective scenarios include measures of intelligence, attitudes and personality that are assessed by eliciting responses to indicators. A fundamental characteristic of reflective models is that a change in the latent variable causes variation in all individual indicators simultaneously.

The formative model is common in economics and sociology. A typical example of formative model is socioeconomic status (SES), which is defined as a combination of education, income, occupation, and residence. If any one of these indicators increases,

[2] Some authors describe a greater number of steps (e.g., imputation of missing data). We report only the fundamental steps.

SES would increase (even if the other indicators did not change); conversely, if a person's SES increases, this would not necessarily be accompanied by an increase in all four indicators (Diamantopoulos and Winklhofer, 2001).

Defining the model measurement is very important, because it is closely related with the selection and aggregation steps.

2.3.4.2 The selection of the indicators

In this step, the number and nature of the components that will make up part of the composite indicator need to be determined. Then, the specific indicators employed in estimating each of the component index must be selected. Such selection is generally based on theory, empirical analysis, pragmatism or intuitive appeal (Booysen, 2002).

The strengths and weaknesses of a composite indicator largely derive from the quality of the underlying indicators. Ideally, indicators should be selected according to their relevance, analytical soundness, timeliness, accessibility, etc. (OECD, 2008).

The selection step is the result of a trade-off between possible redundancies caused by overlapping information and the risk of losing information. A statistical approach to the choice of indicators involves calculating the correlation between potential indicators and including the ones that are less correlated in order to minimize redundancy (Salzman 2003). However, the selection process depends on the measurement model used: in a reflective model, all the individual indicators must be inter-correlated; whereas in a formative model they can show negative or zero correlations (Diamantopoulos, 2008).

2.3.4.3 The normalization

Normalization step aims to make the indicators comparable. Normalization is required before any data aggregation as the indicators in a data set often have different measurement units and ranges. In such cases, without normalization, composite indices will be biased towards variables with high ranges (implicit weighting scheme) and meaningful changes in a value may significantly affect the composite indicator. Therefore, it is necessary to bring the indicators to the same standard, by transforming them into pure, dimensionless, numbers. Another motivation for the normalization is the fact that some indicators may be positively correlated with the phenomenon to be measured (positive polarity), whereas others may be negatively correlated with it (negative polarity). We want to normalize the indicators so that an increase in the normalized indicators corresponds to increase in the composite indicator (Salzman, 2003).

Formally, we have to move from the data matrix X={x_{ij}}, with n rows (statistical units) and m columns (individual indicators), to the normalized matrix Y={y_{ij}}:

$$\mathbf{X}_{n,m} = \begin{pmatrix} x_{11} & \dots & x_{1j} & \dots & x_{1m} \\ \dots & \dots & \dots & \dots & \dots \\ x_{i1} & \dots & x_{ij} & \dots & x_{im} \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & \dots & x_{nj} & \dots & x_{nm} \end{pmatrix} \Rightarrow \mathbf{Y}_{n,m} = \begin{pmatrix} y_{11} & \dots & y_{1j} & \dots & y_{1m} \\ \dots & \dots & \dots & \dots & \dots \\ y_{i1} & \dots & y_{ij} & \dots & y_{im} \\ \dots & \dots & \dots & \dots & \dots \\ y_{n1} & \dots & y_{nj} & \dots & y_{nm} \end{pmatrix}$$

where x_{ij} is the original value of indicator *j* for unit *i* and *yij* is the normalized value of indicator *j* for unit *i*.

There are various normalization methods, some of which transform the range or variance of the indicators to a common basis and others which emphasizes percentage change. The following classification is here used: no normalization, ranking, standardization (or Z-scores), re-scaling (or Min-Max), distance from a reference (or Indicization).

The researcher must identify the most suitable normalisation methods to apply to the problem at hand, taking into account their properties and robustness against possible outliers in the data. Different normalization methods will produce different results for the composite indicator. Therefore, a robustness analysis should be carried out to assess their impact on the results (Freudenberg, 2003).

The polarity issue

The polarity of an individual indicator is the sign of the relation between the indicator and the phenomenon to be measured. For example, in the case of development, the ‘Life expectancy’ has positive polarity, whereas the ‘Infant mortality rate’ has negative polarity. When a composite indicator must be constructed, all the individual indicators must have positive polarity, then it is necessary to ‘invert’ the sign of the indicators with negative polarity. Inversion of polarity may be performed before normalizing or jointly. However, in most of cases the results are identical. There are two basic methods for inverting polarity: a) linear transformation, and b) non-linear transformation.

a) linear transformation takes the complement with respect to maximum value, as follow:

$$x'_{ij} = max_i(x_{ij}) - x_{ij} \tag{1}$$

where max_i is the maximum of indicator j. This is the simplest technique and it allows to save the same 'distance' between units, with a different origin. It is particularly used with ranking, standardization and re-scaling;

b) non-linear transformation takes the reciprocal of the value:

$$x'_{ij} = \frac{1}{x_{ij}} \tag{2}$$

This technique is typically used with indicization, but it modifies the 'distances' between units and thus it can be criticized. Furthermore, it requires all values are greater than 0.

Sometimes, polarity of an indicator may be positive below a certain threshold and negative above it or vice versa. For example, in the case of gender parity, the 'Percentage of women elected in Parliament on the total of the elects' has positive polarity below 50% and negative polarity above 50%. We call this the 'Double-polarity question'.

The simplest method for moving from a double-polarity to a standard case (positive or negative polarity) is the triangular transformation.

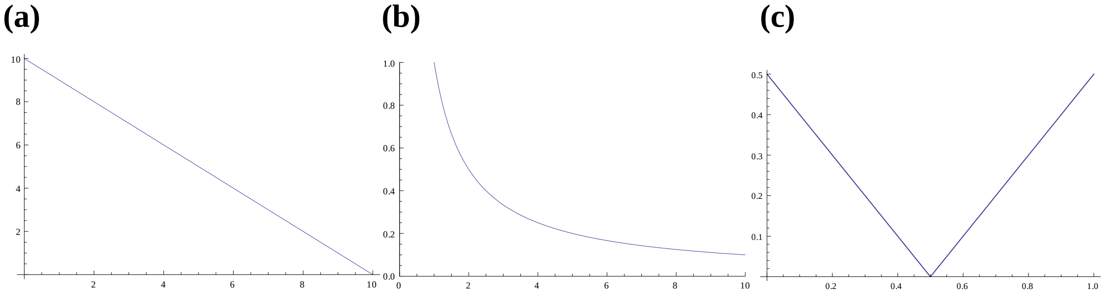
Triangular transformation has the form:

$$x'_{ij} = abs(\lambda_j - x_{ij}) \tag{3}$$

Where λ_j is the threshold for indicator j. If the obtained polarity is negative, an additional linear or non-linear transformation is required.

In Figure 2.3.4.3.1 three examples of linear transformation (a), non-linear transformation (b), and triangular transformation (c) are shown.

Figure 2.3.4.3.1. Linear, non-linear and triangular transformation



No normalization

The first method, no normalization, involves an aggregation of original data. This may be a good technique if all the indicators have the same unit of measurement and similar ranges or they are expressed as percentages or ratios. Otherwise, aggregating individual indicators without normalization will cause the index to be dominated by implicit weights coming from the units and range used to measure indicators.

Ranking

This method simply ranks units for each indicator as follows:

$$y_{ij} = \text{rank}(x_{ij}) \qquad (4)$$

where $rank(x_{ij})$ is the rank of unit i with respect to indicator j. Units with the same value receive a rank equal to the mean of the ranks they span, so that the sum of the ranks is $n\frac{n+1}{2}$. If indicator j has negative polarity, the rank order must be reversed. This is equivalent to apply (1) or (2) and then (4). Ranking is based on ordinal levels and it is not affected by outliers. However, differences between the units cannot be evaluated as absolute level information is lost. So, the method allows the performance of units to be followed over time only in terms of relative positions (rankings).

Standardization (or Z-scores)

Standardization converts indicators to a common scale with a mean of zero and standard deviation of one. The formula is:

$$y_{ij} = \frac{x_{ij} - \mathrm{M}_{x_j}}{\mathrm{S}_{x_j}} \qquad (5)$$

where M_{x_j} and S_{x_j} are, respectively, the mean and standard deviaton of indicator j. If indicator j has negative polarity, formula (5) is multiplied by -1. This is equivalent to apply (1) and then (5). Standard scores may be further adjusted if calculations yield awkward values. For example, we can multiply each score by 10 and add 100 to obtain more visually manageable scores (Booysen, 2002). Standardization does not transform indicators to a common range. So, it is allows extreme values to influence the results because the range between the minimum and maximum standard scores will vary for each indicator.

Re-scaling (or Min-Max)

Re-scaling normalizes indicators to have an identical range [0, 1] as follows:

$$y_{ij} = \frac{x_{ij} - min_i(x_{ij})}{max_i(x_{ij}) - min_i(x_{ij})} \qquad (6)$$

where $min_i(x_{ij})$ and $max_i(x_{ij})$ are, respectively, a minimum and a maximum value that represent the possible range of indicator *j* (goalposts). If indicator *j* has negative polarity, the complement of (6) with respect to 1 is calculated[3]. This is equivalent to apply (1) and then (6). The goalposts can be selected relative to the observed minimum and maximum values of the indicator, be it for a specific year or over an extended

[3] The 'complement with respect to 1' is the number to add to make 1.

period of time. Alternatively, they can be fixed by experts. Re-scaling is based on the range and it is sensitive to outliers. On the other hand, the range for indicators with very little variation will increase and these will contribute more to the composite indicator than they would using another method.

Distance from a reference (or Indicization)

This method takes the percentage ratio between original values and a reference for each indicator. The indicized value is given by:

$$y_{ij} = \frac{x_{ij}}{x_{oj}} 100 \qquad (7)$$

where x_{0j} is the reference value for indicator j (generally, the maximum or an external benchmark). In this method, the reference is given a value of 100 and units receive a score depending on their distance from it. Values greater (less) than 100 indicate above (below) reference performance. If indicator j has negative polarity, formula (4) can be preliminarily applied; however indicization is recommended only for indicators with positive polarity. Moreover, it is less robust to the influence of outliers than other methods.

In table 2.3.4.3.1 is reported an example of normalization with some hypothetical data for five statistical units. The table provides the normalized indicator by the different methods, for positive and negative polarity, and the basic statistics of the normalized values (with the characteristics in bold).

Table 2.3.4.3.1 Comparing normalization methods

Unit	Original indicator (x)	Normalized indicator (y)							
		Positive polarity (+)				Negative polarity (-)			
		Ranking	*Z*-scores	Re-scaling	Indicization	Ranking	*Z*-scores	Re-scaling	Indicization
1	450.0	1.0	1.81	1.00	100.0	5.0	-1.81	0.00	11.1
2	200.0	2.5	0.00	0.38	44.4	3.5	0.00	0.63	25.0
3	200.0	2.5	0.00	0.38	44.4	3.5	0.00	0.63	25.0
4	100.0	4.0	-0.73	0.13	22.2	2.0	0.73	0.88	50.0
5	50.0	5.0	-1.09	0.00	11.1	1.0	1.09	1.00	100.0
Min	50.0	1.0	-1.09	**0.00**	11.1	1.0	-1.81	**0.00**	11.1
Max	450.0	5.0	1.81	**1.00**	**100.0**	5.0	1.09	**1.00**	**100.0**
Mean	200.0	**3.0**	**0.00**	0.38	44.4	**3.0**	**0.00**	0.63	42.2
Std	137.8	1.4	**1.00**	0.34	30.6	1.4	**1.00**	0.34	31.5
CV (%)	68.9	45.9	-	91.9	**68.9**	45.9	-	55.1	74.6

Note that normalized indicators by ranking have a mean of $\frac{n+1}{2} = \frac{5+1}{2} = 3$. Z-scores have a mean of 0 and standard deviation of 1, so that the variability 'effect' is nullified. Re-scaled indicators range between 0 and 1 and variability does not change by inverting polarity (standard deviation = 0.34); however the mean of the normalized values for negative polarity is the complement with respect to 1 of the mean for positive polarity, so the coefficient of variation (CV) is different (91.9 versus 55.1). Finally, indicized indicators have a maximum of 100 and save the original CV, but only for positive polarity (CV=68.9).

The main pros and cons of different normalization methods are summarized in table 2.3.4.3.2.

Table 2.3.4.3.2 Pros and Cons of normalization methods

Normalization method	Pros	Cons
Ranking	Applicable to indicators with positive, negative and zero values. Suitable both for bounded and unbounded indicators[4]. No/low implicit weighting (normalized indicators have equal or similar variances). Insensitive to outliers.	Loss of information (from interval/ratio scale to ordinal scale). Assumes equal intervals between consecutive values. Aggregation by a mathematical function is questionable for ordinal data.
Standardization (or *Z*-scores)	Applicable to indicators with positive, negative and zero values. No implicit weighting (normalized indicators have equal variances).	Not very suitable for bounded indicators. Produces negative values. Sensitive to outliers.
Re-scaling (or Min-Max)	Applicable to indicators with positive, negative and zero values. Low implicit weighting (normalized indicators have similar variances).	Not very suitable for unbounded indicators. The mean reference can be lost. Sensitive to outliers (the range depends on extreme values).
Distance from a reference (or Indicization)	Suitable both for bounded and unbounded indicators. Saves the coefficient of variation (only for indicators with positive polarity).	Not applicable to indicators with negative values (zero values are accepted only for indicators with positive polarity). High implicit weighting (normalized indicators have different variances). Very sensitive to outliers.

Potential problems include the loss of interval level information (e.g., ranking), sensitivity to outliers (e.g., standardization, re-scaling and indicization), and implicit weighting (e.g., indicization). The different transformations will therefore have significant effects on the construction of the composite indicator, and important incentive effects on the behaviour of units being assessed (Jacobs et al., 2004).

2.3.4.4 The aggregation

Aggregation is the combination of all the components to form one or more composite indices. This step requires the definition of the importance of each individual indicator (weighting system) and the identification of the technique (compensatory, partially

[4] Indicators can be divided in 'bounded' and 'unbounded'. We say that an indicator is 'bounded' when it ranges between fixed values. An example of bounded indicator is the 'Employment rate' that always ranges between 0 and 100. We say that an indicator is 'unbounded' when there are no predetermined upper or lower limits. An example of unbounded indicator is the 'Household disposable income', because there is theoretically no limit to how high the income could be.

compensatory or non-compensatory) for summarizing the individual indicator values into a single number.

Formally, we have to move from the normalized matrix $Y=\{y_{ij}\}$, with n rows (statistical units) and m columns (normalized indicators), to the vector $C=\{c_i\}$, with n rows:

$$\mathbf{Y}_{n,m} = \begin{pmatrix} y_{11} & \cdots & y_{1j} & \cdots & y_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{i1} & \cdots & y_{ij} & \cdots & y_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{n1} & \cdots & y_{nj} & \cdots & y_{nm} \end{pmatrix} \Rightarrow \mathbf{C}_n = \begin{pmatrix} c_1 \\ \cdots \\ c_i \\ \cdots \\ c_n \end{pmatrix},$$

where c_i is the value of the composite indicator for unit *i*.

The literature offers a wide variety of aggregation methods, each with its pros and cons. They range from the simple arithmetic o geometric mean to multivariate statistical methods. In this chapter, some traditional and more recent methods are reported: the Power mean of order r, Wroclaw Taxonomic Method, Mean-Min Function, Mazziotta-Pareto Index, and Principal Component Analysis.

Aggregation is the most important and delicate step of the procedure. In this stage, the choices of the researcher assume a fundamental role, from a methodological point of view, as even minimal changes in the methods applied can have major impact on the result. Therefore, data aggregation has always been an interesting but controversial topic in composite indicator construction (Saltelli, 2007).

The weighting system

In addition to the implicit weights introduced during normalization, explicit weights may be defined during aggregation. The aim with explicit weighting is that weights should reflect the relative importance (significance, reliability or other characteristics) of the individual indicators. The weights given to different indicators heavily influence the outcomes of the composite indicator. So, weights ideally should be selected according to an underlying theoretical framework for the composite indicator.

The most widely used techniques for weighting individual indicators are the following:

a) if no explicit weighting is defined other than that implicitly introduced during the normalization, equal weights are applied to all individual indicators. This implies that all indicators in the composite have equal importance, which may not be the case. However, if there are no statistical or empirical grounds for choosing different weights, this may be a valid approach in some contexts[5];

b) expert weighting is typically set by a group of specialists who define weights for each indicator. The values determined by specialists are then averaged. Weights are sometimes defined by policy makers or social surveys about how meaningful or important individual indicators are to people;

c) PCA can be used to set weights by using the coefficients of the first principal component. This is an empirical and relatively more objective option for weight selection and it has the advantage of determining that set of weights which explains the largest variation in the original indicators[6].

Since different weighting systems imply different results and, given the subjectivity inherent many of these criteria, no explicit weighting should be the norm and the burden of proof should fall on differential weighting (Booysen, 2002).

The compensability issue

A fundamental issue concerning composite indicator construction is the degree of compensability or substitutability of the individual indicators.

The components of a composite indicator are called ‘substitutable’ if a deficit in one component may be compensated by a surplus in another (e.g., a low value of “Proportion of people who have participated in religious or spiritual activities” can be offset by a high value of “Proportion of people who have participated in meetings of cultural or recreational associations” and vice versa). Similarly, the components of a composite indicator are called ‘non-substitutable’ if a compensation among them is not allowed (e.g., a low value of “Life expectancy at birth” cannot be offset by a high value

[5] Note that the equal weighting approach may give extra weight to certain performance aspects if several individual indicators are in effect measuring the same attribute. As a remedy, indicators could be tested for statistical correlations, and lower weights could be given to variables strongly correlated with each other. On the other hand, correlations may merely show that unit performance on these indicators is similar (Freudenberg, 2003).

[6] Although PCA has a number of excellent mathematical properties, its use in weighting components of social indices is dubious. For example, it may lead to indicators which have little variation being assigned small weights, irrespective of their possible contextual importance (Salzman, 2003).

of "GDP per capita" and vice versa)[7]. Thus we can define an aggregation approach as 'compensatory' or 'non-compensatory' depending on whether it permits compensability or not (Casadio Tarabusi and Guarini, 2013).

Compensability is closely related with the concept of unbalance, i.e., a disequilibrium among the indicators that are used to build the composite indicator. In any composite indicator each dimension is introduced to represent a relevant aspect of the phenomenon considered, therefore a measure of unbalance among dimensions may help the overall understanding of the phenomenon. In a non-compensatory or partially compensatory[8] approach, all the dimensions of the phenomenon must be balanced and an aggregation function that takes unbalance into account, in terms of penalization, is often used.

A compensatory approach involves the use of additive methods, such as the arithmetic mean. A non-compensatory or partially compensatory approach generally requires the use of non-linear functions, such as the geometric mean (OECD, 2008) or Multi-Criteria Analysis (MCA) (Munda and Nardo, 2009).

Power mean of order r

The power mean of order r aggregates normalized indicator as follows:

$$M_i^r = (\sum_{j=1}^{m} y_{ij}^r w_j)^{\frac{1}{r}}$$

where w_j is the weight of indicator j ($0 < w_j < 1$) and $\sum_{j=1}^{m} w_j = 1$.

For $r = 1$, we have an additive averaging. In particular, if $w_j = \frac{1}{m}$, then M_i^1 is the simple arithmetic mean. This technique is advantageous because of its methodological transparency, but it implies full compensability, such that poor performance in some indicators can be compensated for by sufficiently high values in other indicators.

[7] Note that compensability/non-compensability does not imply dependence/independence and vice-versa. For example, "Hospital beds (per 1,000 people)" and "Hospital doctors (per 1,000 people)" are two dependent (positively correlated) indicators but they are non-substitutable, because a deficit in beds cannot be compensated by a surplus in doctors and vice-versa (Mazziotta and Pareto, 2016).

[8] Note that a 'partially compensatory' approach can be considered 'non-compensatory', since it is not full compensatory.

In table 2.3.4.4.1 are reported some special cases of power mean of order r. The table also provides the type of approach and the features (intensity and direction) of the penalization for unbalanced values. If the composite indicator to be constructed is ‘positive’, i.e., increasing values of the index correspond to an improvement of the phenomenon (e.g., socio-economic development), a downward penalization must be used. On the contrary, if the composite indicator is ‘negative’, i.e., increasing values of the index correspond to a worsening of the phenomenon (e.g., poverty), an upward penalization must be used. In any cases, an unbalance among indicators values will have a negative effect on the value of the index[9].

Table 2.3.4.4.1 Special cases of the power mean of order r

Order	Formula	Aggregation function	Approach	Penalization	
				Intensity	Direction
$r \to -\infty$	$\mathrm{M}_i^{-\infty} = \min_j (y_{ij})$	Minimum	Non-compensatory	Maximum	Downward
$r=-1$	$\mathrm{M}_i^{-1} = \left(\sum_{j=1}^{m} \frac{w_j}{y_{ij}} \right)^{-1}$	Harmonic mean	Partially compensatory	High	Downward
$r \to 0$	$\mathrm{M}_i^{0} = \prod_{j=1}^{m} y_{ij}^{w_j}$	Geometric mean	Partially compensatory	Low	Downward
$r=1$	$\mathrm{M}_i^{1} = \sum_{j=1}^{m} y_{ij} w_j$	Arithmetic mean	Compensatory	None	-
$r=2$	$\mathrm{M}_i^{2} = \left(\sum_{j=1}^{m} y_{ij}^2 w_j \right)^{\frac{1}{2}}$	Quadratic mean	Partially compensatory	Low	Upward
$r=3$	$\mathrm{M}_i^{3} = \left(\sum_{j=1}^{m} y_{ij}^3 w_j \right)^{\frac{1}{3}}$	Cubic mean	Partially compensatory	High	Upward
$r \to +\infty$	$\mathrm{M}_i^{+\infty} = \max_j (y_{ij})$	Maximum	Non-compensatory	Maximum	Upward

Due to the penalization (upward or downward), we have:

$$\mathrm{M}_i^{-\infty} \le \ldots \le \mathrm{M}_i^{-1} \le \mathrm{M}_i^{0} \le \mathrm{M}_i^{1} \le \mathrm{M}_i^{2} \le \mathrm{M}_i^{3} \le \ldots \le \mathrm{M}_i^{+\infty}$$

[9] Note that a simple non-compensatory approach uses the minimum (maximum) value of the normalized indicators so that the other values cannot increase (decrease) the value of the index. This function realizes the maximum penalization for unbalanced values of the indicators (Casadio Tarabusi and Guarini, 2013).

and the means are equal if and only if $y_{ij}=y_{ik}$ $(j \neq k)$.

Note that not all aggregation functions are compatible with all normalization methods. For example, if the individual indicators are transformed in z-scores (standardization), they cannot be aggregated by a geometric mean because it is defined only for sets of positive values.

One approach commonly used in economics is to calculate the Jevons Index (geometric mean of indicized indicators). This method allows to build, for each unit, two closely interrelated composite indices: a 'static' index for space comparisons, and a 'dynamic' index for time comparisons (Mazziotta and Pareto, 2016).

Given a set of individual indicators with positive polarity, let x_{ij}^{t} denote the value of the indicator j for unit i, at time t , where $x_{ij}^{t} > 0$ (j=1, …, m; i=1, …, n; t=t0, t1). The 'static' composite indicator may be defined as follows:

$$\mathrm{SJ}_i^t = \prod_{j=1}^{m} \left(\frac{x_{ij}^t}{x_{oj}^t} 100 \right)^{\frac{1}{m}}$$

where x_{0j}^{t} is the reference value for indicator j at time t (e.g., the average).

In order to compare the data from time t0 to t1, for each unit, we can construct a 'dynamic' composite indicator given by:

$$\mathrm{DJ}_i^{t_1/t_0} = \prod_{j=1}^{m} \left(\frac{x_{ij}^{t_1}}{x_{ij}^{t_0}} 100 \right)^{\frac{1}{m}} .$$

For the 'circularity' or 'transitivity' property of the index number theory, SJ and DJ are linked by the relation:

$$\mathrm{DJ}_i^{t_1/t_0} = (\mathrm{SJ}_i^{t_1} / \mathrm{SJ}_i^{t_0})\, \mathrm{DJ}_o^{t_1/t_0} .$$

SJ and DJ are meaningful only for indicators with positive values. They give more weight to the low values and penalize downwards the unbalance among components.

Examples of well-known composite indices based on the power mean of order r are the United Nations' Human Development Index (geometric mean of re-scaled values) and Human Poverty Index (cubic mean of re-scaled values).

Wroclaw Taxonomic Method

This method was developed by a group of Polish mathematicians and applied to the aggregation of indicators of economic development (Harbison et al., 1970). It rests on the concept of 'ideal unit': a hypothetical unit that has, for each indicator, the most desirable value within the data set (optimal score).

The Euclidean distance from each unit to the 'ideal unit' is then calculated as follows:

$$\mathrm{D}_i = \sqrt{\sum_{j=1}^{m}(y_{ij} - y_{oj})^2}$$

where y_{ij} is the standardized value by (7) and y_{0j} is equal to $min_i(y_{ij})$ or $max_i(y_{ij})$ according to whether indicator j has negative or positive polarity. The composite indicator for unit i is given by:

$$\mathrm{d}_i = \frac{\mathrm{D}_i}{\mathrm{M_D} + 2\mathrm{S_D}}$$

where M_D and S_D are, respectively, the mean and standard deviation of the distances D_i.

The index is equal to zero when the distance between a given unit and the 'ideal unit' is null (all the values coincide). The higher is the index, the greater is the difference between the two units. The main weakness of this method is the criterion for defining the 'ideal unit' (Silvio-Pomenta, 1973).

Mean-Min Function

The Mean-Min Function (MMF) is a two-parameter function that incorporates two extreme cases of penalization of unbalance: the zero penalization represented by the arithmetic mean (compensatory approach) and the maximum penalization represented by the minimum function (non-compensatory approach). The function penalizes downwards and all other possible cases are intermediate.

The composite indicator is defined as:

$$\mathrm{MMF}_i = \mathrm{M}_{y_i} - \alpha\left(\sqrt{(\mathrm{M}_{y_i} - \min_j\{y_{ij}\})^2 + \beta^2} - \beta\right) \qquad (0 \le \alpha \le 1;\ \beta \ge 0)$$

where M_{y_i} is the mean of the normalized values for unit i, and the parameters α and β are respectively related to the intensity of penalization of unbalance and degree of complementarity between indicators (Casadio Tarabusi and Guarini, 2013).

The function reduces to the arithmetic mean for $\alpha = 0$ (in this case β is irrelevant) and to the minimum function for $\alpha = 1$ and $\beta = 0$. So, the interval of definition of the values of the composite indicator is: $min_j\{y_{ij}\} \le MMF \le M_{y_i}$.

The MMF is independent from the choice of the normalization method. By choosing the values of parameters appropriately one should obtain the aggregation function that best suits the specific theoretical approach. However, there is not a general rule for tuning these values (Mazziotta and Pareto, 2015).

Mazziotta-Pareto Index

The Mazziotta-Pareto Index (MPI) is a composite indicator for summarizing a set of indicators that are assumed to be not fully substitutable. It is based on a non-linear function which, starting from the arithmetic mean of the normalized indicators, introduces a penalty for the units with unbalanced values of the indicators (De Muro et al., 2011). Two version of the index have been proposed: a) MPI, and b) adjusted MPI (AMPI). The first version is the best solution for a ‘static’ analysis (e.g., a single-year analysis), whereas the second one is the best solution for a ‘dynamic’ analysis (e.g., a multi-year analysis).

a) MPI

The MPI is based on the following normalization:

$$z_{ij} = 100 + 10 y_{ij}$$

where yij is given by (5)[10].

Denoting with M_{z_i}, S_{z_i}, cv_{z_i}, respectively, the mean, standard deviation, and coefficient of variation of the normalized values for unit i, the composite indicator is given by:

$$\mathrm{MPI}_i^{+/-} = \mathrm{M}_{z_i} \pm \mathrm{S}_{z_i} \mathrm{cv}_{z_i}$$

where the sign ± depends on the kind of phenomenon to be measured. If a downward penalization is required, then the MPI^- is used, else the MPI^+ is used.

Therefore, the MPI decomposes the score of each unit in two parts: mean level (M_{z_i}) and penalty ($S_{z_i} cv_{z_i}$). The penalty is a function of the indicators' variability in relation to the mean value ('horizontal variability') and it is used to penalize the units. The aim is to reward the units that, mean being equal, have a greater balance among the indicators values.

b) AMPI

The AMPI normalizes indicators as follows:

$$r_{ij} = y_{ij} 60 + 70$$

where y_{ij} is given by (7). To facilitate the interpretation of results, the 'goalposts' can be chosen so that 100 represents a reference value (e.g., the average in a given year). Let Inf_{x_j} and Sup_{x_j} be the minimum and maximum of indicator j across all time periods considered, and Ref_{x_j} be the reference value for indicator j. Then the 'goalposts' are defined as: $Ref_{x_j} \pm \Delta$, where and $\Delta = \frac{Sup_{x_j} - Inf_{x_j}}{2}$ [11].

[10] Normalized indicators have a mean of 100 and standard deviation of 10.
[11] Normalized indicators range approximately between 70 and 130.

Denoting with M_{r_i}, S_{r_i}, cv_{r_i} respectively, the mean, standard deviation, and coefficient of variation of the normalized values for unit i, the composite indicator is given by:

$$\mathrm{AMPI}_i^{+/-} = \mathrm{M}_{r_i} \pm \mathrm{S}_{r_i}\mathrm{cv}_{r_i}$$

where the sign ± depends on the kind of phenomenon to be measured. If a downward penalization is required, then the AMPI- is used, else the AMPI+ is used.

The main difference between MPI and AMPI is the normalization method. The MPI is based on a standardization of the individual indicators that is repeated independently for each time period, so it is not possible to appreciate any absolute change in unit performance. The AMPI is based on a re-scaling and measures absolute variations with respect to prefixed goalposts. Moreover, the AMPI allows to compute the score of each unit independently of the others, in contrast to the MPI where the mean and standard deviation of the individual indicators are required. For a comparison between the two versions, see Mazziotta and Pareto (2016).

Principal Component Analysis

Principal Component Analysis (PCA) is a multivariate statistical method that, starting from a large number of individual indicators, allows to identify a small number of composite indices (principal components of factors) that explain most of the variance observed (Dunteman, 1989). The first principal component is often used as the 'best' composite indicator. It is defined as:

$$\mathrm{C}_{i1} = \sum_{j=1}^{m} a_{j1} x_{ij}$$

where a_{j1} is the weight of indicator j for factor 1.

This composite indicator has many optimal mathematical properties. The most important is that it explains the largest portion of variance of the individual indicators.

This is obtained by maximizing the sum of the squares of the coefficients of correlation between the composite indicator and the individual indicators. However, the first principal component accounts for a limited part of the variance in the data, so we can lose a consistent amount of information. Moreover, the PCA based index is often 'elitist' (Mishra, 2007), with a strong tendency to represent highly inter-correlated indicators and to neglect the others, irrespective of their possible contextual importance. So many highly important but poorly inter-correlated indicators may be unrepresented by the composite indicator.

An alternative method is the weighted mean of the factors (Giudici and Avrini, 2002). This approach consists in aggregating individual indicators by a weighted mean of factor scores, with weights proportional to the variance explained by each of the components. The composite indicator for unit *i* is:

$$S_i = \frac{\sum_{h=1}^{p} C_{ih}\lambda_h}{\sum_{h=1}^{p} \lambda_h}$$

where C_{ih} is the value of factor *h* for unit *i*, λh is the percentage of variance explained by factor *h*, and *p* is the number of considered factors ($p \leq m$). If $p = m$, no information is loss. The method assigns decreasing order of importance to the factors, according to their amount of variance explained.

2.3.4.5 The validation

Validation step aims to assess the robustness of the composite indicator, in terms of capacity to produce correct and stable measures, and its discriminant capacity. As seen above, the outcomes and rankings of individual units on the composite indicator may largely depend on the decisions taken at each of the preceding steps (selection of individual indicators, normalization and aggregation). For this reason, statistical analyses should be conducted to explore the robustness of rankings to the inclusion and exclusion of individual indicators and setting different decision rules to construct the composite indicator (Freudenberg, 2003).

Robustness of a composite indicator is assessed by two different methodologies: Uncertainty analysis (UA) and Sensitivity analysis (SA). UA focuses on how uncertainty in the input factors propagates through the structure of the composite indicator and affects the results. SA studies how much each individual source of uncertainty contributes to the output variance (Saisana et al., 2005). UA and SA can be used synergistically and iteratively during composite indicator construction to help in indicator selection, add transparency to the index construction process, and explore the robustness of alternative composite indicator designs and rankings (USAID, 2014).

Discriminant capacity of a composite indicator is assessed by exploring its capacity in: a) discriminating between units and/or groups; b) distributing all the units without any concentration of individual scores in a few segments of the continuum; c) showing values that are interpretable in terms of selectivity through the identification of particular reference values or cut-points (Maggino and Zumbo, 2012)[12].

Uncertainty analysis (UA)

UA is essentially based on simulations that are carried out on the various equations that constitute the underlying model. A valid approach for evaluating output uncertainty is the Monte Carlo method, which is based on multiple evaluations of the model with a set of randomly selected input factors (OECD, 2008).

The steps of the procedure are summarized below:

1. identify k input factors F_i (i = 1, …, k) that can introduce uncertainty in the results (e.g., errors in individual indicators, exclusion of an individual indicator, etc.);
2. assign a probability density function to each input factor (e.g., normal distribution for the errors in individual indicators; discrete uniform distribution to select the individual indicator to be excluded, etc.);
3. generate randomly L combinations or samples of independent input factors F_1^l, F_2^l,…, F_k^l (l = 1, 2,…, L) and calculate the corresponding value of the

[12] Point (a) can be verified by applying the traditional approaches of statistical hypothesis testing, whereas specific coefficients were proposed for evaluating (b) (Guilford, 1954). Receiver operating characteristic (ROC) analysis allows to identify discriminant *cut-points* in (c).

composite indicator for each unit $c_i^l = f(x_{i1}, x_{i2}, ..., x_{im}; F_1^l, F_2^l, ..., F_k^l)$ $(i = 1, 2, ..., n; l = 1, 2, ..., L)$;

4. calculate the average shift in countries' ranks $\overline{\mathrm{R}}^l = \frac{1}{n}\sum_{i=1}^{n}\left|r_i^l - r_i\right|$ $(l = 1, 2, ..., L)$ where $r_i^l = rank(c_i^l)$ is the rank assigned by the composite indicator to unit *i* for sample *l* and r_i is the original rank of unit *I*;
5. analyse the distribution of $\overline{\mathrm{R}}^l$ and/or r_i^l $(l = 1, 2, ..., L)$. The main characteristics of this distributions, such as the mean and variance, are estimated with an level of precision related to the size of the simulation *L*. In general, the lower the variance, the greater the robustness.

A particular case of UA is the Influence analysis (IA) that aims to empirically quantify the 'weight' of each individual indicator in the calculation of the composite indicator. Given m individual indicators, the IA perform steps 3 and 4, with L = m, by excluding each time indicator l. The value of $\overline{\mathrm{R}}^l$ represents the 'weight' of indicator l (Mazziotta C. et al., 2010).

Sensitivity analysis (SA)

SA examines the degree of influence of each input factor on the composite indicator, thereby helping to reveal how much each individual source of uncertainty contributes to the output variance (OECD, 2008).

The importance of a given input factor Fi can be measured via the so-called sensitivity index, which is defined as the fractional contribution to the model output variance due to the uncertainty in Fi. For k independent input factors, the sensitivity indices can be computed by using the following decomposition formula for the total variance of the output ($\overline{\mathrm{R}}^l$ or r_i^l):

$$\mathrm{V} = \sum_i \mathrm{V}_i + \sum_i \sum_{j>i} \mathrm{V}_{ij} + ... + \mathrm{V}_{12..k}$$

where Vi is the output variance due to the uncertainty in F_i, V_{ij} is the output variance due to uncertainty of the interaction between F_i and F_j, and so on.

A first measure of the fraction of the output variance V that is accounted for by the uncertainty in F_i is the first-order sensitivity index for the factor F_i defined as:

$$S_i = \frac{V_i}{V}$$

A measure that concentrates in one single term all the interactions involving a given factor F_i is the total effect sensitivity index, given by:

$$S_{Ti} = \frac{V_i}{V} + \sum_{j \neq i} \frac{V_{ij}}{V} + \ldots + \frac{V_{12..k}}{V} = S_i + \sum_{j \neq i} S_{ij} + \ldots + S_{12..k}$$

where S_{ij} is the second-order sensitivity index for the factors F_i and F_j, and so on.

If the model has no interactions among its input factors (additive model), we have $S_{T_i} = S_i$, (i = 1, 2, …, k), and $\sum_i S_{T_i} = 1$. In general, $\sum_i S_{T_i} \geq 1$ and a significant difference between S_{T_i} and S_i signals an important interaction role for the factor F_i in the output.

Estimators for both (S_i, S_{T_i}) are provided by a variety of methods, such as the method of Sobol' (Saisana et al., 2005).

2.4. Best practices

As we have seen above, there does not exist a composite indicator universally valid for all areas of application, since its validity depends on the strategic objectives of the research. In this Section we propose a scheme with some general guidelines to follow for constructing a composite indicator.

The main factors to take into account in the choice of the method to be adopted for summarizing a set of individual indicators are as follows (Mazziotta and Pareto, 2013):

- type of indicators (substitutable/non-substitutable);

- type of aggregation (simple/complex);
- type of comparisons (absolute/relative);
- type of weights (objective/subjective).

There is not always a ‘well-established’ solution, and sometimes it may be necessary to renounce to some requirements, to satisfy others.

Type of indicators

It is one of the main factors that influence the choice of the aggregation method. If the individual indicators are substitutable, then a compensatory approach is indicated, else a non-compensatory or partially compensatory approach is required.

Type of aggregation

The choice of the aggregation method also depends on the aim of the work and on the type of ‘users’ (researchers or people). Generally, an aggregation method can be considered ‘simple’ or ‘complex’. We say that an aggregation method is ‘simple’ when a easily understandable mathematical function is used (e.g., the HDI). On the contrary, an aggregation method is said to be ‘complex’ if a sophisticated model or multivariate method is used (e.g., PCA).

Type of comparisons

Data normalization firstly depends on the type of comparisons required. All the normalization methods allow for space comparisons, whereas time comparisons of the units may be difficult to make or to interpret. Comparisons over time may be ‘absolute’ or ‘relative’. We say that a time comparison is ‘relative’ when the composite indicator values, at time t, depend on one or more endogenous parameters (e.g., mean and variance of the individual indicators at time t). Similarly, we say that a time comparison is ‘absolute’ when the composite indicator values, at time t, depend on one or more exogenous parameters (e.g., minimum and maximum of the individual indicators fixed by the researcher). Ranking and standardization allow only for relative comparisons since they are based exclusively on values of the individual indicators at time t. Other methods, such as re-scaling or indicization, require that the minimum and maximum (e.g., the ‘goalposts’ of the HDI) or the base of index numbers are independent from the time t, in order to perform comparisons in absolute terms (Tarantola, 2008).

Type of weights

The question of the choice of a weighting system in order to weigh the individual indicators, according to their different importance in expressing the considered phenomenon, necessarily involves the introduction of an arbitrary component.

A subjective weighting can be adopted, implicitly, by assigning the same weight to all the components (equal weighting) or, explicitly, by a group of experts. Alternatively, an objective weighting can be applied, implicitly, by choosing a normalization method that assigns a weight proportional to the variability of the indicator or, explicitly, by multivariate statistical methods, such as PCA.

Figure 2.4.1 shows the flow chart for the choice of the ‘best’ method in constructing a composite indicator, with the main possible solutions (normalization, weighting and aggregation) for each ‘path’ followed (assumptions and requirements).

If the phenomenon to be measured is decomposable into more dimensions, each of them is represented by a subset of individual indicators, it may be more convenient to build a composite indicator for each dimension (or ‘pillar’) and then obtain the overall index by means of the aggregation of the partial composite indices. In this case, it is possible to follow a compensatory approach within each dimension and a non-compensatory or partially compensatory approach among the various dimensions.

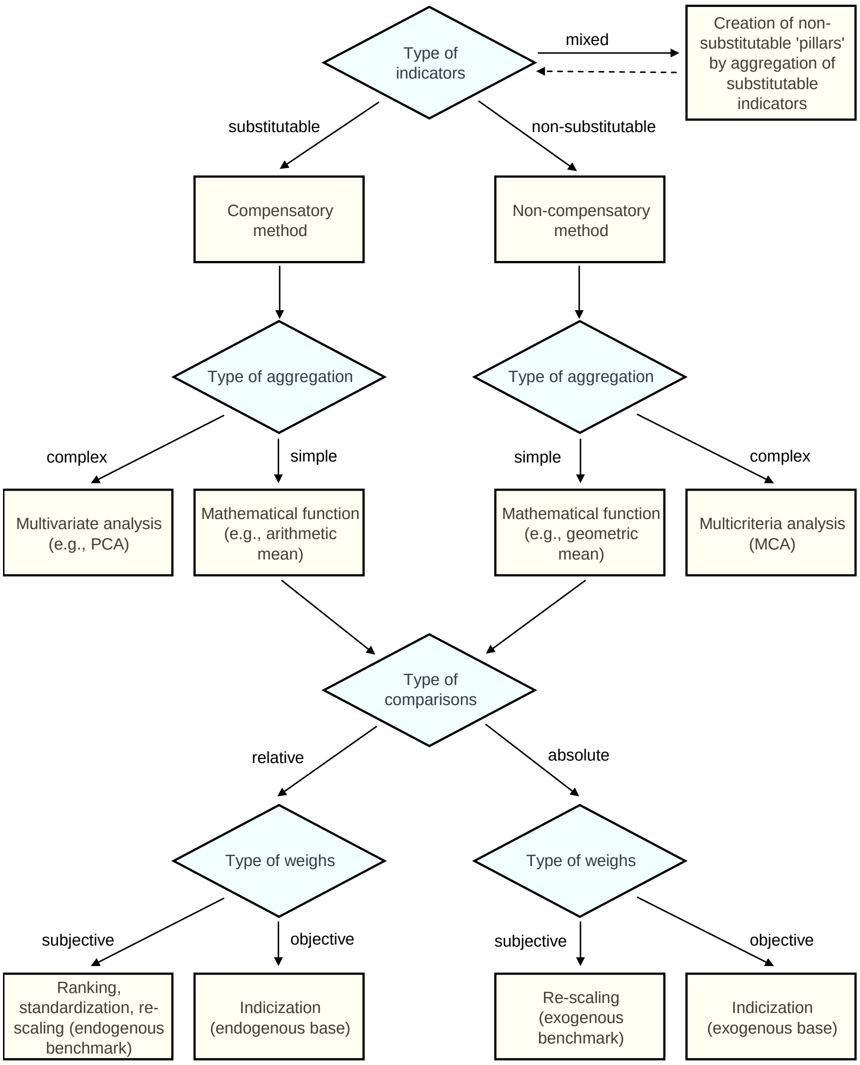
The most used aggregation methods for substitutable indicators are the additive ones, such as the arithmetic mean (simple) or PCA (complex). For non-substitutable indicators, non-linear methods are instead used, such as multiplicative functions (simple) or MCA (complex).

Focusing on methods based on the use of mathematical functions, the type of normalization depends on the nature of the space-time comparisons to do and on the weight to be assigned to the individual indicators.

For relative comparisons with subjective weighting (equal or different weights), we recommend ranking, standardization or re-scaling with endogenous goalposts. For assigning objective weights proportional to the variability of the indicators is more suitable an indicization where it is assumed as a base the mean, the maximum value or another reference value of the distribution (endogenous base).

For absolute comparisons, it is not possible use ranking or standardization. In the case of subjective weighting, it is necessary to resort to a re-scaling with minimum and maximum values independent of the distribution (exogenous benchmark), whereas in the case of objective weighting, a indicization with externally fixed base may be a good solution (exogenous base).

Figure 2.4.1. Flow chart for the choice of the 'best' method



Source: Mazziotta and Pareto, 2013

2.5. AMPI method

2.5.1 Method and formulas

The MPI (Mazziotta-Pareto Index) is a formative composite indicator for summarizing a set of indicators that are assumed to be non-substitutable, i.e., all components must be balanced (De Muro et al. 2011)[13]. It is based on a non-linear function which, starting from the arithmetic mean, introduces a penalty for the units with unbalanced values of the indicators.

The index is designed in order to satisfy the following properties: (i) normalization of the indicators by a specific criterion that deletes both the unit of measurement and the variability effect[14]; (ii) synthesis independent of an 'ideal unit', since a set of 'optimal values' is arbitrary, non-univocal and can vary with time; (iii) simplicity of computation; (iv) ease of interpretation.

The steps for computing the MPI are the following.

Given the matrix $\mathbf{X}=\{x_{ij}\}$ with *n* rows (statistical units) and *m* columns (individual indicators), we calculate the standardized matrix $\mathbf{Z}=\{z_{ij}\}$ as follow[15]:

$$z_{ij} = 100 \pm \frac{(x_{ij} - \mathrm{M}_{x_j})}{\mathrm{S}_{x_j}} 10 \qquad (1)$$

where M_{x_j} and S_{x_j} are, respectively, the mean and standard deviation of the indicator[16] j and the sign ± is the 'polarity' of the indicator *j*, i.e., the sign of the relation between the indicator *j* and the phenomenon to be measured (+ if the individual indicator represents a dimension considered positive and – if it represents a dimension considered negative).

[13] To overcome the assumption of complete substitutability among the indicators, some authors propose multiplicative aggregation methods, such as the geometric mean (OECD 2008; Zhou P. et al. 2010). However, it can be used only for sets of positive values which are interpreted according to their product and not their sum. Besides, the value of the geometric mean is 'biased' low. Thus it may be useful for measuring phenomena like development (e.g., the HDI), but not like poverty.

[14] Variability effect may be minimized by normalizing individual indicators with a method that brings them to have equal or similar variances.

[15] Note that individual indicators are converted to a common scale with a mean of 100 and standard deviation of 10. So, the transformed values will fall approximately in the range (70; 130). The *z*-scores are adjusted to avoid negative values and obtain more visually manageable scores (Booysen 2002).

[16] They refer to column values of the matrix **X**.

Denoting with M_{z_i} and S_{z_i}, respectively, the mean and standard deviation of the standardized values of the unit[17] i, the generalized form[18] of MPI is given by:

$$\mathrm{MPI}_i^{+/-} = \mathrm{M}_{z_i} \pm \mathrm{S}_{z_i} \mathrm{cv}_i \qquad (2)$$

where $\mathrm{cv}_i = \mathrm{S}_{z_i} / \mathrm{M}_{z_i}$ is the coefficient of variation for the unit i and the sign ± depends on the kind of phenomenon to be measured.

If the composite indicator is ‘increasing’ or ‘positive’, i.e., increasing values of the index correspond to positive variations of the phenomenon (e.g., socio-economic development), then MPI^- is used. On the contrary, if the composite indicator is ‘decreasing’ or ‘negative’, i.e., increasing values of the index correspond to negative variations of the phenomenon (e.g., poverty), then MPI^+ is used. In any cases, a unbalance among indicators will have a negative effect on the value of the index. For some applications, see De Muro et al. (2011); Mazziotta and Pareto (2011).

Therefore, the MPI decomposes the score of each unit in two parts: mean level (M_{z_i}) and penalty ($\mathrm{S}_{z_i}\mathrm{cv}_i$). The penalty is a function of the indicators’ variability in relation to the mean value (‘horizontal variability’) and it is used to penalize the units. The aim is to reward the units that, mean being equal, have a greater balance among the indicators values.

The method provides a ‘robust’ measure and less ‘sensitive’ to inclusion or exclusion of individual indicators (Mazziotta C. et al. 2010).

2.5.2 Properties and observations

Given the matrix $\mathbf{X}=\{x_{ij}\}$ and the corresponding standardized matrix $\mathbf{Z}=\{z_{ij}\}$, we have the following results:

(i) the MPI^+ and the MPI^- of the unit i are reflexive, i.e., if $z_{ij} = z_i$ ($j = 1, \ldots, m$), that is $\mathrm{S}_{z_i} = 0$, then:

---

[17] They refer to row values of the matrix **Z**.

[18] It is a generalized form since it includes ‘two indices in one’.

$$\mathrm{MPI}_i^+ = \mathrm{MPI}_i^- = z_i \,.$$

(ii) the MPI$^+$ of the unit i is greater or equal than the MPI$^-$ of the same unit, that is:

$$\mathrm{MPI}_i^+ \geq \mathrm{MPI}_i^- \,.$$

In particular, $\mathrm{MPI}_i^+ = \mathrm{MPI}_i^-$ iff $\mathrm{S}_{z_i} = 0$.

(iii) the MPI$^+$ and the MPI$^-$ of the unit i are linked by the relation:

$$\mathrm{MPI}_i^- = 2\mathrm{M}_{z_i} - \mathrm{MPI}_i^+ \qquad \text{or} \qquad \frac{\mathrm{MPI}_i^- + \mathrm{MPI}_i^+}{2} = \mathrm{M}_{z_i} \,.$$

(iv) given two units i and h ($i \neq h$), with $\mathrm{M}_{z_i} = \mathrm{M}_{z_h}$, we have:

$$\mathrm{MPI}_i^- > \mathrm{MPI}_h^- \;\text{ iff }\; \mathrm{S}_{z_h} > \mathrm{S}_{z_i} \,;$$

$$\mathrm{MPI}_i^+ > \mathrm{MPI}_h^+ \;\text{ iff }\; \mathrm{S}_{z_i} > \mathrm{S}_{z_h} \,.$$

(v) given two units i and h ($i \neq h$), with $\mathrm{M}_{z_i} > \mathrm{M}_{z_h}$, we have:

$$\mathrm{MPI}_i^- > \mathrm{MPI}_h^- \;\text{ iff }\; \mathrm{M}_{z_i} - \mathrm{M}_{z_h} > \mathrm{S}_{z_i}\mathrm{cv}_i - \mathrm{S}_{z_h}\mathrm{cv}_h \,;$$

$$\mathrm{MPI}_i^+ > \mathrm{MPI}_h^+ \;\text{ iff }\; \mathrm{M}_{z_i} - \mathrm{M}_{z_h} > \mathrm{S}_{z_h}\mathrm{cv}_h - \mathrm{S}_{z_i}\mathrm{cv}_i \,.$$

(vi) let $\mathrm{r}(x_j, x_k)$ be the linear correlation coefficient between the indicators j and k; if $\mathrm{r}(x_j, x_k) = 1$, for each j and k ($j \neq k$), then:

$$\mathrm{MPI}_i^+ = \mathrm{MPI}_i^- = \mathrm{M}_{z_i} \,.$$

This result derives from the fact that, for the unit i, we have $z_{ij} = z_{ik}$ for $j \neq k$.

Property (vi) is very interesting because it shows the relation between the behaviour of the MPI and the structure of the correlations among the individual indicators.

We now consider the case in which $m = 2$; see Table 2.5.2.1 for an example.

Table 2.5.2.1 Relation between behaviour of the MPI and correlations among indicators

Statistical unit	Original indicators		Standardized indicators		Mean	Std. dev.	MPI^{+}	MPI^{-}
	x_1	x_2	z_1	z_2				
				$r(x_1, x_2) = 1$				
1	11	100	114.1	114.1	114.1	0.0	114.1	114.1
2	9	80	107.1	107.1	107.1	0.0	107.1	107.1
3	7	60	100.0	100.0	100.0	0.0	100.0	100.0
4	5	40	92.9	92.9	92.9	0.0	92.9	92.9
5	3	20	85.9	85.9	85.9	0.0	85.9	85.9
				$r(x_1, x_2) = -1$				
1	3	100	85.9	114.1	100.0	14.1	102.0	98.0
2	5	80	92.9	107.1	100.0	7.1	100.5	99.5
3	7	60	100.0	100.0	100.0	0.0	100.0	100.0
4	9	40	107.1	92.9	100.0	7.1	100.5	99.5
5	11	20	114.1	85.9	100.0	14.1	102.0	98.0
				$r(x_1, x_2) = 0$				
1	11	100	88.4	114.1	101.3	12.9	102.9	99.6
2	16	80	110.7	107.1	108.9	1.8	108.9	108.9
3	14	60	101.8	100.0	100.9	0.9	100.9	100.9
4	16	40	110.7	92.9	101.8	8.9	102.6	101.0
5	11	20	88.4	85.9	87.1	1.3	87.2	87.1

If there is maximum positive correlation between the indicators, then all the units have a standard deviation S_{z_i} of zero and the MPI depends exclusively on the mean M_{z_i} ($MPI_i^{+} = MPI_i^{-}$). If there is maximum negative correlation between the indicators, then all the units have a mean M_{z_i} of 100 and the MPI depends exclusively on the standard deviation S_{z_i} ($MPI_i^{+} \geq MPI_i^{-}$).

In the first case, the MPI ranks the units according to the mean level, whereas in the second one it ranks the units according to the variability level. Otherwise (e.g., when the indicators are uncorrelated), the MPI is a combination of both the 'mean effect' and the 'variability effect'. Therefore, the MPI may be a useful tool to summarize uncorrelated variables, such as the principal components, in a non-compensatory perspective.

In general, the greater the discordance among individual indicators, the higher the 'horizontal variability' (i.e., the penalty) for each unit, with consequent increasing of the difference between MPI and arithmetic mean.

2.5.3 A variant for space-temporal comparisons

The MPI is based on a normalization of the individual indicators, at the reference time, that allows assessing only relative changes (with respect to the mean) over time.

To appreciate absolute changes over time, we propose a different procedure of normalization of data based on a re-scaling of the individual indicators according to two 'goalposts', i.e., a minimum and a maximum value that represent the possible range of each indicator for all time periods considered (Tarantola 2008).

The steps for computing the variant of the MPI for space-temporal comparisons, namely Adjusted MPI (AMPI), are given below.

Given the matrix $\mathbf{X}=\{x_{ij}\}$, we calculate the normalized matrix $\mathbf{R}=\{r_{ij}\}$ as follow:

$$r_{ij} = \frac{(x_{ij} - \mathrm{Min}_{x_j})}{(\mathrm{Max}_{x_j} - \mathrm{Min}_{x_j})} 60 + 70 \tag{3}$$

where Min_{x_j} and Max_{x_j} are the 'goalposts' for the indicator j. If the indicator j has negative 'polarity', the complement of (3) with respect to 200 is calculated. In both cases, the range of the normalized values is (70; 130).

Denoting with M_{r_i} and S_{r_i}, respectively, the mean and standard deviation of the normalized values of the unit i, the generalized form of AMPI is given by:

$$\mathrm{AMPI}_i^{+/-} = \mathrm{M}_{r_i} \pm \mathrm{S}_{r_i} \mathrm{cv}_i \tag{4}$$

where $cv_i = \frac{S_{r_i}}{M_{r_i}}$ is the coefficient of variation for the unit i.

To facilitate the interpretation of results, we suggest to choose the 'goalposts' so that 100 represents a reference value (e.g., the average in a given year).

A simple procedure for setting the 'goalposts' is the following.

Let Inf_{x_j} and Sup_{x_j} be the overall minimum and maximum of the indicator *j* across all units and all time periods considered. Denoting with Ref_{x_j} the reference value for the indicator *j*, the 'goalposts' are defined as:

$$\begin{cases} \mathrm{Min}_{x_j} = \mathrm{Ref}_{x_j} - \Delta \\ \mathrm{Max}_{x_j} = \mathrm{Ref}_{x_j} + \Delta \end{cases}$$

where $\Delta = \frac{Sup_{x_j} - Inf_{x_j}}{2}$.

The normalized values will fall approximately in the range (70; 130), where 100 represents the reference value.

The AMPI has the same properties than the MPI, except property (vi). Nevertheless, the AMPI allows to compute the score of each unit independently of the others, in contrast to the MPI where the mean and standard deviation of the individual indicators are requested.

The 'price' to pay for having scores comparable over time is that indicators with different variability are aggregated. However, normalized indicators in an identical range have much more similar variability than original ones (Mazziotta and Pareto 2013).

2.5.4 Theoretical aspects

In this Section, a study of the aggregation function of the MPI is presented and its main properties are shown. The same results are obtained for the AMPI, simply by substituting z_{ij} with r_{ij}[19].

MPI^{+} and MPI^{-} can be written in compact form as follows:

[19] Note that a change on z_{ij} for the unit *i* implies a change on z_{hj} for the unit *h* ($h \neq i$), so that the mean and standard deviation of the standardized indicator *j* are 100 and 10, respectively. On the contrary, a change on r_{ij} for the unit *i* does not affect the value of r_{hj} for the unit *h* ($h \neq i$).

$$\mathrm{MPI}_i^+ = \frac{\sum_{j=1}^{m} z_{ij}^2}{\sum_{j=1}^{m} z_{ij}} \qquad (5)$$

and

$$\mathrm{MPI}_i^- = \frac{2}{m}\sum_{j=1}^{m} z_{ij} - \frac{\sum_{j=1}^{m} z_{ij}^2}{\sum_{j=1}^{m} z_{ij}} \qquad (6)$$

where z_{ij} is given by (1).

Observe that the MPI$^+$ is the contraharmonic mean or antiharmonic mean of the standardized values. For $m = 2$, the MPI$^-$ is the harmonic mean. For $m > 2$, the MPI$^-$ is not the harmonic mean, but it has some interesting properties, such as 'reflexivity' and 'homogeneity'. Moreover, the 'distance' between MPI$^+$ and arithmetic mean is the same as the one between arithmetic mean and MPI$^-$, i.e., the arithmetic mean of the standardized values is equal to the arithmetic mean of MPI$^+$ and MPI$^-$.

2.5.4.1 The positive penalty index

In order to study the behaviour of the MPI_i^+ as a function of z_{ik} , we write (5) in the form:

$$\mathrm{MPI}_i^+(z_{ik}) = \mathrm{MPI}_i^+(z_{ik}; z_{ij}, j \neq k) = \frac{z_{ik}^2 + \sum_{j\neq k} z_{ij}^2}{z_{ik} + \sum_{j\neq k} z_{ij}} \qquad (7)$$

The first derivative is the following:

$$\frac{\partial \mathrm{MPI}_i^+}{\partial z_{ik}} = \frac{z_{ik}^2 + 2z_{ik}\sum_{j\neq k} z_{ij} - \sum_{j\neq k} z_{ij}^2}{(z_{ik} + \sum_{j\neq k} z_{ij})^2}$$

and it is equal to zero for $z_{ik} = -\sum_{j\neq k} z_{ij} \pm \sqrt{(\sum_{j\neq k} z_{ij})^2 + \sum_{j\neq k} z_{ij}^2}$.

Besides, we have:

$$\frac{\partial^2 \mathrm{MPI}_i^+}{\partial z_{ik}^2} = 2\frac{(\sum_{j\neq k} z_{ij})^2 + \sum_{j\neq k} z_{ij}^2}{(z_{ik} + \sum_{j\neq k} z_{ij})^3} .$$

Since $\frac{\partial^2 \mathrm{MPI}_i^+}{\partial z_{ik}^2} < 0$ for $z_{ik} < -\sum_{j\neq k} z_{ij}$ and $\frac{\partial^2 \mathrm{MPI}_i^+}{\partial z_{ik}^2} > 0$ for $z_{ik} > -\sum_{j\neq k} z_{ij}$, it follows that the curve is concave down (or concave) in $(-\infty, -\sum_{j\neq k} z_{ij})$ and it is concave up (or convex) in $(-\sum_{j\neq k} z_{ij}$, $+\infty)$. Finally, the function (7) has a vertical asymptote for $z_{ik} = -\sum_{j\neq k} z_{ij}$ and an oblique asymptote of equation: $y = z_{ik} - \sum_{j\neq k} z_{ij}$.

Therefore, for positive values of the abscissa, the MPI$^+$ is a convex function of z_{ik}, with a local minimum at the point $z_{ik} = -\sum_{j\neq k} z_{ij} + \sqrt{(\sum_{j\neq k} z_{ij})^2 + \sum_{j\neq k} z_{ij}^2}$. This point represents the threshold beyond which decreasing z_{ik} results in a penalty effect (positive) greater than the reduction of the arithmetic mean of standardized values.

Note that this result is purely theoretical and, in practice, the function may be considered monotonic increasing in the range (70; 130).

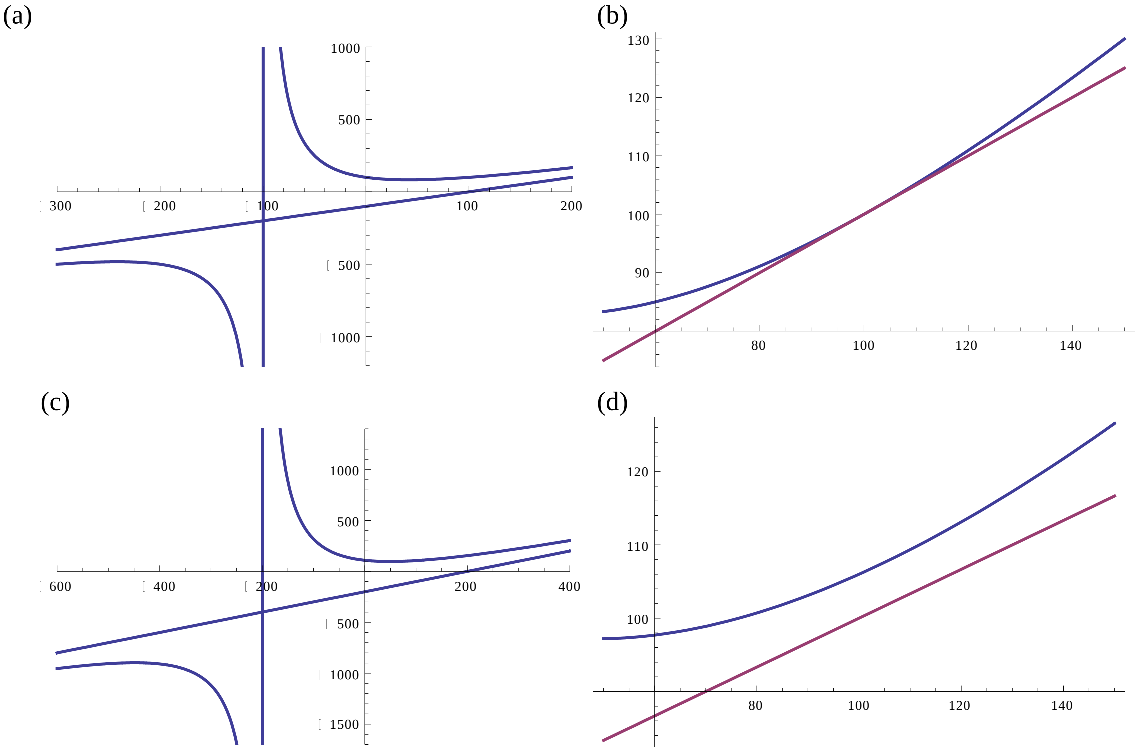
Fig. 2.5.4.1.1 shows some examples of the graph of the function $\mathrm{MPI}_i^+(z_{ik})$ for m = 2 (Figs. a, b) and for m = 3 (Figs. c, d). In Figs. 1b and 1d is also plotted the straight line corresponding to the mean of standardized values, as a function of z_{ik}, of equation:

$$M_{z_i}(z_{ik}) = M_{z_i}(z_{ik}; z_{ij}, j \neq k) = \frac{1}{m}(z_{ik} + \sum_{j \neq k} z_{ij}).$$

For m = 2, consider the function $\mathrm{MPI}_i^+(z_{ik};100)$. In this case (Fig. a), the vertical asymptote is z_{ik} = -100 and the oblique asymptote has equation $y = z_{ik} - 100$. The function attains the local minimum at the point z_{ik} = 41.42 and we have $\mathrm{MPI}_i^+(41.42) = 82.84$. Comparing the curve with the straight line $M_{z_i}(z_{ik};100)$, we see in Fig. b that, forz_{ik} = 100, the MPI$^+$ and the arithmetic mean coincide because the penalty is null; the greater the difference between z_{ik} and 100, the higher the 'horizontal variability' and $\mathrm{MPI}_i^+(z_{ik}) > M_{z_i}(z_{ik})$.

For m = 3, the used function is $\mathrm{MPI}_i^+(z_{ik};70,130)$. How we can see (Fig. 1d), for m > 2 it is always $\mathrm{MPI}_i^+(z_{ik}) > M_{z_i}(z_{ik})$, except the case in which $z_{ik} = z_{ij}$ for each $j \neq k$.

Fig. 2.5.4.1.1 Example of MPI+ function



2.5.4.2 The negative penalty index

Similarly to what we have done in Section 2.4.4, it is possible to express (6) as:

$$\mathrm{MPI}_i^-(z_{ik}) = \mathrm{MPI}_i^-(z_{ik}; z_{ij}, j \neq k) = \frac{2}{m}(z_{ik} + \sum_{j \neq k} z_{ij}) - \frac{z_{ik}^2 + \sum_{j \neq k} z_{ij}^2}{z_{ik} + \sum_{j \neq k} z_{ij}} . \tag{8}$$

In this case, we have:

$$\frac{\partial \mathrm{MPI}_i^-}{\partial z_{ik}} = \frac{2}{m} - \frac{z_{ik}^2 + 2z_{ik}\sum_{j \neq k} z_{ij} - \sum_{j \neq k} z_{ij}^2}{(z_{ik} + \sum_{j \neq k} z_{ij})^2}$$

that for $m > 2$ is null at the point $z_{ik} = -\sum_{j \neq k} z_{ij} \pm \sqrt{\frac{m}{m-2}((\sum_{j \neq k} z_{ij})^2 + \sum_{j \neq k} z_{ij}^2)}$. On the contrary, for $m = 2$ the first derivative does not vanish for any value of z_{ik} and then the function has no local minima or maxima.

The second derivative is:

$$\frac{\partial^2 \mathrm{MPI}_i^-}{\partial z_{ik}^2} = -2\frac{(\sum_{j \neq k} z_{ij})^2 + \sum_{j \neq k} z_{ij}^2}{(z_{ik} + \sum_{j \neq k} z_{ij})^3}$$

and being $\frac{\partial^2 \mathrm{MPI}_i^-}{\partial z_{ik}^2} > 0$ for $z_{ik} < -\sum_{j \neq k} z_{ij}$ and $\frac{\partial^2 \mathrm{MPI}_i^-}{\partial z_{ik}^2} < 0$ for $z_{ik} > -\sum_{j \neq k} z_{ij}$, the curve is convex in $(-\infty, -\sum_{j \neq k} z_{ij})$ and concave in $(-\sum_{j \neq k} z_{ij}, +\infty)$.

At last, (8) has a vertical asymptote for $z_{ik} = -\sum_{j \neq k} z_{ij}$ and an oblique asymptote of equation: $y = (\frac{2}{m} - 1)z_{ik} + (\frac{2}{m} + 1)\sum_{j \neq k} z_{ij}$. For $m = 2$, the asymptote is parallel with the axis of the abscissas and it has the form: $y = 2\sum_{j \neq k} z_{ij}$.

Hence, for positive values of the abscissa, the MPI$^-$ is a concave function of z_{ik} with a local maximum, for m > 2, at the point $z_{ik} = -\sum_{j \neq k} z_{ij} + \sqrt{\frac{m}{m-2}((\sum_{j \neq k} z_{ij})^2 + \sum_{j \neq k} z_{ij}^2)}$. This point represents the threshold beyond which increasing z_{ik} results in a penalty effect (negative) greater than the growth of the arithmetic mean of standardized values.

Also in this case, the overcoming of the threshold value concerns exceptionally large values (*outliers*) and the function may be considered monotonic increasing in the range (70; 130).

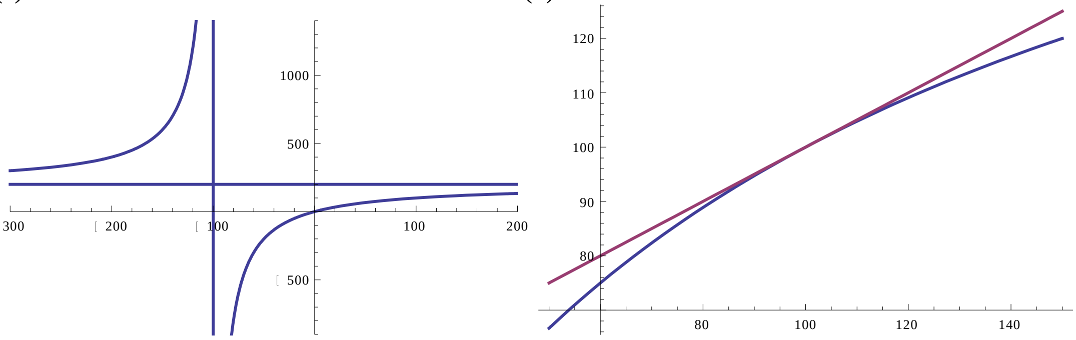
In Fig. 2.5.4.2.1, some examples of the graph of $\mathrm{MPI}_i^-(z_{ik})$ for m = 2 (Figs. a, b) and for m = 3 (Figs. c, d) are displayed.

For m = 2, consider the function $\mathrm{MPI}_i^-(z_{ik};100)$. In this case, the straight line $z_{ik} = -100$ is the vertical asymptote and y = 200 is the horizontal asymptote. Again, the curve and the straight line $\mathrm{M}_{z_i}(z_{ik};100)$ coincide for z_{ik} = 100; the greater the difference between z_{ik} and 100, the higher the 'horizontal variability' and $\mathrm{MPI}_i^-(z_{ik}) < \mathrm{M}_{z_i}(z_{ik})$.

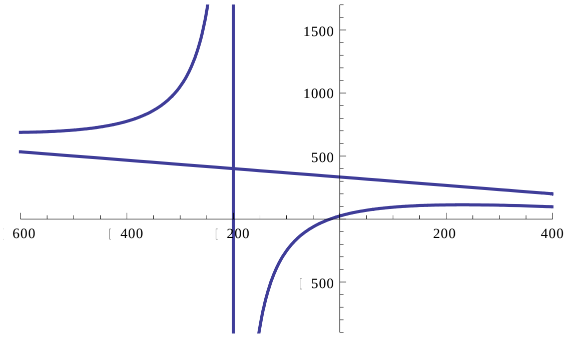
For m = 3, the used function is $\mathrm{MPI}_i^-(z_{ik};70,130)$. It has an oblique asymptote of equation $y = -0.33 z_{ik} + 333.3$ and a local maximum point at z_{ik} = 230.58 with $\mathrm{MPI}_i^-(230.58) = 112.95$. Contrarily to MPI$^+$, for m > 2 it is always $\mathrm{MPI}_i^-(z_{ik}) < \mathrm{M}_{z_i}(z_{ik})$, except the case in which $z_{ik} = z_{ij}$ for each $j \neq k$.

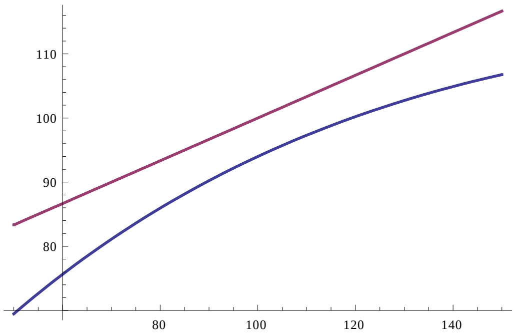
Fig. 2.5.4.2.1 Example of MPI- function

(a) (b)



(c) (d)





2.5.5 Consideration about the method

The change from unidimensional to multidimensional measurement is without any doubt an important theoretical progress and presents many advantages for policy-making. However, there is also a flip side, since multidimensional measurement presents several theoretical, methodological and empirical problems.

The international literature on composite indices offers a wide variety of aggregation methods. The most used are additive methods, but they imply a full substitutability among the components of the index, such that poor performance in some indicators can be compensated for by sufficiently high values in others.

In this paper, a generalized non-compensatory composite indicator (MPI), and its variant for space-time comparisons (AMPI), are considered and their main properties are examined. The index is based on the assumption of non-substitutability of the indicators and can be applied to different scientific contexts, because it is independent of the range and 'polarity' of the individual indicators.

The aggregation function is composed of two parts (a measure of the mean level and a measure of the amount of unbalance) and, differently from other methods, may be used for constructing both 'positive' and 'negative' composite indices. Moreover, the use of a penalty for unbalanced values of the indicators allows to distinguish different situations, in terms of variability, which are not highlighted by a composite indicator based on the simple arithmetic mean.

The main difference between MPI and AMPI is the normalization method. The MPI is based on a standardization of the individual indicators and measures only relative differences with respect to the mean. The AMPI is based on a re-scaling and measures absolute differences with respect to prefixed goalposts.

If only one data matrix is to be analysed (for a given period), the two approaches provide very similar results. However, the MPI is preferable, as it brings all the indicators to have equal variances. If a set of matrices are to be analysed (for different periods), the MPI allows assessing only relative changes in unit performance, whereas the AMPI allows quantifying absolute changes. Therefore, the MPI is the best solution for a ‘static’ analysis (e.g., a single-year analysis), whereas the AMPI is the best solution for a ‘dynamic’ analysis (e.g., a multi-year analysis).

PART II – APPLICATION TO ADMINISTRATIVE DATA

3. Administrative data sources

3.1 Introduction

Administrative records are data collected for the carrying out various non-statistical programs. For example, administrative records are maintained to regulate the flow of goods and people across borders, to respond to the legal requirements of registering particular events such as births and deaths, and to administer benefits such as pensions or obligations such as taxation (for individuals or for businesses). As such, the records are collected with a specific decision-making purpose in mind, and so the identity of the unit corresponding to a given record is crucial. In contrast, in the case of *statistical records*, on which no action concerning an individual or a business is intended or even allowed, the identity of individuals/businesses is of no interest once the database has been finalized.

The use of administrative records gives a number of advantages to a statistical agency and to analysts. Demands for statistics on all aspects of our lives, our society and our economy continue to grow. These demands often occur in a climate of tight budgetary constraints. Statistical agencies also share with many respondents a growing concern over the mounting burden of response to surveys. Respondents may also react negatively if they feel they have already provided similar information (e.g. revenue) to administrative programs and surveys. Administrative records do not incur additional cost for data collection nor do they impose a further burden on respondents. Advancements in technology have permitted statistical agencies to overcome many of the limitations caused by processing large datasets. For all these reasons, administrative records are being used increasingly for statistical purposes.

Statistical uses of administrative records include: (i) use for survey frames, directly as the frame or to supplement/update an existing frame, (ii) replacement of data collection (e.g. use of taxation data for small businesses in lieu of seeking survey data for them), (iii) use in editing and imputation, (iv) direct tabulation, (v) indirect use in estimation (e.g. as auxiliary information in calibration estimation, benchmarking or calendarisation), and (vi) survey evaluation, including data confrontation (e.g. comparison of survey estimates with estimates from a related administrative program).

On the other hand, it is important to be careful in using administrative data as there are a number of limitations to be aware of including (i) the level or the lack of quality control over the data, (ii) the possibility of having missing items or missing records (an incomplete file), (iii) the difference in concepts which might lead to bias problems, as well as coverage problems, (iv) the timeliness of the data (the collection of the data being out of the statistical agency's control, it is possible that due to external events, part or all of the data might not be received on time), and (v) the cost that comes with administrative data: for instance, computer systems need to be clean and complete the data in order to make it useful. For a discussion on the advantages and disadvantages of using administrative data, see Lavallée (2000)[20].

Starting from 2021, the population census and the master sample on households will provide many indicators each year at the municipal level. Integration between direct surveys and administrative sources is the main route of modern statistics where the timeliness of the information must be associated with a very fine spatial detail. In view of the enhancement and integration of administrative sources, the experimentation uses dataset provided by the project ARCHIMEDE (Integrated Archive of Economic and Demographic Micro Data), that collects micro-data relative to the universe of individuals and households living in Italy. Thus, it is possible to calculate indicators relating to household types, income, employment status, job security, social problems, level of education and training and other. It is also possible to estimate, for each municipality, the municipal flows for study or work, and the average mobility times.

Istat Project ARCHIMEDE aims at expanding Istat information by producing longitudinal paths (for example, social and economic) and cross-sectional collections of micro data to be made available to users and useful to social and economic research, to sectorial and territorial planning, and to public policy evaluation at national, regional and local levels. This objective has to be achieved through the exploitation of administrative database information contents integrated into Istat platform SIM (Integrated Micro data System). During the year 2013 three experiments were designed and conducted in relation to the themes "Resident population" (identification, classification and quantification of the population using the territory), "Precarious

[20] https://www150.statcan.gc.ca/n1/pub/12-539-x/2009001/administrative-administratives-eng.htm

employment" (identification, classification and qualification of workers with precarious employment contracts) and "Household socio-economic conditions" (construction of an information structure on households to analyse various aspects of their socio-economic status). The purpose of the experimentation was to assess the real project potential on the one hand, and to propose and assess the feasibility of specific statistical products and systems for the dissemination of information outputs, on the other (Garofalo, 2014).

Recently, several quality analysis of ARCHIMEDE data have been made. Obviously it is not possible to measure quality to communal detail as there are no benchmarks of comparison. However, starting with ARCHIMEDE, the socio-economic indicators are calculated at regional level and compared with those from direct surveys: the differences are very small and the reasons are known.

3.2 Pros and cons

Administrative data are increasingly useful for government agencies as the current administration continues to encourage data analytics and evidence-based program evaluations. These data are not collected for research purposes, but for recordkeeping, typically tracking participants, registrants, employers, or transactions. However, these datasets are rich with information that can be useful for evaluating programs and enforcement activities.

There are many reasons why these data are so useful in analysis. However, these datasets come with certain challenges that must be addressed.

Pros of administrative data:

- typically very large files that provide a lot of information about the programs or activities of interest. The researcher cannot control what data are collected. Metrics and outcomes of interest may not be available;
- information is updated regularly. The most current information can be used in analysis;
- data are already collected, obviating the need for expensive data collection procedures;

- data are often more accurate than self-reported information collected through surveys;

Cons of administrative data:

- the researcher cannot control what data are collected. Metrics and outcomes of interest may not be available;
- although it is updated regularly, historical records that may be useful in some analyses are not always retained;
- data are often messy, with invalid or missing values. There are usually different people who input the data, which may lead to inconsistencies;
- datasets may not be designed to merge with external data, which may be required for analysis.

3.3 ARCHIMEDE

The work has been conducted within the ARCHIMEDE (Integrated archives of economic and demographic microdata) project of the Italian National Institute of Statistics (Garofalo 2014). The collection of microdata we used is produced from the integration of information contained in administrative sources, properly treated, to study the socio-economic situation of households in Italy. The integration of several sources (Municipal Population Registers, Tax Returns Register, Central Register of Pensioners, Social Security Archives, Social Security Benefits Register, Student Registers) allows not only an informational enrichment through the creation of new variables, but also an improvement of data quality. In fact, administrative data are collected for administrative purposes and may be not of good quality when used for statistical purposes. In this project, the integration has the goal of compiling better information than is possible when using the separate source. In practical, a set of decision rules was designed in order to (a) correct for under-coverage or over-coverage of some target populations (e.g., income earners), (b) harmonize data under a single common denominator (e.g., correct classification of income) and (c) correct for measurement errors, resolving inconsistencies in data (e.g., correction of incorrect amount of income). Nonetheless, an accurate assessment of data quality is still needed and future work should concern a measure of the impact of the errors affecting administrative sources on the results. Despite these limitations, the information produced within the ARCHIMEDE project allows to expand significantly the territorial detail (municipal level) to which data are disseminated. ARCHIMEDE is composed by three data bases: Labour, Socio-economic conditions of households, Persons and Places (PP).

3.3.1 Data base "Labour"

The "Labour" database of ARCHIMEDE is created through the integration of various administrative archives and it is aimed at classifying individuals who are regularly employed on the Italian territory based on the level of employment stability and the main working and demo-social characteristics.

The field of observation of the implemented information system is represented by the regular employees present in the administrative archives in the month of October. In essence, the subjects observed are: the employees and subcontractors (para-subordinate) who pay contributions to the Italian tax authorities and the self-employed registered in the Tax Registry.

The main working characteristics of interest reconstructed for the month of October are: number of employers; number of work activities carried out; main contractual condition; main contract type; main contractual condition of the previous year; monthly work intensity of the main activity; overall monthly work intensity; presence of lay-off and / or solidarity contracts.

The process that allowed the realization of this database is based on the following three phases:

1. standardization: the sources are treated in order to report the information contained in them to the same reference period and to bring the same variable observed in different sources to the same classification methods;
2. integration: the sources, already standardized, are integrated through linkage for key variables in order to observe all the work activities carried out by the employed during the reference period;
3. election: among the possible work activities carried out, the most stable type of contract is identified.

The contractual condition in October is produced using different sources; in relation to the subordinate and quasi-subordinate employment, it is possible to observe monthly contribution signals, while on the autonomous work the signs are annual (therefore the number of self-employed workers in the month of October is overestimated).

Coverage (list of populations / sub-populations for which the reference universe is over / under-covered):

- under coverage: Income earners from self-employment from Model 770 subjects not already included in the sources used to identify the reference universe;
- under coverage: the INPS source - Management of Public Employees is partially incomplete with regards to the Ministry of defence and internal Ministry;
- over coverage: self-employed workers (in October) for which administrative sources allow only annual signals to be observed.

3.3.2 Data base "Socio-economic conditions of the households"

The statistical database "socio-economic conditions of the households - ARCHIMEDE" derives from the integration of various administrative archives and is created with the intention of being an instrument of knowledge of the connections between socio-demographic aspects of a household and aspects economic. For this purpose, the families residing in a given territory are described through their demographic structure, work, study and income of the members. The base includes both social and economic variables, referring to the families and individuals that compose them.

The reference universe is made up of all the households whose members are in the Municipality population register (LAC) at the reference date (01/01/2016 for the 2015 database). The unit of analysis is therefore the household registry, understood as a set of individuals residing in the household (are not considered individuals living in cohabitation) and defined as the group of people linked by marriage, kinship, affinity, adoption, protection or affective, cohabiting and having habitual residence in the same municipality. A single person can also constitute an household. In the sample surveys on households conducted by Istat, the unit of detection is constituted, instead, by the "de facto” household, understood as a group of people cohabiting and bound by emotional bonds, of marriage, kinship, affinity, adoption and protection.

The main variables contained in the database describe the demographic structure of the household, work, study and income: they are related to the type of household, to education (from primary school to university), to participation in the Labour market, and to household income and equivalent income. This information allows the user to segment the household universe in a flexible way, enumerating the most functional characteristics to the analysis, identifying and qualifying specific sub-populations.

The reference population of the database is made up of the registry families; however, in order to collect data on the characters of the reference population in an organized way, we started from the collection of information on the individual, which is configured as a unit of detection. The household database "socio-economic conditions of families - ARCHIMEDE" therefore represents a second level output compared to an intermediate individual database, built by the integration of administrative sources.

The input of the process is constituted by the Municipal population register (LAC), from which the individuals deemed "eligible" are selected (i.e. individuals belonging to families in which no component is without identifying codes). The household data file is derived from the individual file: the components of a household are identified by the same combination of the variables province code, common code and household code.

The variables referring to the demographic characteristics of the families (number, age and citizenship of the members, household type) are derived from LACs.

The variables related to income are the result of an integration carried out starting from a selection of variables in the archives available in Istat of the Ministry of Economy and Finance, INPS, Revenue Agency.

The income database of the Ministry of Economy and Finance is the main archive from which information on income items is obtained. The voucher database was not used for the collection of microdata referred to 2013. The integration of these archives allows, on the one hand, to recover some items of income that otherwise would be underestimated (i.e. exempt pensions, an estimate of remuneration of domestic workers, the income from self-employment of the minimum tax payers, some non-taxable public transfers, the amount of ancillary labour income) and, secondly, to reclassify some amounts (i.e. public transfers such as unemployment and Mobility are spun off from employee income and added to income from public transfers). In the use of income information, it should be noted that income items are gross of taxation and do not capture the undeclared.

The variables related to the school and university enrolment derive respectively from MIUR (Ministry of Education, University and Research - Register of students 2015/16 and MIUR - Archive of enrolments and university enrolments 2015/16.

The variable relating to the educational title of the head of the household derives from the 2011 Population Census and subsequent updates derived from MIUR - Outcomes, Register of students, University enrolments, Degrees, Prior qualifications associated with University enrolments and Degrees.

The variables relating to participation in the labour market derive from the ISTAT database Labour described in the previous section.

The elementary data file referring to families is derived by aggregation from elementary data referring to individuals. The household typology variable adopts a six-mode classification: single-member household; couples (married and unmarried) without children; couples (married and unmarried) with children; single-parent household; other; not classifiable. This classification was obtained by implementing an algorithm that uses information related to the relationship and the marital status of individual household members. Gross household income is obtained by adding together the relative income items received by all household members; the equivalent (gross) income is calculated on the basis of the members in LAC.

Work intensity is the ratio of the total months worked by household members during the year of reference, and the total of months potentially available for work activities. The Labour intensity is an annual measure and takes values between 0 and 1 (respectively: total absence of work signals during the year, and continuous participation in the Labour market during the year). The variable takes on value 0 even if the components are inactive (retired, children, housewives). For this reason, in order to allow a correct identification of the reference population for the calculation of any territorial indicators related to the work intensity, the variable number of people aged between 18 and 59 years was included in the database. of students between 18 and 24 years. The labour intensity is finally recoded into classes.

As mentioned previously, the database is the result of integration of administrative micro-data on which no calibration or correction work has been carried out. The control procedures have highlighted the inconsistencies present, the errors of misclassification, measurement, representation (over - under coverage of the reference population), briefly described below. However, these errors do not compromise the overall quality level of the statistical database.

In the data base there is a under-coverage for the resident population of 0.4 percent due to the following reasons:

- for four municipalities the LACs were not available at the start of production (in these municipalities, according to data from the ISTAT Survey on "Municipal resident population by gender, year of birth and marital status", about 9 thousand individuals);
- families in which at least one component lacked the codes necessary for integrating the sources used in the process were excluded from the data file.

Moreover, there is a under-coverage for a part of primary and secondary school students, as information on some schools in the Valle d'Aosta region is not available. For this reason, the variables related to the number of students and to the number of people aged between 15 and 29 who do not study and do not work cannot be used for these territories. Finally, there are situations of under-coverage in relation to members of public schools run by institutions other than the state, hospital schools and prisons.

With regard to income variables, it should be noted that administrative sources do not cover certain types of income:

- income from buildings and land, being derived from tax returns (included in real capital income), are underestimated as some taxpayers are exempt from this obligation;
- the income available in the database, especially income from capital, does not include income subject to substitute tax (e.g. interest on BOTs or other public debt securities) and income subject to withholding tax as tax (e.g. interest on bank or postal current accounts). Some exempt income is not included (e.g. sums received as compensation for damages).

Furthermore, income items are gross of taxation. The variables indicating the number of people aged between 15 and 29 who do not study and do not work refer only to young people not included in a school / university and not engaged in a job. Compared to the so-called "NEET", there is a lack of information sources on vocational training, AFAM (Higher Artistic, Musical and Core) training, I and II level, research doctorates and traineeships. As regards the head of the household's head, a sub-coverage was detected. In particular, information on qualifications obtained abroad after 2011, on the AFAM graduates and on the qualifications of the education and training paths managed by the Regions are not available. Furthermore, the information is missing for part of the population in Uncensored LAC.

Regarding the comparability with other sources, some considerations are listed below.

ISTAT produces official data regarding the economic conditions of families and absolute and relative poverty through some surveys, including the survey on income and living conditions of Eu-Silc families. The latter is a sample survey that provides statistics at the transversal and longitudinal levels producing estimates up to the regional level, while the database "socio-economic conditions of the families - ARCH.IMEDE" is the result of the integration of administrative data only and it is possible to do cross-sectional analysis at level of municipalities.

It should be noted that the microdata of the "socio-economic conditions of families - ARCHIMEDE" databases are not comparable with those disseminated by Eu-Silc. Firstly, the definition of income (and its classification in macro-entries) adopted by Eu-Silc represents an adaptation to the Italian context of the international context reported in the Canberra manual, while the income in the database shows misalignments to the official definition, therefore suffering from a different quantification. The main misalignments are as follows:

- the database includes only income items gross of taxation. Eu-Silc, on the other hand, records net income through direct interviews, subsequently integrated with some data from administrative sources (Revenue Agency, Inps) 11, while taxes and social contributions are calculated by integration with administrative data and estimates from a micro- simulation 12. In Eu-Silc, the percentage of households with an equivalent income of less than 60% of the median equivalent income is calculated using net income and is therefore affected by the redistributive effect of the tax; the analogous percentage calculated on the base data "socio-economic conditions of households" is instead higher, since it is calculated using gross income values;

- there is a lower coverage of income in administrative sources (especially of exempt income, with separate taxation or subject to substitute tax), in addition, the income from the "Household socio-economic conditions" database does not include income from private transfers (from other families) with the exception of periodic payments received by spouses or former spouses, some non-pension transfers, contributions for rents / mortgages / utilities, fringe benefits paid to employees as the company car.
- the equivalent income is calculated based on the members of the registry household and not of the “de facto” household, as in Eu-Silc.

3.3.3 Data base “Persons and Places”

The aim of the database “Persons and places” is to define the insistent population. Population insistent, consisting of all the individuals registered in the registry office (Municipal population register) in Italy and individuals not enrolled but who work/study in Italy. The insistent municipal population is given by the population counted in the municipality of insistence.

The main information is:

- demographic variables (gender, age, citizenship, place of birth);
- municipality of domicile residence;
- municipality of work/study;
- municipality of insistence (defined as the municipality of destination of mobility for work/study in the case of individuals with signs of work/study, and the municipality where the individuals are present in the population register but do not work and do not study;
- type of person (worker, student, other);
- city user: dynamic between municipalities (it lives in a municipality but works/studies in another); dynamic into the same municipality (it lives and works in the same municipality); static (no mobility for work/study);
- distances in kilometres between the municipalities of origin/destination of the mobility.

The database is constructed by integrating administrative archives and statistical registers relating to residence, study and work, i.e. situations linked to a non-occasional presence on the territory. Some archives are used for the construction of the universe of the Population insistent, others for the definition of subpopulations of students and workers, others for the identification of the municipalities of Origin/Destination of travel by work/study. There is no administrative information on the frequency of travel.

The reference universe is made up of all the Italian and foreign individuals who are registered in the municipal population register in Italy at December 31, 2015 - both in the family and in cohabitation, and those who are not registered but have administrative signs of work or study on Italian territory. The unit of analysis is the municipality, which is the minimum unit to which data on the insistent population and its components are released.

The main archive consists of the Registry of Resident Population (Municipal Population Register - LAC - to 1.1.2016), which integrates individuals not registered in LAC who have signs of work / study in Italy in the month of December year t. Administrative signals are calculated for all units in the database. Administrative Signal means the presence of at least one record associated with the detection unit (individual) within an administrative archive at the reference date.

The registers in which the signals are sought are from Istat archives (ASIA et al.), Ministry of Education, University and Scientific Research (MIUR), Ministry of Economy and Finance (MEF), National Institute of Social Security Social (INPS), The National Institute of Social Security and Assistance for Public Administration Employees (INPDAP), Revenue Agency, the National Insurance Institute for Accidents at Work (INAIL) (for details, see Garofalo, 2014).

Since the database is obtained through the integration of microdata coming from different administrative archives, the identification of non-sampling errors is carried out through controls on the data in order to solve the following cases:

- multiplicity of presence/rules for the choice of a single record;
- missing values/recovery rules from linked variables;
- multiplicity of status/rules for the choice of a single status;
- rules of eligibility of units.

There is a partial misalignment between the municipalities present in the elementary archives - and therefore in the integrated database referred to December 2015 - compared to the list of municipalities at December 31, 2015. For the production of the 2015 data base, the LACs of 7,998 municipalities were acquired (out of 8,046 official municipalities as of 1.1.2016). However, the 48 municipalities codes missing from the LACs (81,311 individuals) correspond almost entirely to 25 codes of municipalities (for a total of 72,094 individuals) created by merging the previous ones on 1/01/2016. The gap is therefore only apparent and follows from the different registration date of the municipalities' list in the two sources.

The resident population entered in the process is built by joining all the Municipal Registry Lists received by Istat and validated by the start date of the production process, and acquired in the SIM (Integrated System of Microdata) system. They have 60,751 million individuals as of 1 January 2016. The considered non-resident population is shaped by combining all the records with work / study signals from the archives and statistical registers considered. All non-residents who are not registered in the Labour or Study files considered are excluded: non-residents not employed, non-residents enrolled in foreign universities in Italy, non-residents not regularly present in Italy, etc. The total insistent population for 2015 is 61,472 million. The individuals considered in the output as registered in the LAC are 60,681 million. About 30 million are individuals who do not have administrative signs of work, study, university enrolment in December, or who have a signal during the year. The population residing in the Demographic Balance as of 31.12.2015 is 60,665,551. The difference is about 0.03%.

For the purpose of the insistent population it is considered worker who has a work signal in December in at least one of the administrative archives and statistical registers. These archives are related to the people who work in companies resident on the Italian territory, and not to the residents Italy working. Workers in the integrated database work in Italy and are both residents and non-residents; compared to the labour force survey, they are distinguished by they do not include residents in Italy who work abroad, and include non-residents who work in Italy (i.e. they have signs of administrative work).

The individuals considered for the purpose of the insistent population and mobility for study are those who are registered and attending in the registry of the students of Miur (primary and secondary schools). Data from students of non-parish institutions enrolled in the appropriate register, considered valid for the fulfilment of the obligation, but not for the issue of recognized qualifications, are excluded from these archives. Data from students of foreign educational institutions based in Italy. The personal data and the educational and scholastic path of the students of the state and equivalent schools of Bolzano, for which only the individual data relating to the names of the promoted with honours are transmitted, as there is a prize. The data of the students of the “paritarie” institutes of Trento. A similar situation concerning the students of the institutions of Aosta is being overcome. There are problems of under-coverage in relation to the data of the subjects who fulfil the compulsory education at reformers or neighbourhood houses, as well as to the students of military schools (who are enrolled at 16 years, after the obligation, and which are the seat of state examinations).

The individuals considered are those enrolled in a university course of both the old and the new system. Students from branch offices in Italy of foreign universities and private universities are excluded. Information on course attendance is not available. Students working for mobility purposes are considered workers.

Furthermore, it is assumed that:

- the mobility considers the place of origin the residence registry for registered members, and for non-members is the tax domicile;
- the place of destination is the seat of the local unit of the company with which you have a contract of employment, is the school building of the institution or the seat of the university course in which you are registered;
- the time reference is in December, so if the individual exercises more work/study activities during the year, it is considered carried out in December. If the individual works and studies at the same time in December, the work activity prevails among others.
- for each source it may happen that some workers have more working relationships with different companies, in this regard, to be able to assign to each individual a single geographical reference is attributed to each subject a single employment relationship following the criterion of the hierarchically superior contract;
- worker students enter in the mobility flows as workers.

Regarding the comparability of outputs with benchmark sources, it is necessary to underline that: the target universe was constructed by integrating units and administrative variables referring to the year 2015. We started from the population registered in the Municipal population Register referred to 1.1.2016, purified by any duplication of individual code to which were added individuals not registered in the registry in 2015 who had administrative signals work or study in December. The registered residence in 2014 to these individuals were given, if registered in the registry office in 2014 - in the case of under-coverage - otherwise the 2015 fiscal residence was assigned.

With regard to mobility for work studies, it is necessary to clarify some differences between administrative output and census output. The information on mobility for study/work contained in the thematic database of the Persons & Places administrative source (P&P) differs from those collected from the census survey (general census of population and housing of the year 2011). Therefore, the P & P data are not directly comparable with those of the Census: they however cover a greater number of displacements and individuals. Since the Census estimates that daily commuting has an average radius of 90 km, the census data are partially comparable with those of P & P for distances Origin / destinations > = 90 km.

In conclusion, the ARCHIMEDE system is one of the first cases in the literature of integrated database for non-exclusive study purposes. Over the next few years, together with the permanent census of the population, a real revolution in the area of socio-economic indicators will be implemented. For now this first set of indicators, with some flaws and limitations but many advantages, is a first attempt to characterize the territory at the municipal level with the same measurement system, as if it were a standardization.

Furthermore, some indicators of ARCHIMEDE and other indicators were officially published by Istat in August 2018 and can be found at the following website http://amisuradicomune.istat.it/aMisuraDiComune/

4. Well-being of Italian Municipalities

4.1 Introduction

In line with the theories presented in the first section of the thesis, the individual indicators, extracted from administrative sources, are collected in domains of well-being. The theoretical framework adopted is represented, therefore, by the conceptual and methodological one developed by Istat and CNEL (National Council of Economy and Labour) for the BES project (Istat, 2015), so that the selection of the individual indicators is driven by the national BES, however the availability of the indicators has been a determining factor because, in this case, the territorial level is the municipality and the administrative sources cannot cover all the dimensions of well-being; for example, subjective well-being can never be calculated from administrative sources (at most, particular studies on social networks could be carried out but they are certainly not treated in this work). Furthermore, the importance of the indicator in a context of municipal well-being has been taken into account. In fact, some indicators can have considerable weight in a local context and less in a national one: the attractiveness index is a clear example.

The section presents an application conducted on all the municipalities of Italy where nine domains of BES are selected (Population and Household, Health, Education, Labour, Economic well-being, Environment, Economy on the territory, Research and Innovation, Infrastructure and mobility). The process for measuring well-being at level of municipalities is based on two steps:

1. for each of the nine domains, some individual indicators are calculated starting from administrative sources. So that the starting matrix has 7,998 rows (the municipalities) and a number of columns (the individual indicators) depending on the domain. Then composite indicators are computed in order to have a unidimensional measure. At the end of this step, nine composite indicators are computed;

2. starting from the new matrix composed by all the Italian municipalities (7,998), on the rows, and nine composite indicators, on the columns, a new composite indicator is computed and it is a measure of well-being of Italian municipalities.

The adopted methodology is AMPI (see section 2) because the influence analysis demonstrates the validity compared to other methods in terms of robustness. The results present interesting reflections and the analyses carried out in the following paragraphs show that a road is possible to measure such complex phenomena at such small territorial levels. The year of reference of the data is the last available at this moment that is 2015. In the paragraph 4.2 domains, individual indicators and composite indicators are presented. In the paragraph 4.3 the analysis of the results is shown with comments about the situation of some cases.

4.2 Domains, Individual indicators and composite indicators

As mentioned in the introduction, the phenomenon "well-being" is represented by nine domains and twenty individual indicators contained in the domains themselves. The list of domains and elementary indicators used in the analysis are presented in the table below.

Table 4.2.1 – Domains and Individual Indicators

Domain and indicator	Description	Source
Population and Household		
Total migration rate	Ratio between the migration balance and the average annual amount of the resident population, per 1,000. The migration balance is the surplus or the lack of registration for immigration with respect to the cancellations due to emigration in a given year and includes foreign and internal migration.	Istat- Municipal resident population by gender, year of birth and marital status
Old age dependency ratio	Residents at 1 January 2015 in elderly age (65 years and over) for 100 persons of working age (aged 15 to 64)	Istat- Municipal resident population by gender, year of birth and marital status
Health		
Standardized mortality ratio	Ratio between the observed number of deaths in a target population and the number of deaths would be expected, based on the age- and sex-specific rates in a standard population and the age and sex distribution of the study population. If the ratio of observed/expected deaths is greater than 1.0, there is said to be "excess deaths" in the study population.	Istat – Movement and calculation of the resident population

Education			
	NEET[1]	Persons in population municipal register of 15-29 years not occupied or included in an education or training for 100 persons in population municipal register of 15-29 years.	
	Persons (25-64 years old) who have obtained secondary school	Persons in population municipal register of 25-64 years who have completed at least the second grade secondary school (title not less than Isced 3) for 100 persons in population municipal register aged 25-64.	Istat: ARCHIMEDE project
	Persons (30-34 years old) who have obtained a university degree	Persons in population municipal register who have obtained a university degree (title Isced 5, 6, 7 or 8) for 100 persons in population municipal register aged 30-34.	
Labour			
	Percentage of regular employed[2] of 20-64 years on the population of 20-64 years	Persons in population municipal register of 20-64 years with regular employment in October per 100 persons in population municipal register of 20-64 years .	Istat: ARCHIMEDE project
	Rate of job insecurity	Persons in population municipal register that are temporary workers in October per 100 persons in population municipal register employed[2].	
Economic well-being			
	Gross income per capita	Ratio between the total gross income of the households in population municipal register and the total number of members of the household in population municipal register.	
	Low work intensity of the households	Households in population municipal register with work intensity less than 20% of their potential for 100 households in population municipal register.	
	Income gaps before tax	Ratio between the total income equivalent owned by 20% of the population (in municipal register) with the highest income and the one owned by 20% of the population (in municipal register) with the lowest income.	Istat: ARCHIMEDE project
	Households in population municipal register with equivalent income with equivalent income lower than the amount of the social allowance	Households in population municipal register with equivalent income with equivalent income lower than the amount of the social allowance per 100 households in population municipal register	
Environment			
	Separate collection of municipal waste	Urban waste subject to separate collection for 100 units of urban waste collected.	Istat – ELabourations of ISPRA data
	Cars on the road with emission standards lower than the Euro 4 class	Number of cars in the euro 0-3 class circulating for 1,000 persons in municipal population register.	Istat – ELabourations of ACI data (Public Vehicle Register)
	Soil consumption	Ratio between hectares of land consumed and the total of hectares of land consumed, not consumed and not classified.	ISPRA
Economy on the territory			
	Entrepreneurship rate	Number of companies for 1,000 persons in municipal population register.	Istat – ELabourations of Statistical register of active companies (ASIA)
	Density of local units	Number of local units for 1,000 persons in municipal population register.	Istat – ELabourations of Statistical register of active companies (ASIA)

Research and Innovation			
	Real estate units reached by broadband	Real estate units reached by broadband per 100 Real estate units	Ministry of Economic Development
	Production specialization in high-tech sectors	Employees in the high technology sectors of manufacturing and services for 100 employees of local units	Istat – ELabourations of Statistical register of active companies (ASIA)
Infrastructure and mobility			
	Attractiveness index	Ratio between the flows of individuals who work or study inbound with respect to the total number of active incoming individuals, active outgoing residents and active in the municipality of residence	Istat: ARCHIMEDE project

Notes of the table A1:
[1]Currently in ARCHIMEDE there is not the information on the attendance at professional training courses, so that this indicator at municipality level is an over estimation of the phenomenon.
[2] In ARCHIMEDE the people who have a working signal for at least one month in the year are considered as employed.

It seems necessary to point out that the individual indicators taken from administrative sources cannot be perfectly matched to those calculated by direct sample surveys since there are differences from a theoretical point of view. For example, the “employment rate” is calculated as a ratio between people of 20 to 64 years old enrolled in a population register with a regular employment on the total number of people enrolled in the population register of 20-64 years old. Of course, irregular workers are excluded from this rate, and it is known that the population registered (resident) is not the same population living habitually in the generic municipality. Therefore, the “employment rate” is composed by a numerator and a denominator that are different, depending on whether the source is administrative or the classical sample survey on labour force. Likewise, the poverty indicators presented in this paper are based on Italian tax returns (administrative source) and not on the sample survey of households’ consumptions; and education indicators are based on data from the Ministry of Education and Scientific Research. Conversely, sample surveys fail to provide data to municipality detail and therefore, at this particular historical moment, researchers are trying to experiment with the best way to integrate them with administrative sources, even if this means dealing with distortion more or less significant. Recent tests on the municipalities of Basilicata and Emilia Romagna have been made and the results have confirmed the validity of the use of these administrative sources for statistical use.

As mentioned in the introduction, the process to obtain a unique measure of well-being for each municipality is composed by two steps. First of all, a composite indicator in the domain is calculated and then a composite indicator of the nine composite indices is calculated and the latter represents the well-being measure of the 7,998 Italian municipalities of the analysis. If in the domain only one individual indicator is present then only normalization is performed and, obviously, there is no composite indicator.

The nine domains and the twenty individual indicators are subjected to the following analysis:

- exploratory data analysis: Correlation matrix and scatter plot matrix;
- composite indicator: map of the Italian municipality obtained by AMPI methodology;
- influence analysis: Coefficient of variation of the shift and scatter plot between AMPI and the mean of (0-1).

The exploratory data analysis wants to discover possible statistical relations among the individual indicators in order to measure their reciprocal influence. The correlated indicators are parallel and move in the same or in the opposite direction; uncorrelated indicators are orthogonal and therefore maximize statistical information. A Principal Component Analysis (PCA) or others factor analysis are not applied because the number of individual indicators is too small in each domain.

A composite indicator for each domain is computed with AMPI methodology in order to synthesize the information in a unique measure that can facilitate the reading also through the use of maps. Note that AMPI provides values in the range 70-130 and that 100 is the reference value (Italy - 2015) obtained with the goalpost (see section 2). Values above 100 have a well-being above the reference term and, conversely, values below 100 mean a level of municipal well-being below the reference term. The composite indicator is graphically represented by a map of Italy in which the increasing shades of green indicate more well-being and the increasing shades of red lesser well-being.

Influence Analysis (IA) is, in the “field” of composite indicators, the robustness test of the model. It is included into the “big family” of Uncertainty Analysis (UA). With regard to the UA, an IA on the composite indicators is calculated in the work: the aim is to assess the robustness of the composite indicators, in terms of capacity to produce correct and stable measures, and its discriminant capacity. In particular, IA wants to empirically quantify the ‘weight’ of each individual indicator in the calculation of the composite indicator. Given K individual indicators (K=6, in this case), K replications are conducted, removing each time a different indicator and calculating the values of the composite indicator based on the remaining *K-1* indicators. For each replication, the rankings of the Italian municipalities are constructed according to the various methods and, for each municipality, the absolute differences of rank between the position in the original rank and the position in the ranking for the *K-1* indicators are calculated. Subsequently, the arithmetic mean, the standard deviation and the Coefficient of Variation (CV) of absolute rank differences are calculated: obviously, the method with the lowest variation coefficients is the most robust because it is less influenced by disturbance factors (Mazziotta C. et al, 2010; Mazziotta and Pareto, 2017). The figures presented below mainly provide two pieces of information: the first is the comparison of CVs between the composite indices in order to discover the lowest and therefore the most robust method; the second is that the implicit weight of each individual indicator in determining the composite indicator could be fairly constant or not. This can be seen from the uniformity of the bars and it is a very positive aspect since the weight of each individual indicator on the latent factor is similar. For this case study two methods of synthesis are chosen: one representing the family of non-compensatory, or partially non-compensatory functions (AMPI) and one that is purely compensatory (Mean (0-1)).

These two methods are chosen because they are characterized by the same method of standardization (Min-Max Function). They are different exclusively for the aggregation method; in fact, although both are composed of arithmetic means, the AMPI presents a penalty function that corrects it by making it lower. It is precisely this penalty that allows the AMPI to be considered a partially non-compensatory method (for details, see Chapter 2).

4.2.1 Population and Households

This domain is selected because it wants to represent the part of municipal well-being linked to the exchange of people and generations of an area. A municipality must attract people because it means that it offers jobs and services even for younger people. An area that does not renew and does not develop cannot be a place where the quality of life is dignified and, inevitably with time, it will see a rapid aging of the population.

The development of an area is the result of the people who live and invest in it so that their life can be the best possible. In this domain two individual indicators are selected:

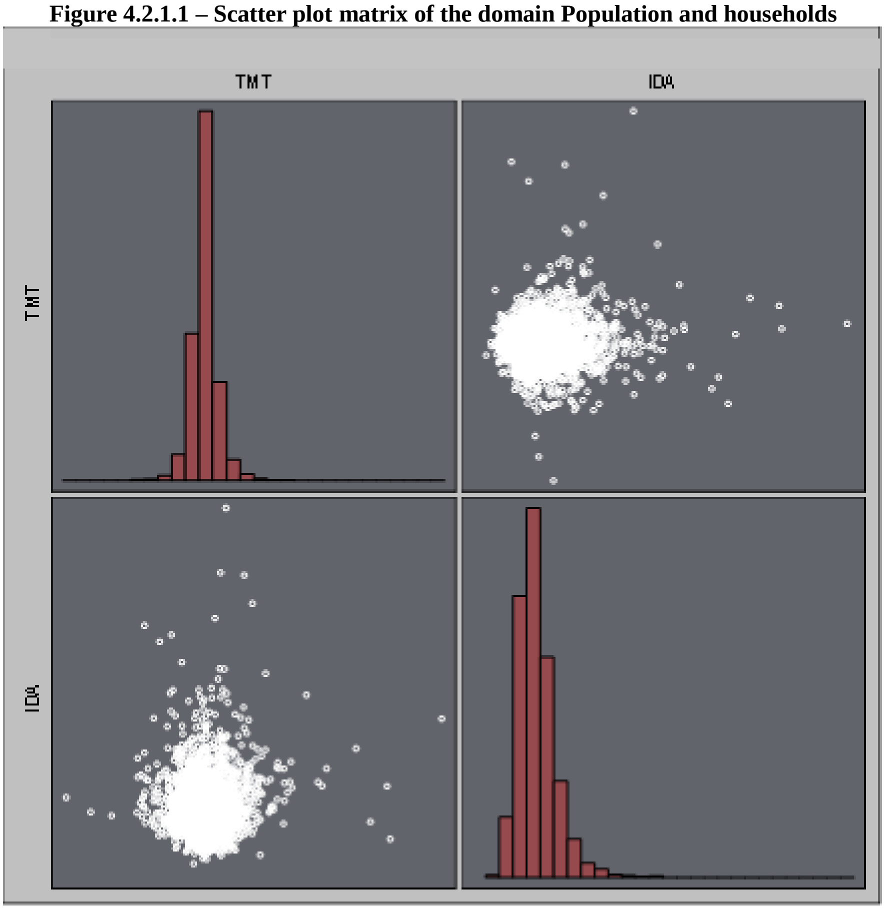
- total migration rate (TMT);
- old age dependency ratio (IDA).

Table 4.2.1.1 – Correlation Matrix

Individual Indicator	TMT	IDA
TMT	1.000	0.053
IDA	0.053	1.000

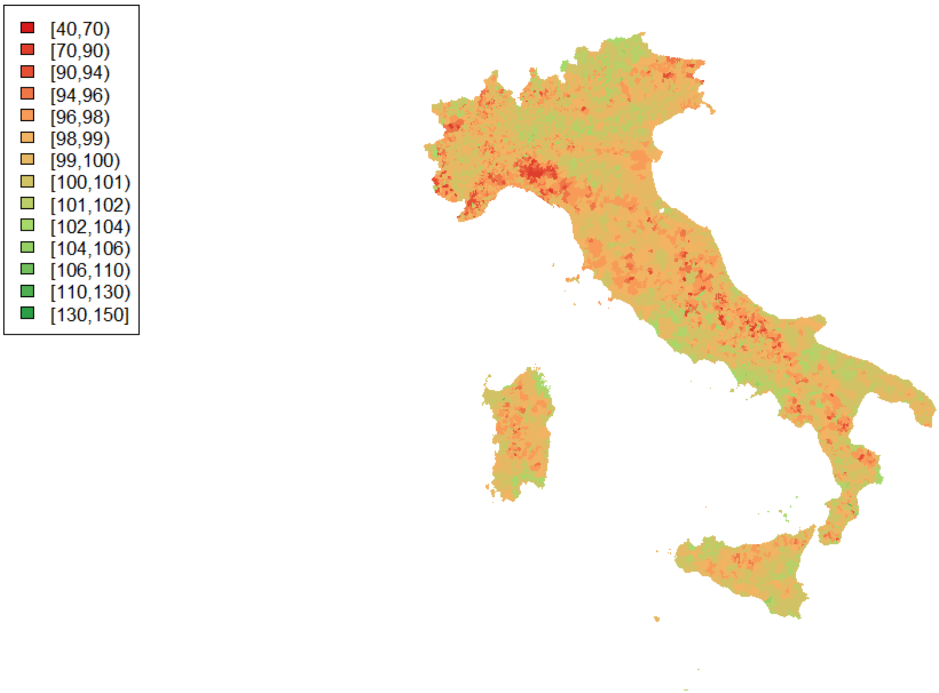
As mentioned in the previous paragraph, the exploratory data analysis is composed by correlation matrix and Scatter plot matrix. In the domain Population and Households the individual indicator Total migration rate has positive polarity (see section 2) and old age dependency ratio negative. The two individual indicators are not correlated because the Bravais-Pearson coefficient is equal to 0.053: this means that they are highly informative. From a graphical point of view, the scatter plot matrix (Figure 4.2.1.1) shows that the points form the classic figure of rose which, in fact, indicates, not correlation.

Figure 4.2.1.1 – Scatter plot matrix of the domain Population and households



In the figure 4.2.1.2, the representation of AMPI computed for the 7,998 municipalities is presented. The areas with a greater level of well-being seem to be the plains, the areas around the big cities, the provinces of Trento and Bolzano. The lowest level of well-being is concentrated along the Apennine mountain range which is, probably, affected by the phenomenon of youth abandonment.

Figure 4.2.1.2 – Map of AMPI of the domain Population and households



In the Figures 4.2.1.3 and 4.2.1.4 a representation of influence analysis is presented. As mentioned in the paragraph 4.2, the arithmetic mean, the standard deviation and the coefficient of variation (CV) of absolute rank differences are calculated: obviously, the method with the lowest variation coefficients is the most robust because it is less influenced by disturbance factors. For example, considering AMPI, if the individual indicator total migration rate is removed then, on average, a generic municipality changes, compared to the standard composite indicator, 948 positions. In this way it is possible to compute standard deviation of the shift and then the coefficient of variation.

The values of the influence analysis of Mean (0-1) are very close to the values of AMPI.

Figure 4.2.1.3 – Influence analysis by AMPI

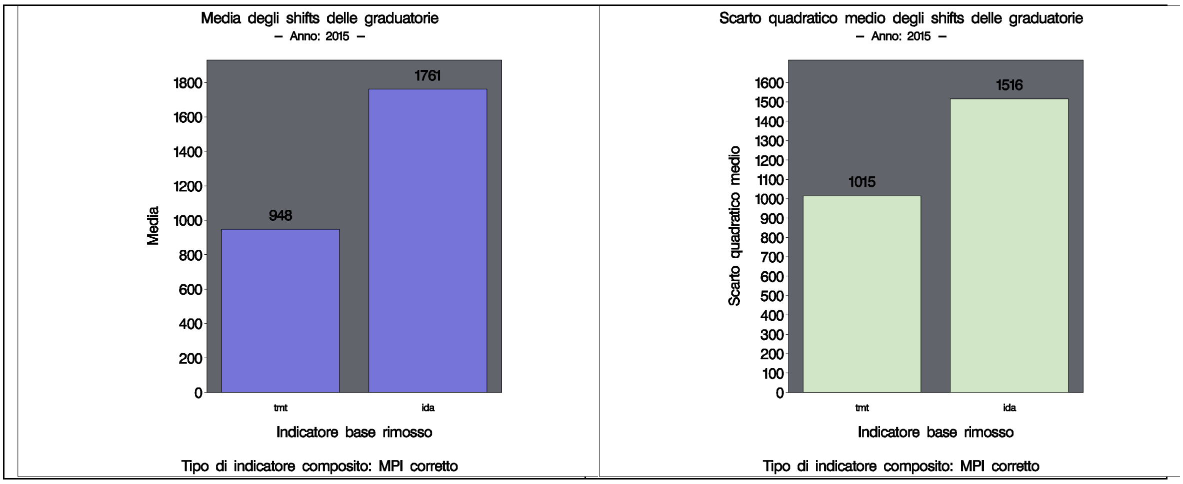


Figure 4.2.1.4 – Influence analysis by Mean (0-1)

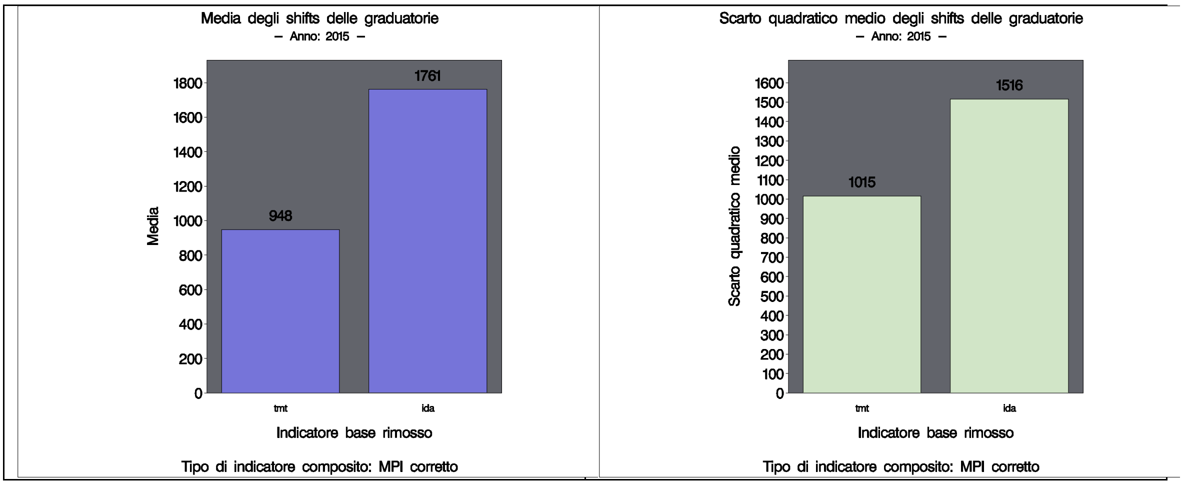
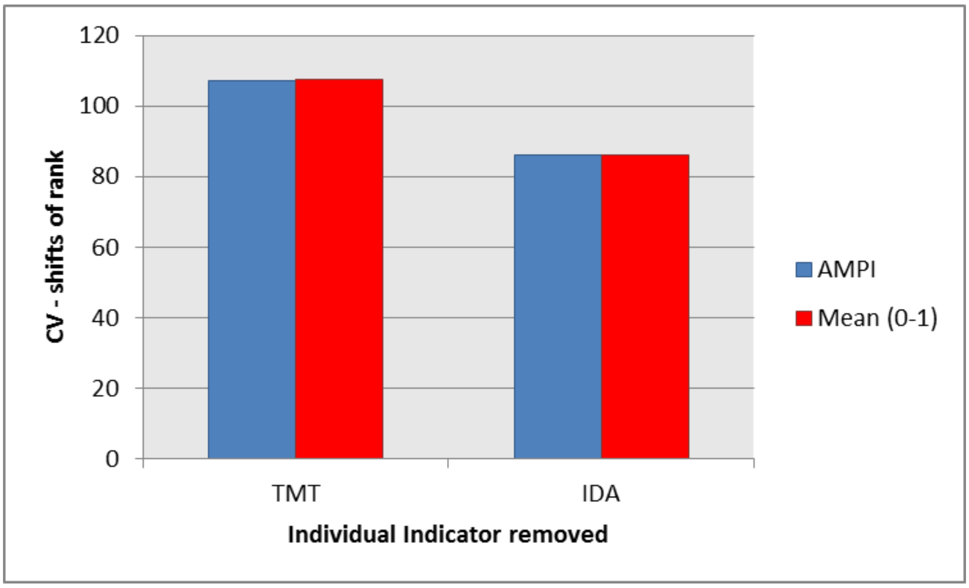
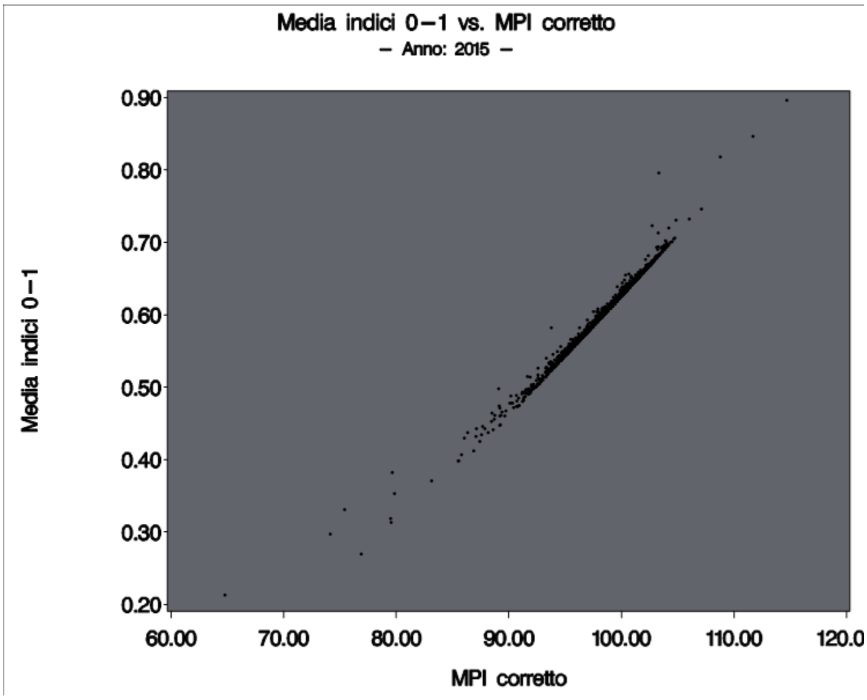


Figure 4.2.1.5 – Influence analysis by CV of shift of rank



The figure 4.2.1.5 demonstrates the equal robustness of the two methods; in fact, AMPI (partially non compensative) and Mean (0-1) (compensative) have the coefficient of variations very similar.

Figure 4.2.1.6 – Scatter plot between AMPI and Mean (0-1)

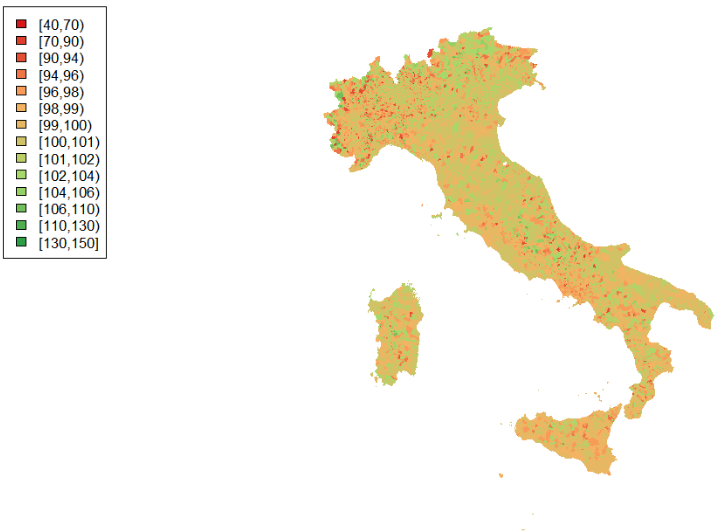


The figure 4.2.1.6 confirms that the behaviour of the two methods is very similar since the points (the municipalities) are approximately on the same line, except for some municipalities that, evidently, show a high variability between the two elementary indicators and therefore the penalty function of the AMPI acts by distancing the two methods.

4.2.2 Health

Health is a central element in life and an indispensable condition for the individual well-being and prosperity of populations, as documented globally by the work of the World Health Organization Commission on Macroeconomics and Health. health has consequences that affect all dimensions of the individual's life in its various phases, modifying the conditions, behaviours, social relationships, opportunities, perspectives of individuals and, often, of their families. As the age grows, the role played by the health condition tends to become increasingly important, until it is almost exclusive for the well-being of the elderly, when the risk of ill health is greater and its impact on the quality of life of people can also be very strict. The domain Health probably is one of the most important because the Italians had established by voting, on the Istat website in 2012 before the release of the first BES Report. It seems a joke but in reality the saying "If there is health then there is everything" was the main argument supported by respondents to the survey conducted by Istat. During the work of the technical commission of the BES there was a long discussion of the elementary indicators of the domain and one of the conclusions was that if we wanted to reduce the entire dashboard of 134 welfare indicators in Italy to only one then that indicator would come from this domain, and in particular it would have been the life expectancy. Unfortunately, in the municipal database we do not have many alternatives to spend on this important domain. However, the total standardized mortality rate could be considered a proxy for life expectancy. Since only one individual indicator is selected then only the map of standardized values is presented because it makes no sense to develop the exploratory analysis and it is impossible to calculate the composite indicator.

Figure 4.2.2.1 – Map of the domain Health.



The values of the elementary indicator seem absolutely in line with the data of life expectancy (compared to the provincial level). Given that, fortunately, Italy is the second most long-lived country in the world and that the variability, between regions and provinces, is very low, the standardized mortality rate seems to be very close to the data of life expectancy. The areas with lower values are concentrated in Campania, Piedmont, Sicily and central Sardinia. Very high values are recorded in Trentino Alto Adige, large areas of Tuscany, Emilia Romagna, Umbria, Marche and throughout Puglia.

4.2.3 Education

Education, training and skills level influence people's well-being and open opportunities that are otherwise precluded. Education not only has an intrinsic value, but also influences people's well-being in a direct way. People with higher levels of education have more opportunities to find work, even if there is an important variability by type of diploma and degree. Generally those who are more educated have a higher standard of living live more and better because they have healthier lifestyles and have more opportunities to find work in less risky environments. Furthermore, higher levels of education and training correspond to higher levels of access and enjoyment of cultural goods and services and, in general, more active lifestyles. Usually, the level of education is positively correlated with the best aspects of life.

In this domain three individual indicators are selected:

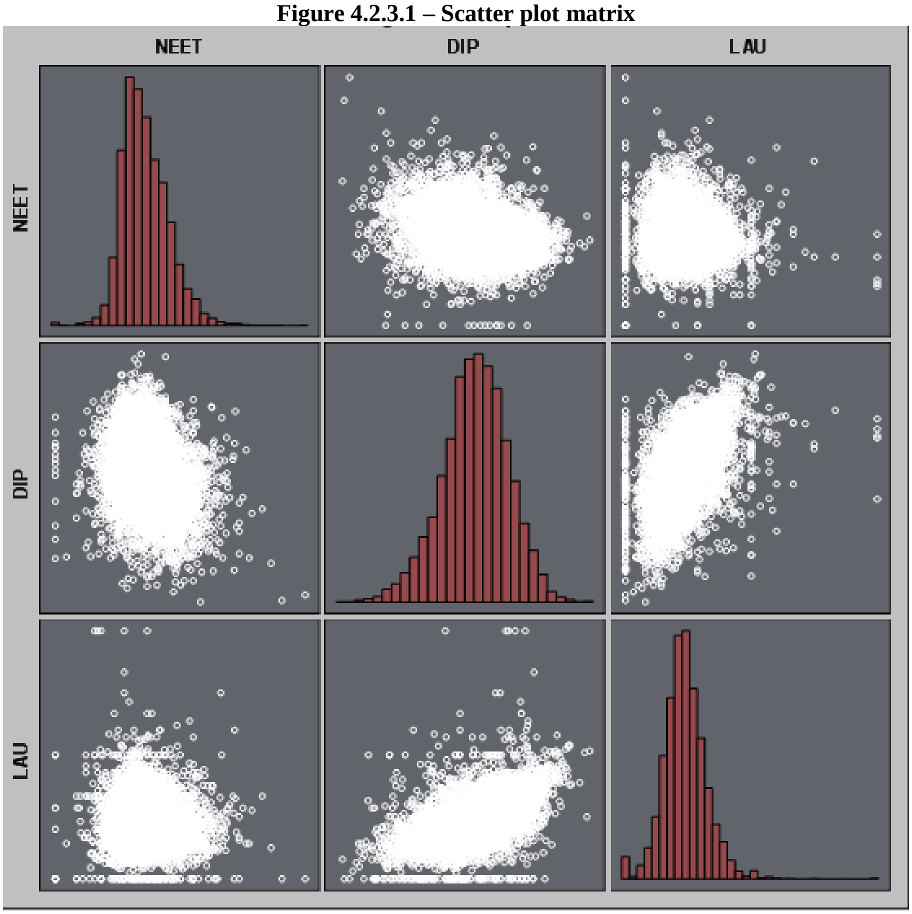
- "NEET" (young people who do not work and do not study);
- Persons (25-64 years old) who have obtained secondary school (DIP);
- Persons (30-34 years old) who have obtained a university (LAU).

Table 4.2.3.1 – Correlation matrix

Individual Indicator	NEET	DIP	LAU
NEET	1.000	-0.256	-0.092
DIP	-0.256	1.000	0.518
LAU	-0.092	0.518	1.000

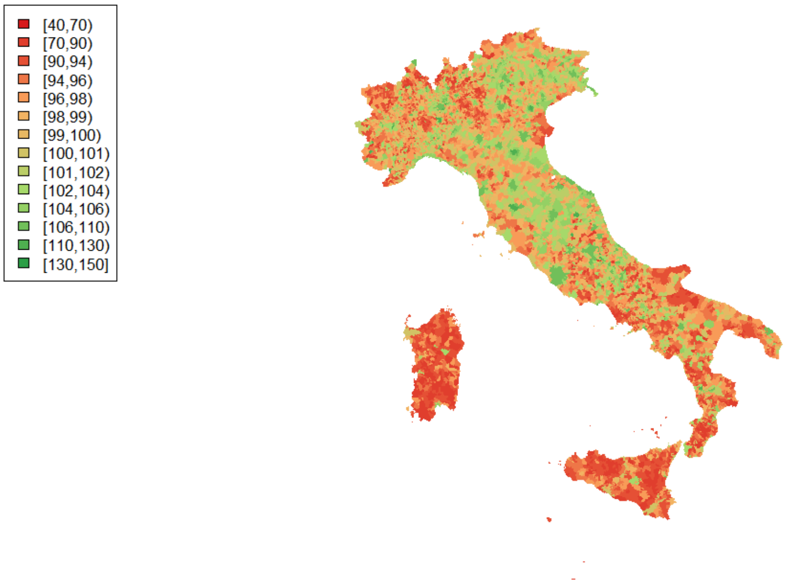
The correlation matrix of the three individual indicators and the scatter plot matrix show the absence of correlation between NEET and graduates. The slight negative correlation between NEET and people with diplomas seems interesting: where one increases, the other decreases. The strong positive correlation between people with diplomas and people with a degree is obvious because those with a degree also have a diploma. Ultimately, the three individual indicators seem to be statistically very informative.

Figure 4.2.3.1 – Scatter plot matrix



The composite indicator at the municipal level (Figure 4.2.3.2), calculated on indicators from the administrative source, validates the well-known theories on Education in Italy also compared to other European countries. Education and well-being are very interrelated, but Italy is not yet able to offer all young people the possibility of adequate education. The delay with respect to the European values and the very strong territorial gap depends very much on the social extraction, the socio-economic context and the territory. The training course is aimed at increasing the employability of people, encouraging development and creating lifestyles appropriate to the complex society in which one lives. In this perspective the training path is a continuous process that starts first from compulsory schooling, with the stimuli received in the family and extends beyond secondary school or university with continuous training and, more generally, with activities of cultural participation. A better level of education that intervenes to reduce territorial and social inequalities and guarantees greater opportunities for young people from disadvantaged backgrounds appears, therefore, a priority of our country.

Figure 4.2.3.2 – Map of AMPI of the domain Education



The influence analysis shows that the level of robustness of the two methods (partially non-compensatory - AMPI - and compensatory - Medium (0-1)) is very similar because the coefficients of variation are very close.

Figure 4.2.3.3 – Influence analysis by AMPI

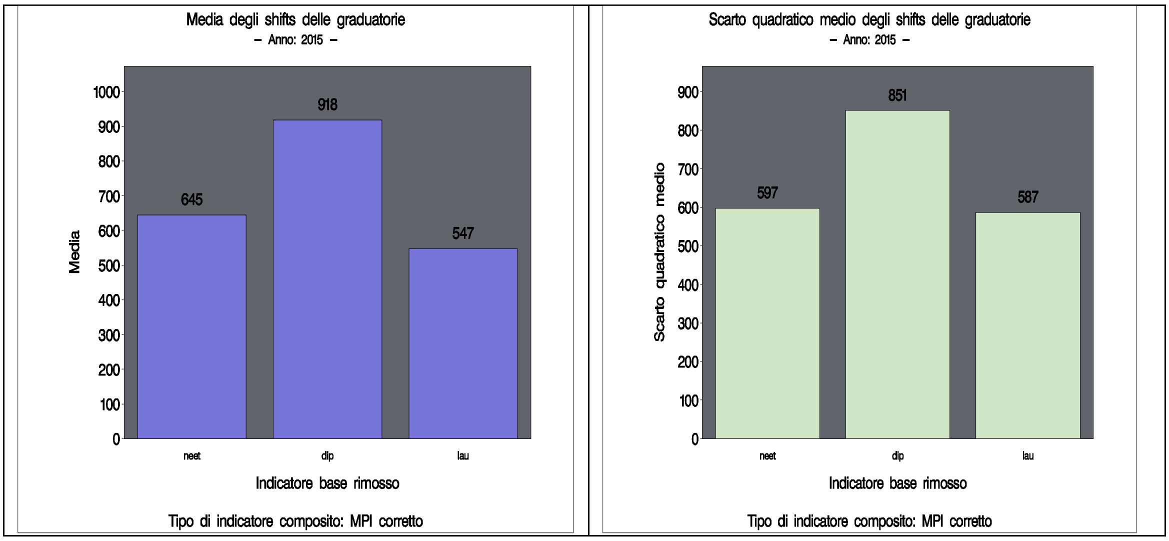


Figure 4.2.3.4 – Influence analysis by Mean (0-1)

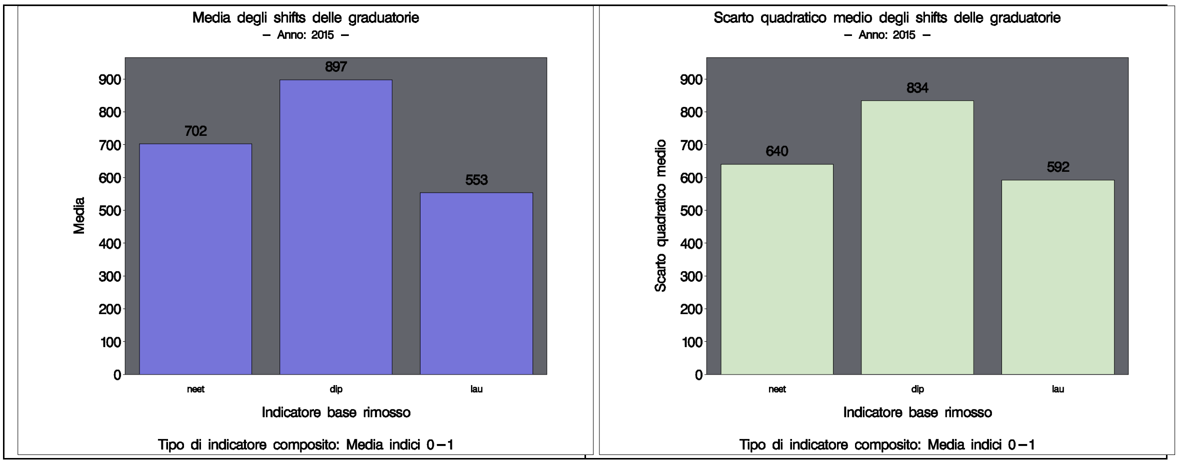
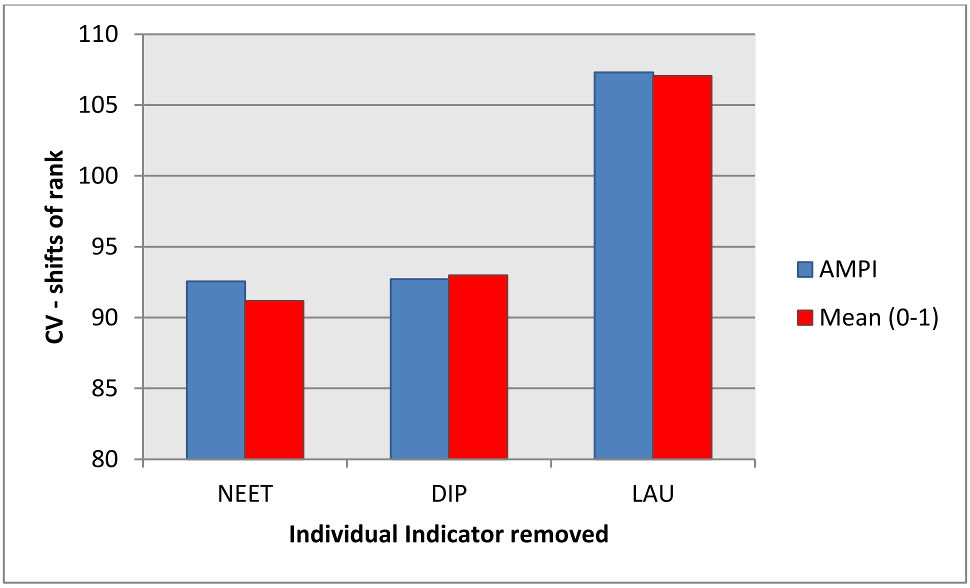
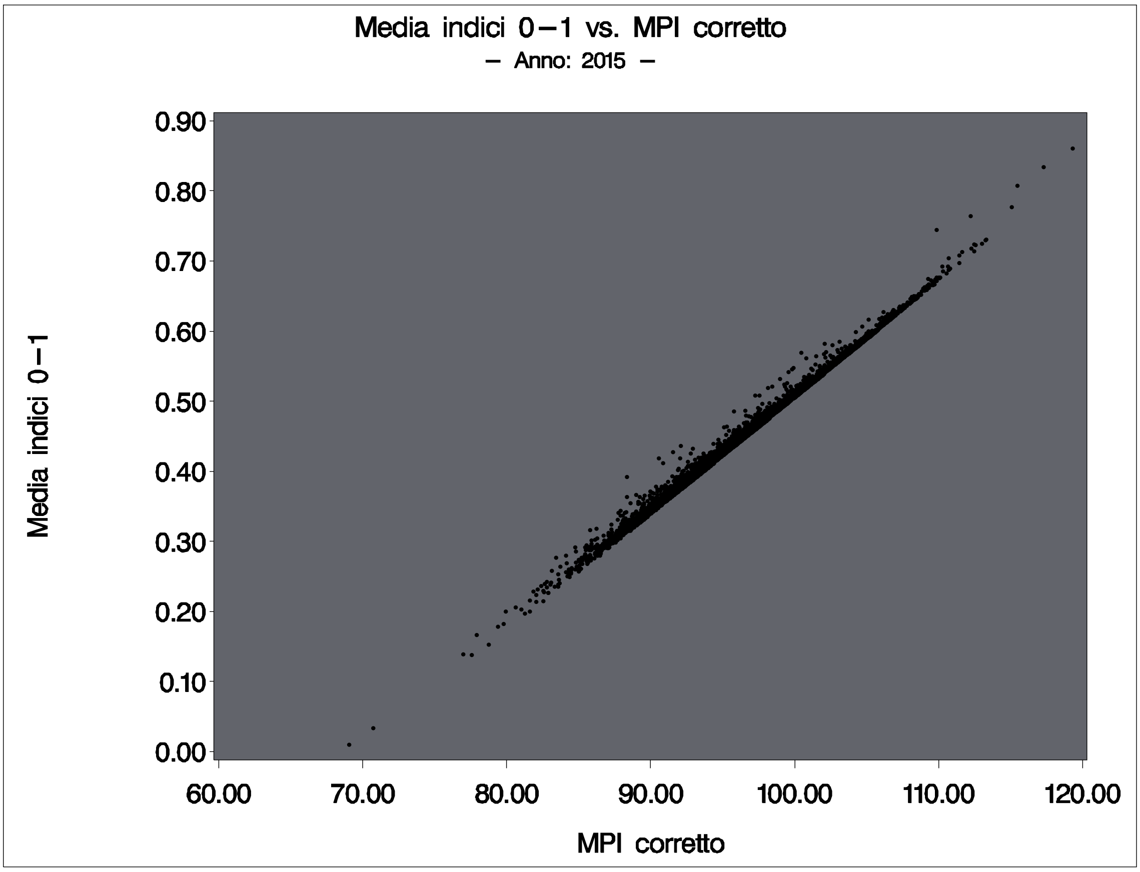


Figure 4.2.3.5 – Influence analysis by CV of shift of rank



The scatter plot between the two tested methods shows a very high correlation; the points above the darkest section are the municipalities that have a high variability of the elementary indicators and, consequently, are subject to deduction from the penalty function of the AMPI.

Figure 4.2.3.6 – Scatter plot between AMPI and Mean (0-1)



4.2.4 Labour

An appropriately remunerated activity, reasonably secure and corresponding to the skills acquired in the training path, constitutes a universal aspiration and contributes decisively to the well-being of people. If the lack of "good employment" has a negative impact on the level of well-being, an equally negative impact has work commitments that prevent reconciliation of work and family and social life.

In this domain two individual indicators are selected:

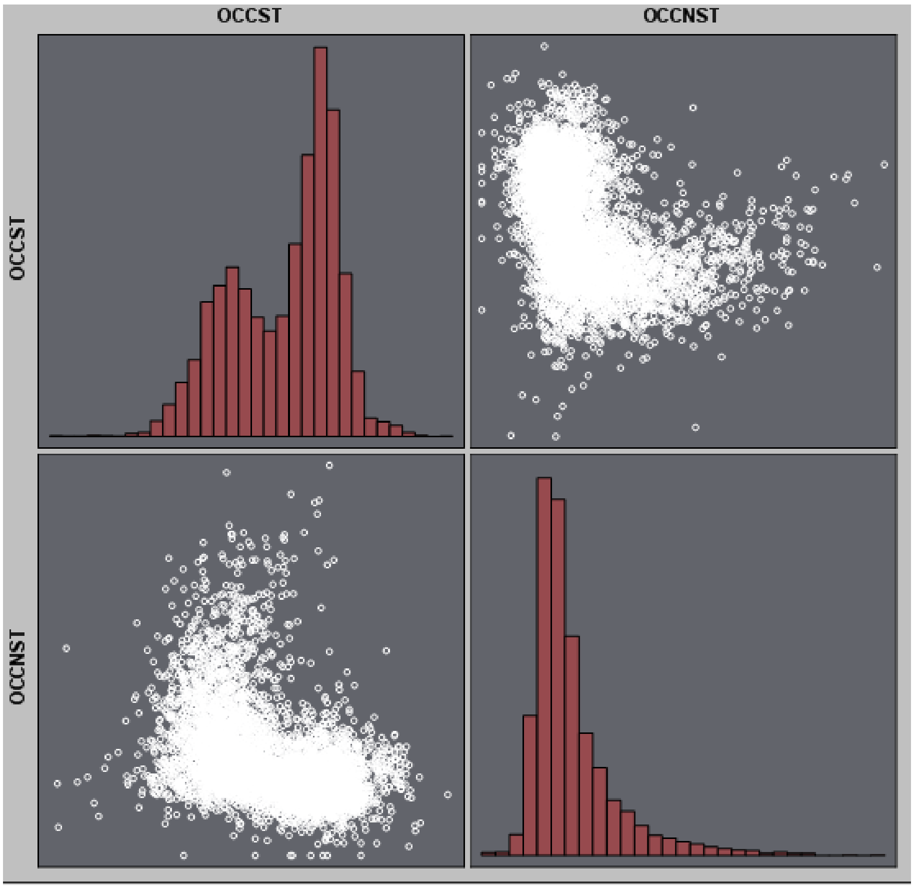
- Percentage of regular employed of 20-64 years on the population of 20-64 years (OCCST);
- Rate of job insecurity (OCCNST).

In the choice of indicators, in addition to availability, the solidity component of the work has influenced since it is one of the drivers of well-being. The first individual indicator is a proxy of the employment rate. Obviously, there are differences because the indicator from the administrative source considers only regular contracts. The second individual indicator wants to measure instability and precariousness as phenomena that delay the definition of a normal standard of quality of life.

Table 4.2.4.1 – Correlation matrix

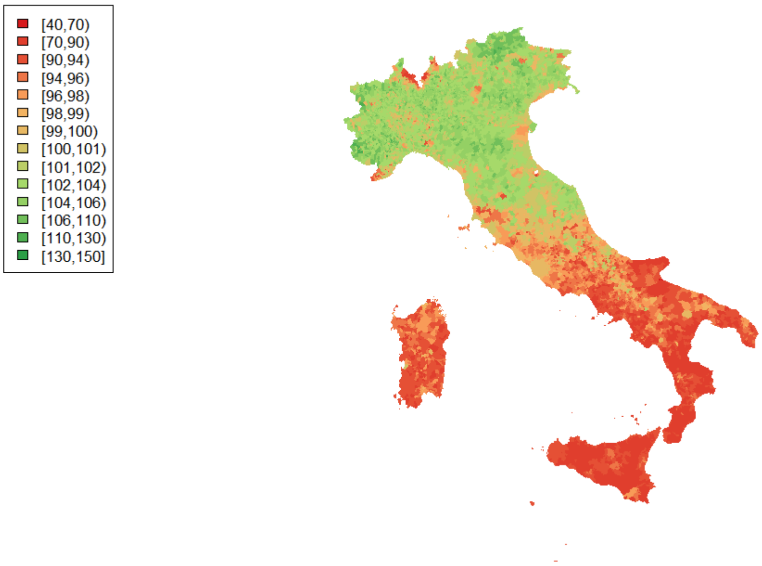
Individual Indicator	OCCST	OCCNST
OCCST	1.000	-0.480
OCCNST	-0.480	1.000

Figure 4.2.4.2 – Scatter plot matrix



The correlation analysis presents a medium negative value (-0.48) which shows that where the share of regular work is high, the share of irregular work is low and vice versa.

Figure 4.2.4.3 – Map of AMPI of the domain Labour



On the map that represents the composite indicator of the domain Labour the difference between North, Centre and South (including the Islands) is really very clear and every comment seems superfluous. It is interesting to focus on the border municipalities of Lombardy (especially in the province of Como) where it seems that employment levels are very low. In reality it is one of the major defects of administrative data that are impossible to solve: people of working age registered in the municipal population register of the border municipalities work in Switzerland therefore do not have any regular contract registered with the National Institute of Social Security (INPS). This phenomenon also occurs in the municipalities of Liguria bordering France and the Principality of Monaco. Therefore, being people who live in Italy and work abroad, they "escape" the administrative register constituting a problem that the sample surveys do not have. Precisely for this reason, it seems essential that the two data sources are integrated in order to solve each other's problems.

Figure 4.2.4.4 – Influence analysis by AMPI

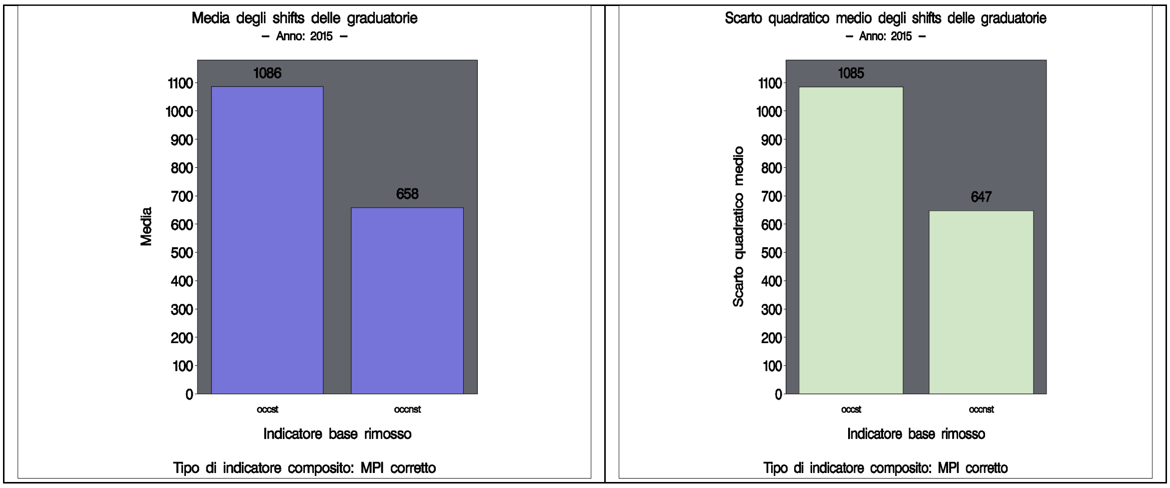


Figure 4.2.4.5 – Influence analysis by Mean (0-1)

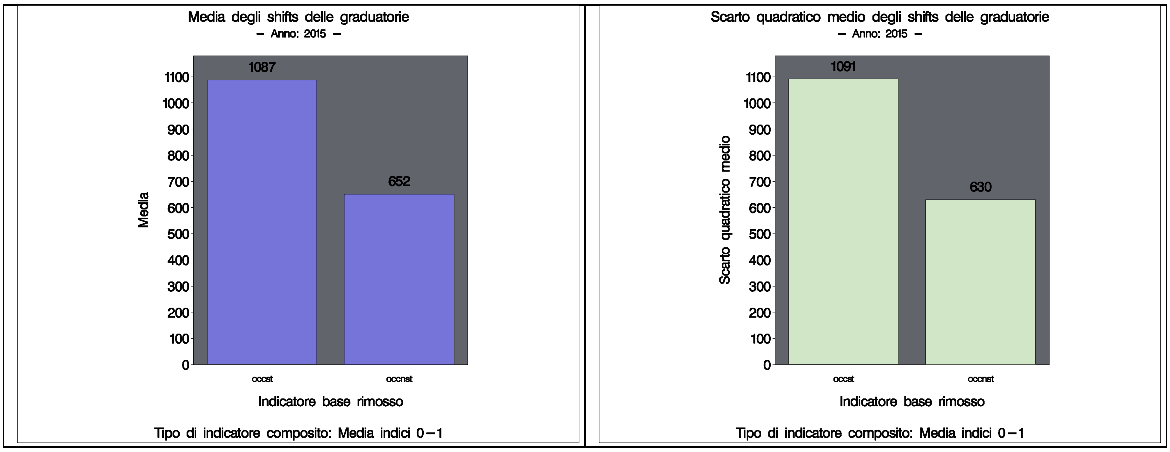
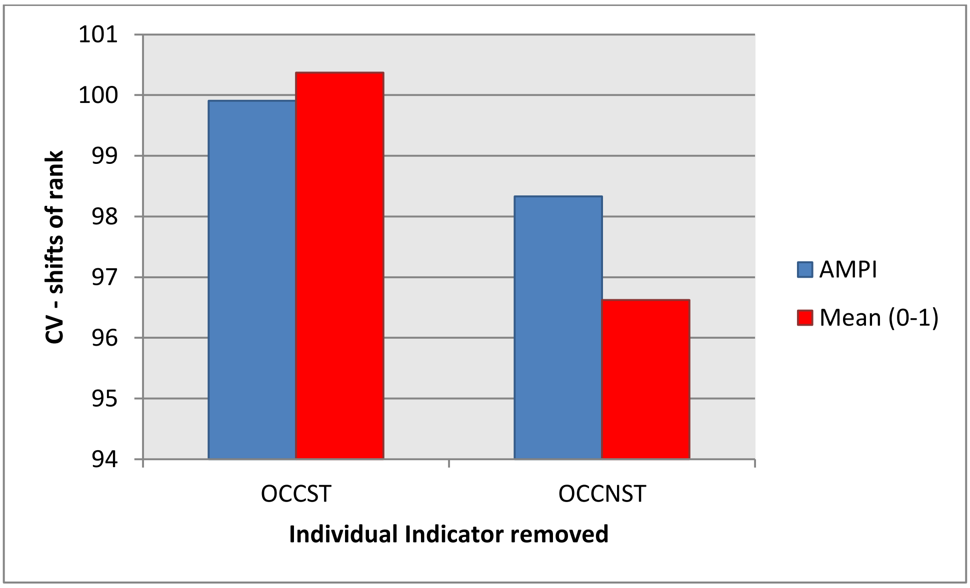
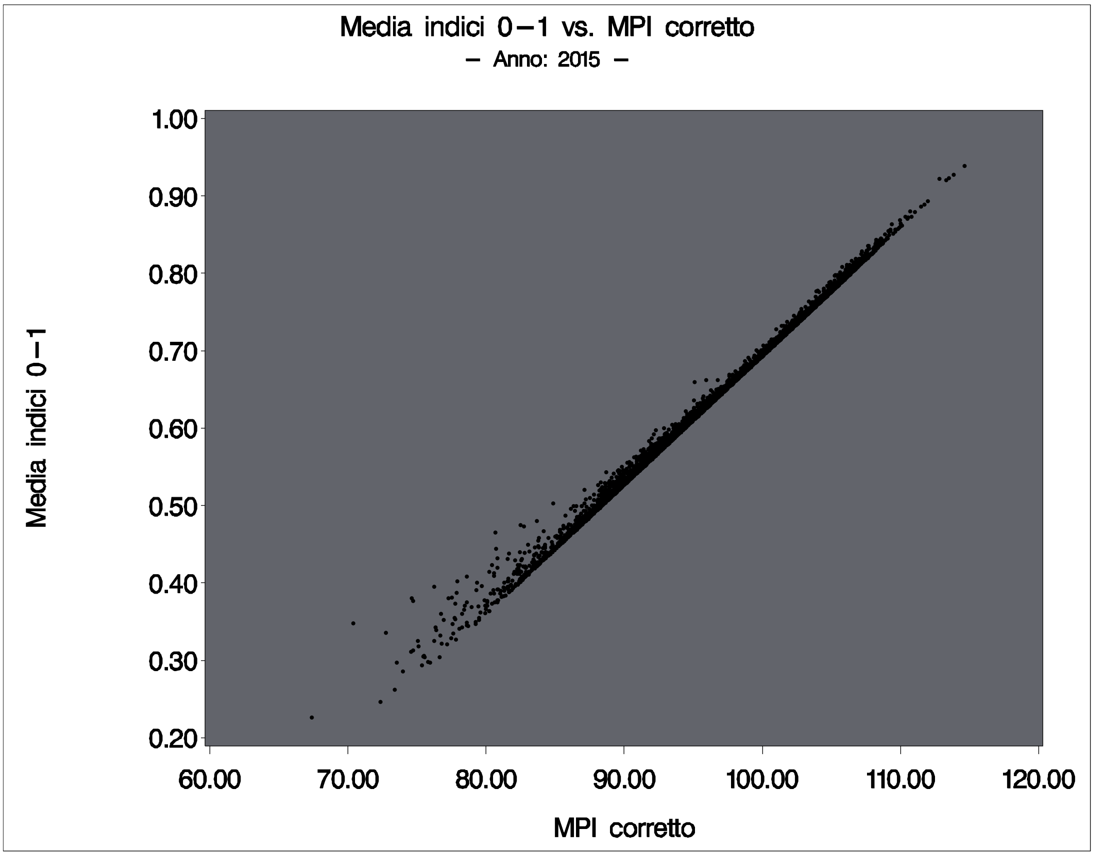


Figure 4.2.4.5 – Influence analysis by CV of shift of rank



Also in the Labour domain the tested methods (partial non-compensatory and compensatory) do not show significant differences: AMPI is more robust if the indicator Percentage of regular employed of 20-64 years on the population of 20-64 years is removed while the Media (0-1) is more robust in case the indicator Rate of job insecurity is removed.

Figure 4.2.4.6 – Scatter plot between AMPI and Mean (0-1)



The scatter plot shows that the two methods of synthesis differ at most for the municipalities that have a lower level of well-being in the domain. This aspect seems very interesting because it means that the municipalities in which the labour factor is suffering show a high variability among the elementary indicators. Since they have a low level of well-being it means that at a low intensity of the phenomenon they associate a high variability: practically the worst possible condition.

4.2.5 *Economic Well-being*

For the purposes of defining overall well-being, income capacities and economic resources are the indispensable means by which an individual can sustain a dignified standard of living. As in most other dimensions of well-being, the analysis of this aspect cannot be limited to considering the average levels of the chosen indicators, but must also account for the distribution of economic resources. In fact, the overall level of material well-being of a society also depends on how income and wealth are shared among the citizens. In our country income inequality is higher than the European average and it is even higher in the South. Moreover, the total wealth possessed by the richest 10% of the population has increased in recent years, increasing the inequality.

In this domain four individual indicators are selected:

- Gross income per capita (RED);
- Low work intensity of the households (BIL);
- Income gaps (before tax) (DRLI);
- Households in population municipal register with equivalent income lower than the amount of the social allowance (RFIAS).

Table 4.2.5.1 – Correlation matrix

Individual Indicator	RED	BIL	DRLI	RFIAS
RED	1.000	-0.785	0.013	-0.789
BIL	-0.785	1.000	0.142	0.916
DRLI	0.013	0.142	1.000	0.097
RFIAS	-0.789	0.916	0.097	1.000

The correlation analysis presents values in line with expectations. The individual indicator Gross income per capita has a strong negative correlation with the Low work intensity of the household indicator, i.e. if the latter increases then the income decreases.

This negative correlation also occurs in the case of the indicator Income per capita and the indicator Households in population municipal register with equivalent income lower than the amount of the social allowance: if income decreases then the poorest families increase. The correlation is very high (0.916) between the indicator low work intensity of the households and the indicator Households in population municipal register with equivalent income lower than the amount of the social allowance: fewer members of a family work and more families become poor.

Figure 4.2.5.1 – Scatter plot matrix

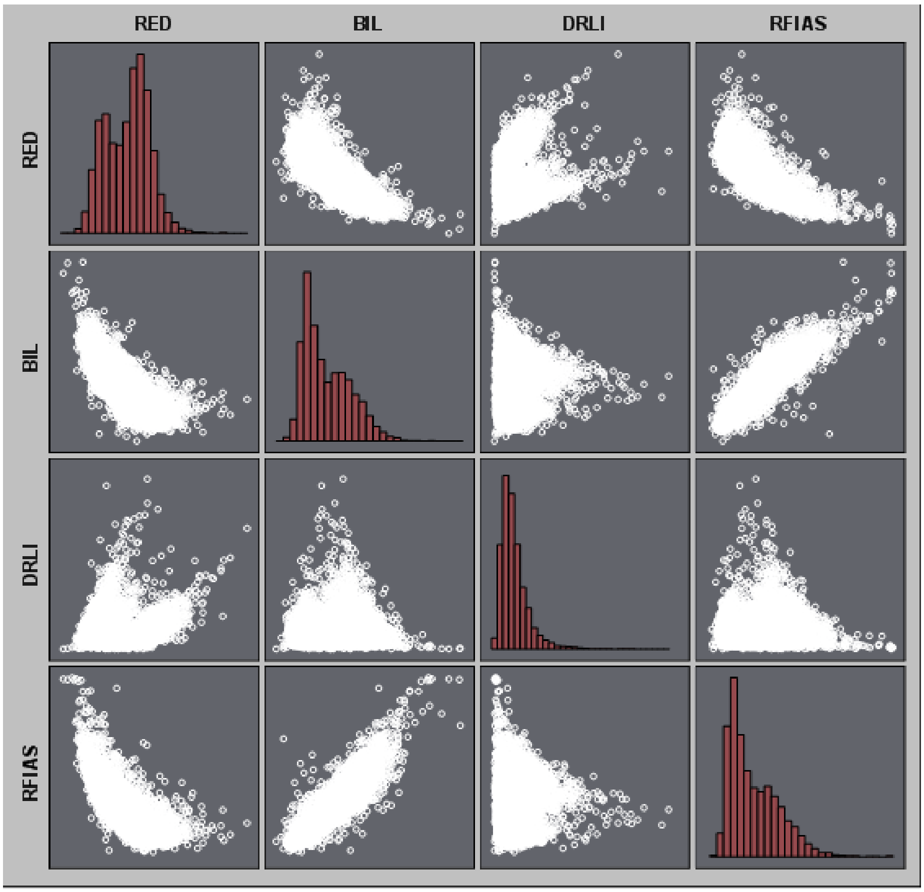
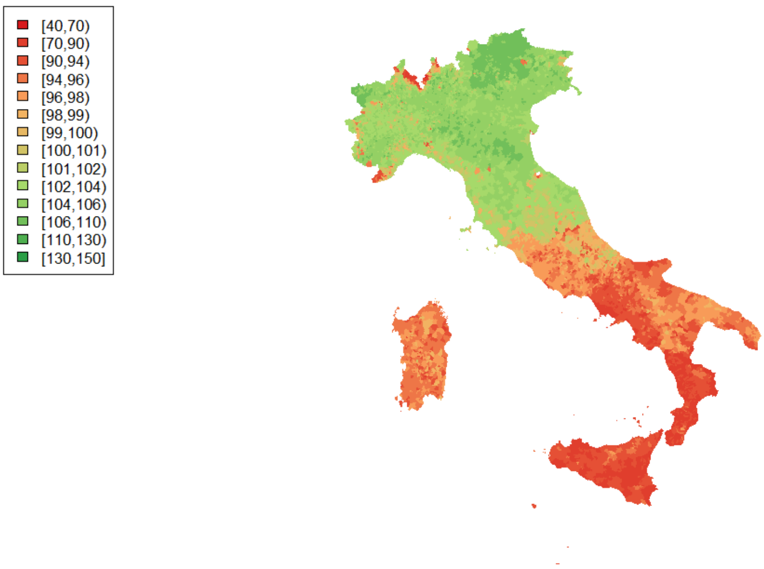


Figure 4.2.5.2 – Map of the domain economic well-being by AMPI



The cartography of the composite indicator of economic well-being seems absolutely in line with that of the work domain. There is a clear difference between the municipalities of North, Centre and South (including the Islands). In the south the situation in Campania, Calabria and Sicily seems to be worse than in other regions. The economic well-being of the municipalities of Trentino Alto Adige is much higher than all the other municipalities in which the well-being already has values above average.

Italian families are traditionally characterized by a high propensity to save, a widespread property ownership, a low recourse to indebtedness and an inequality of wealth. In the presence of a welfare system that has always concerned above all the social security component, the family, also in an enlarged sense, has functioned as a social buffer to defend the weakest members (young and old). The economic crisis of the last few years has shown the limits of this model, accentuating the inequalities between the social classes, the deep territorial differences (Figure 4.2.5.2) and further reducing the scarce social mobility. During the crisis some segments of the population and areas of the country were particularly affected by both the reduction in jobs and the reduction in purchasing power. The families have tampered with this situation, affecting the assets, saving less and, in some cases, borrowing. The map of Italy is a clear proof of the deep separation, in terms of economic well-being, of the areas of the country.

Figure 4.2.5.3 – Influence analysis by AMPI

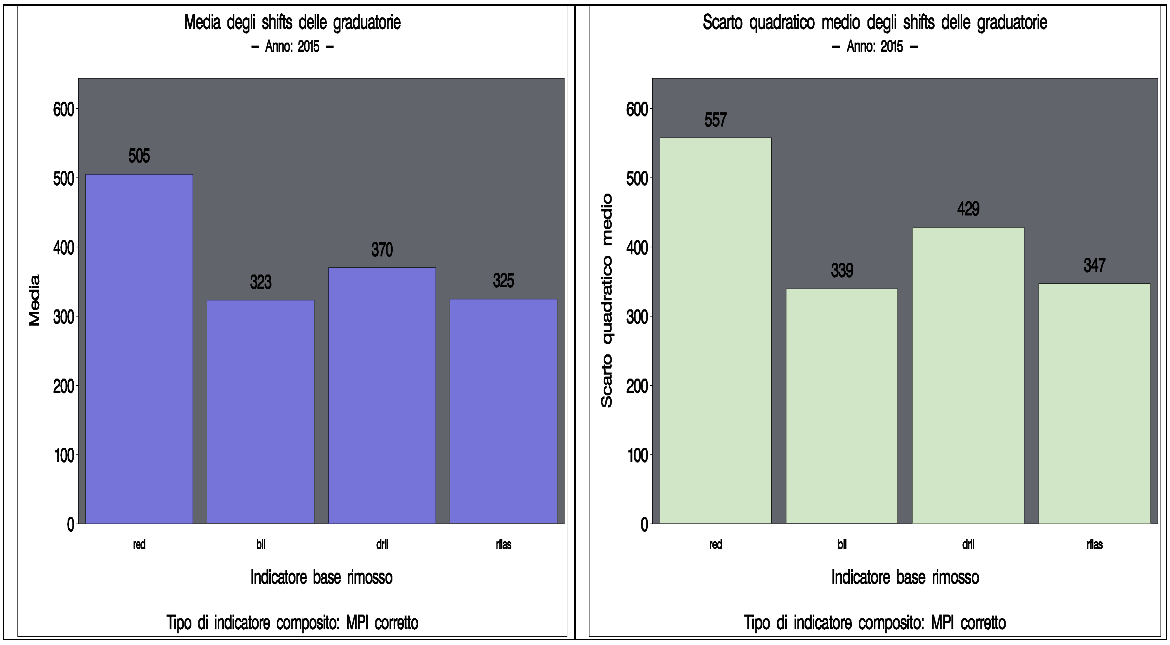


Figure 4.2.5.4 – Influence analysis by Mean (0-1)

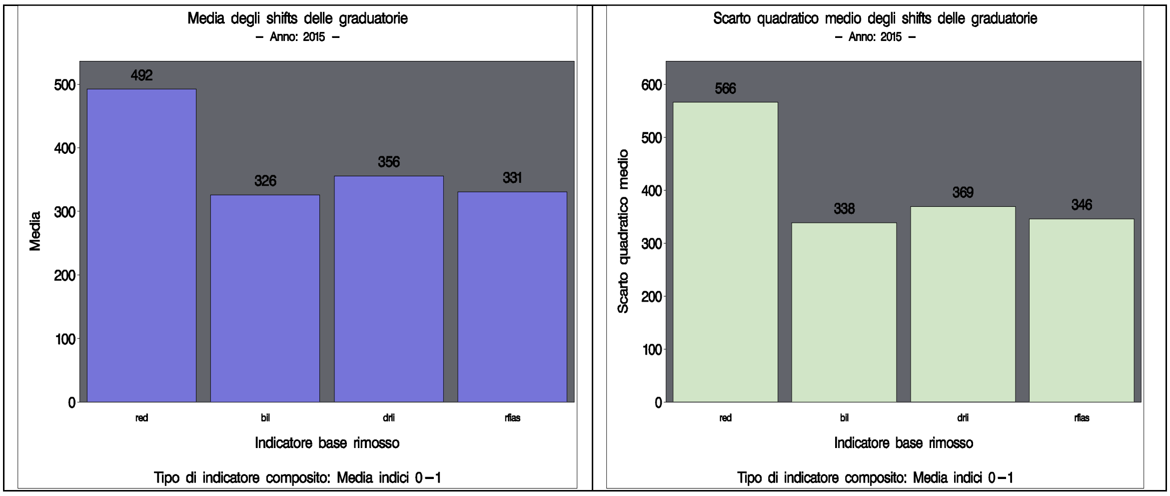
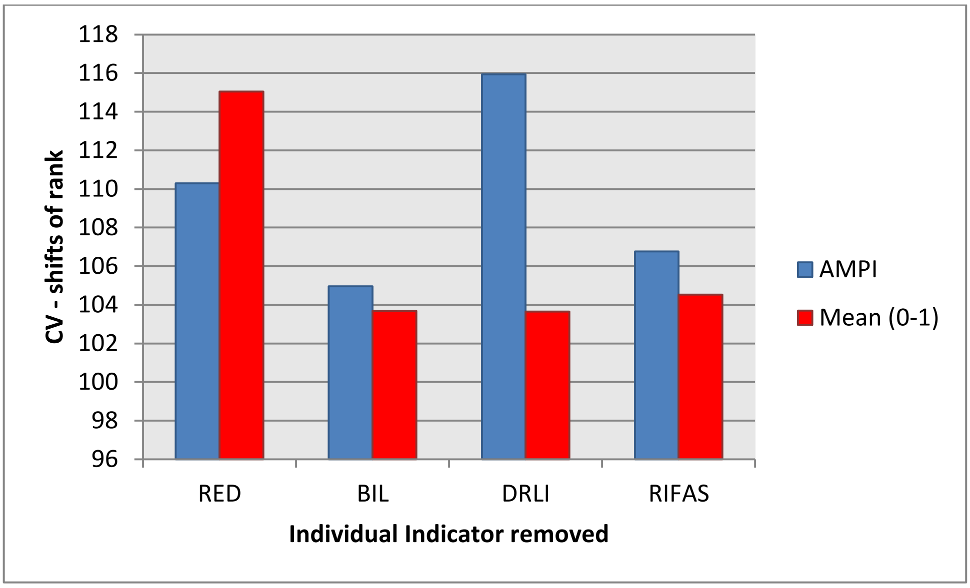
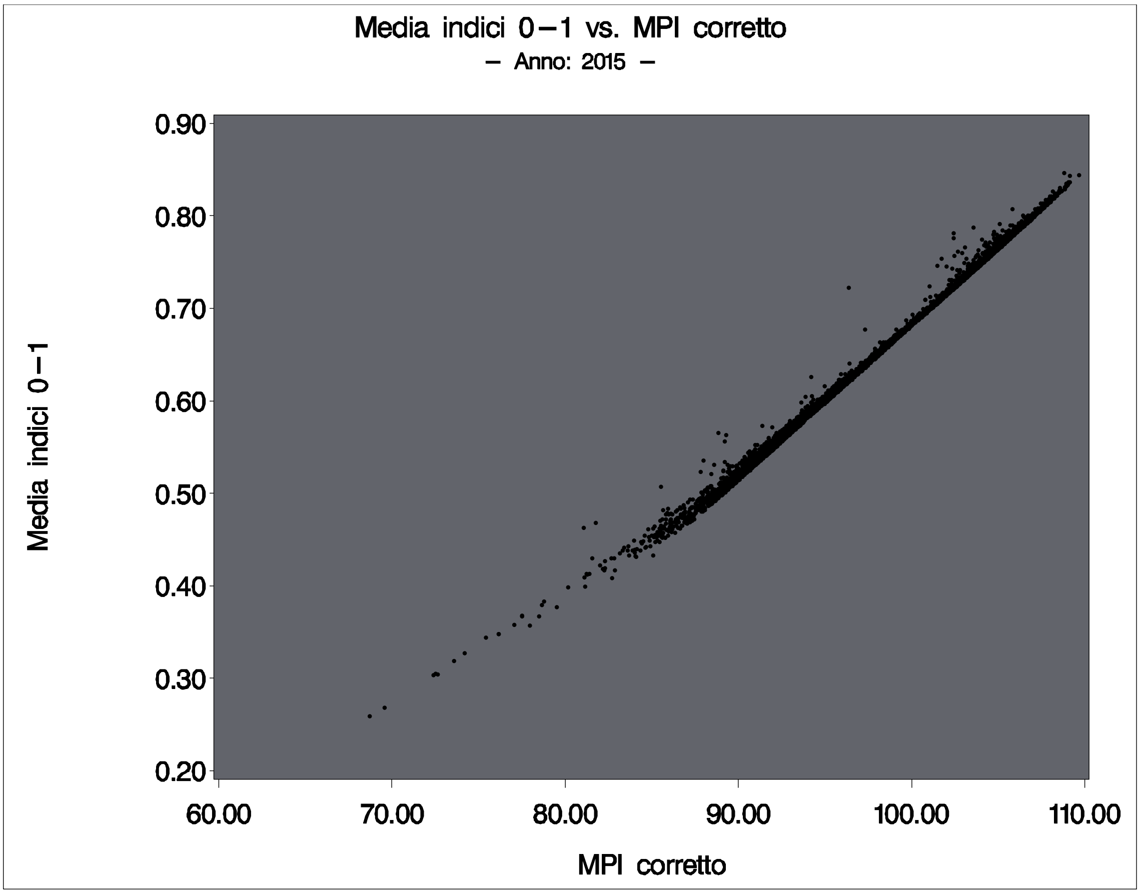


Figure 4.2.4.5 – Influence analysis by CV of shift of rank



The influence analysis shows that, apart from the gross income per capita indicator, all the other indicators have a very similar weight. The difference between the two methods seems more pronounced than the other domains. The AMPI method finds a greater weight on the indicator on the difference in income which is very significant because it means that the indicator is very variable on the territory.

Figure 4.2.4.6 – Scatter plot between AMPI and Mean (0-1)



The scatter plot between the two composite indices seems to draw a convex figure in which the right tail is formed by a few municipalities. Some outliers (above the darkest line) demonstrate the difference between the compensatory and the partially non-compensatory method in which the penalty acts by correcting (reducing) the value of the mean.

4.2.6 Environment

In order to improve people's current and future well-being, it is essential to seek the satisfaction of human needs by promoting activities that do not compromise the conditions and balances of natural ecosystems. A vital environment that is able to respond positively to changes is a fundamental requirement for guaranteeing genuine well-being for all components of citizenship. Uncontaminated water, air and food are only possible in a "healthy" environmental context, in which the dimension of naturalness can be integrated with human, productive and social activities. The

availability and use by man of natural goods and services require the attribution of a central role to the natural heritage. Forward, an enhancement of environmental resources offers everyone the opportunity to enjoy the tangible and intangible goods that nature offers, also contributing for reducing the inequalities in society.
In this domain three individual indicators are selected:

- Separate collection of municipal waste (RDRU);
- Cars on the road with emission standards lower than the Euro 4 class (ACEIQ);
- Soil consumption (CS).

Table 4.2.6.1 – Correlation matrix

Indicatore base	RDRU	ACEIEQ	CS
RDRU	1.000	-0.409	0.228
ACEIEQ	-0.409	1.000	-0.338
CS	0.228	-0.338	1.000

The correlation analysis shows an average level of negative correlation between the individual indicators "separate collection" and "polluting cars": if the separate collection of waste increases then the percentage of polluting cars in circulation is lower and therefore the quality of the air is better. This interesting negative correlation can be interpreted as an aspect of the civic sense of a community. The other correlations do not seem to provide relevant topics for reflection, except that values decidedly close to 0 signify a good information capacity of the selected individual indicators.

Figure 4.2.6.1 – Scatter plot matrix

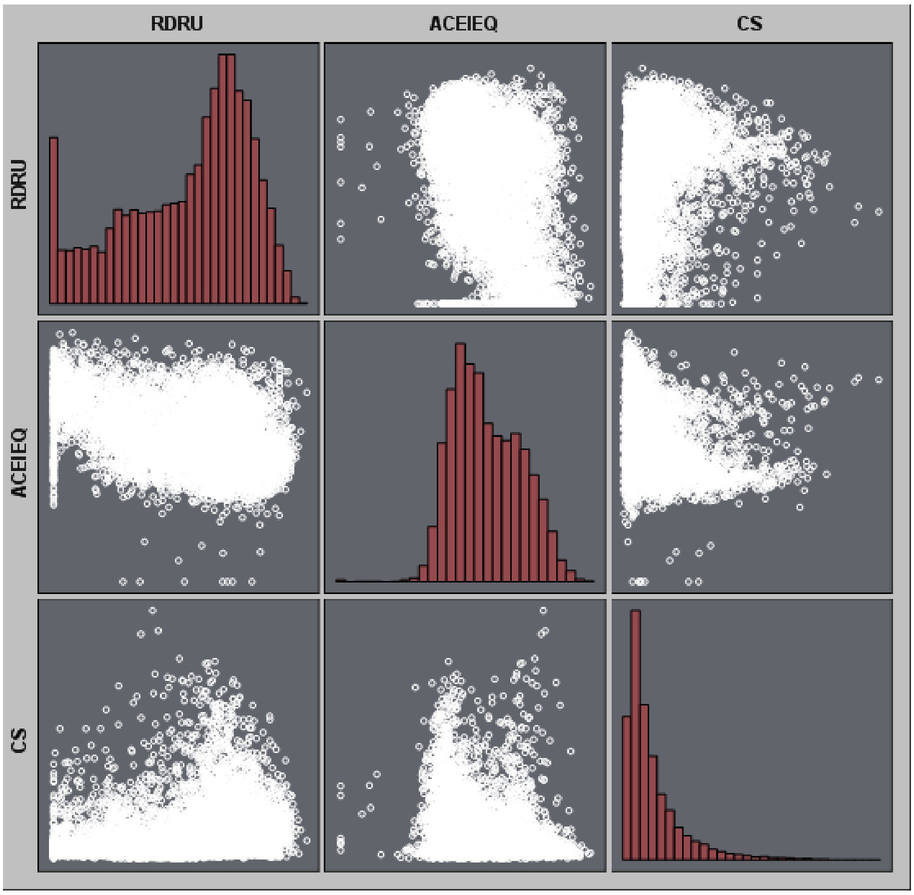
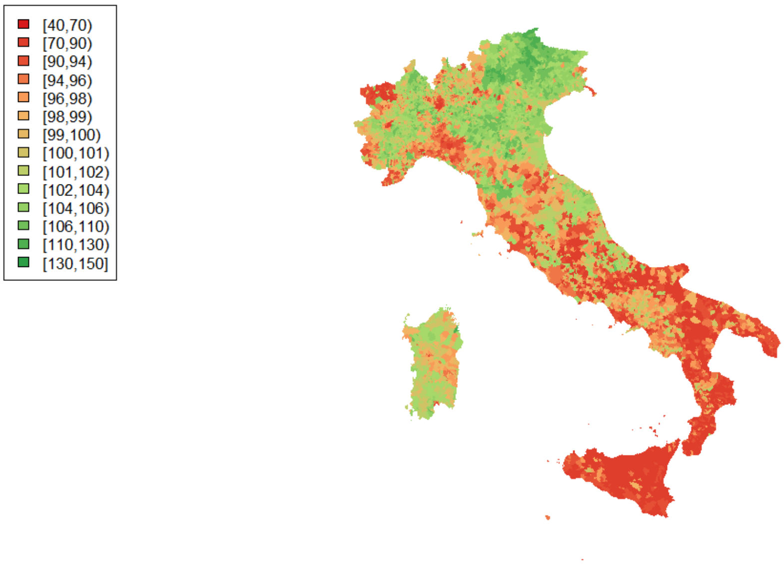


Figure 4.2.6.2 – Map of AMPI of the domain Environment



People's wellbeing is closely linked to the state of the environment in which they live, to the stability and consistency of available natural resources. Consequently, in order to guarantee and increase people's current and future well-being, it is essential to seek the satisfaction of human needs by promoting development activities that do not compromise the conditions and balances of natural eco-systems. In Italy, contrasting signals emerge with respect to the quality of the soil and the territory, moreover the hydrogeological instability still represents a serious natural risk distributed throughout the national territory. Moreover, the risk to health and to the natural environment due to the pollution present in different areas of the country has be added, in fact air quality is a fundamental aspect that directly affects the well-being and health of citizens. The map seems to highlight the problems mentioned above: the country looks like a leopard spot even if the areas are very characterized. The municipalities of the north-east and large areas of Piedmont, Tuscany, Marche, Umbria and Sardinia seem to enjoy a situation much better than the rest of the nation. The conditions of many municipalities in Basilicata, Calabria and Sicily are very worrying.

Figure 4.2.6.3 – Influence analysis by AMPI

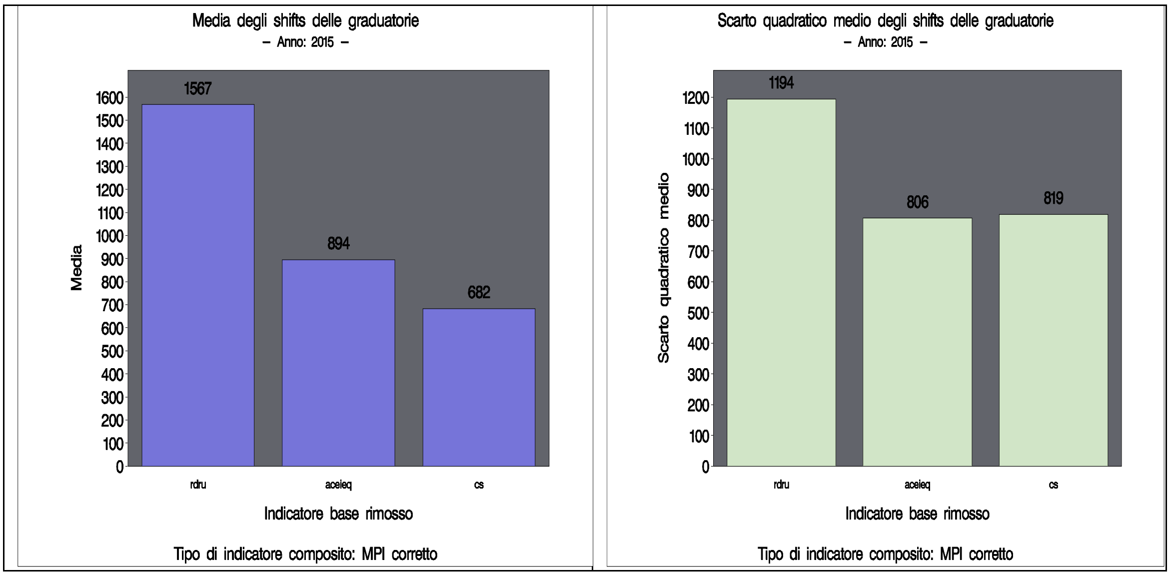


Figure 4.2.6.4 – Influence analysis by Mean (0-1)

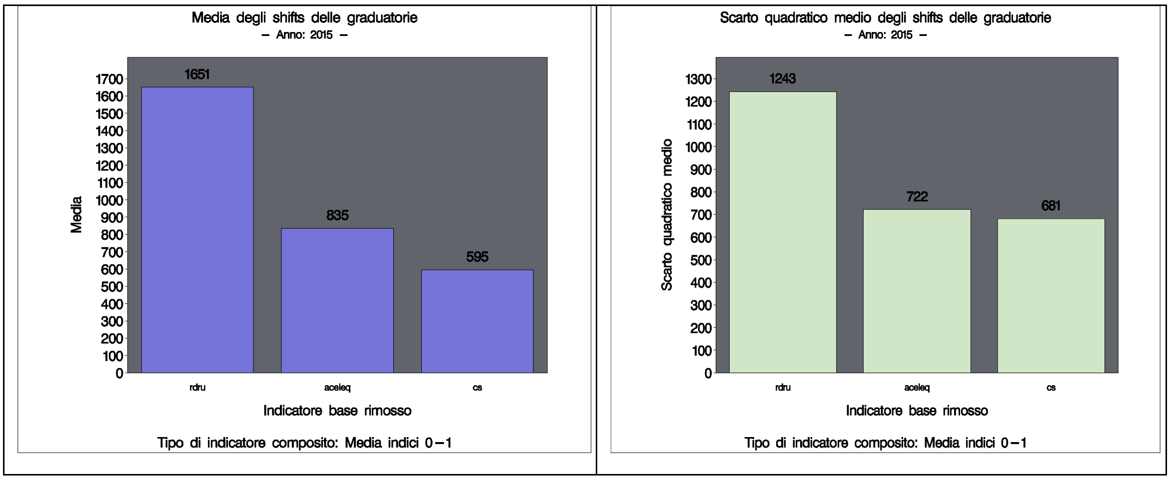
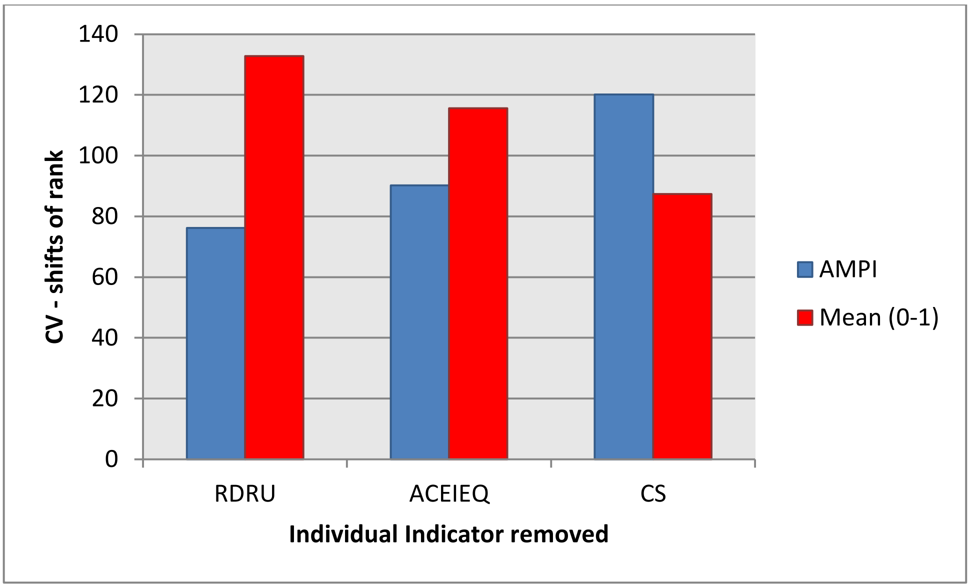
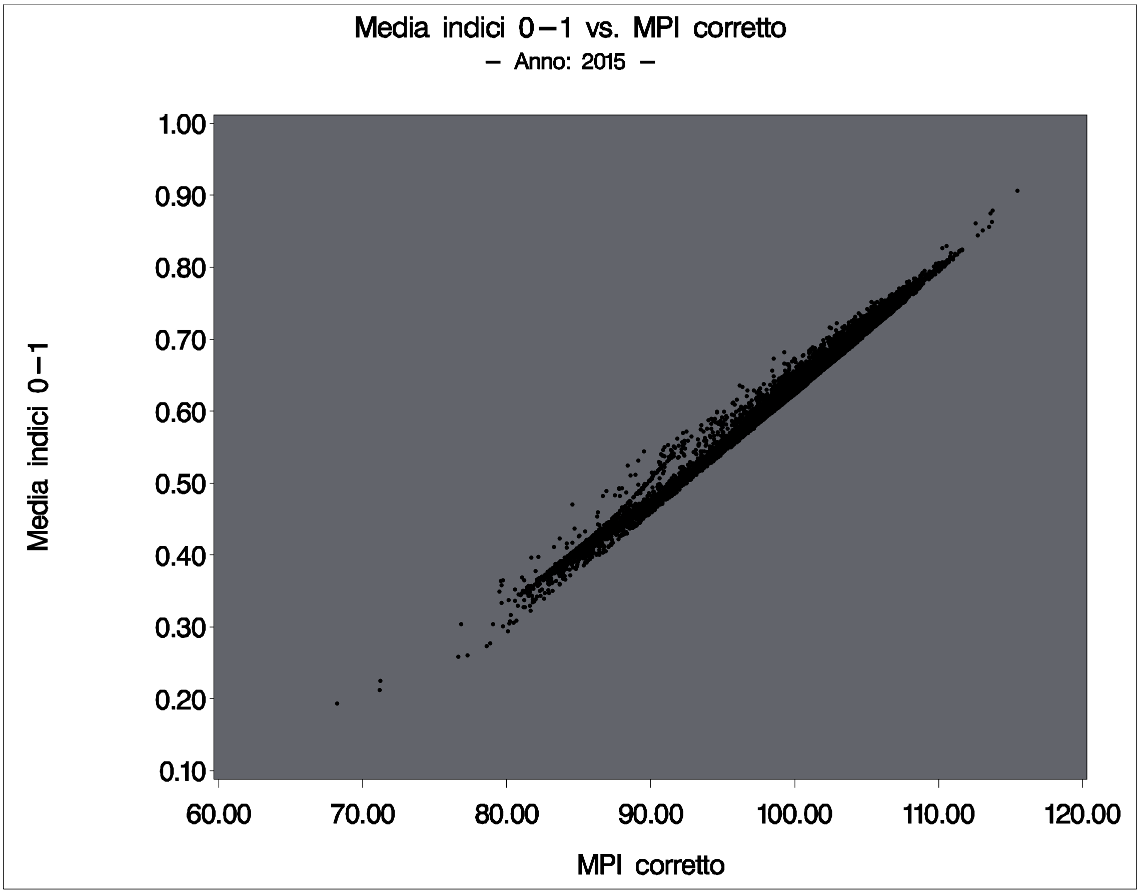


Figure 4.2.6.5 – Influence analysis by CV of shift of rank



The influence analysis shows that the individual indicator on the separate collection of municipal waste has a greater weight than the other two. In fact, if it is removed, on average, each municipality changes about 1,600 positions: and this is true for both the synthesis methods used. These methods, if compared in terms of CV of shift, certify a greater robustness of AMPI if the first two individual indicators are removed; in case of removal of the indicator on soil consumption the average (0-1) is more robust.

Figure 4.2.6.6 – Scatter plot between AMPI and Mean (0-1)



The scatter plot shows that the two methods, although being very positively correlated, have some differences along the whole line of the darker line. This shows that the compensatory effect and the penalty function of the AMPI are particularly divergent.

4.2.7 Economy on the territory

The well-being of an area, even a very small one like a municipality, can be influenced by the entrepreneurial structure and the ability to create jobs and infrastructures suitable for development. The domain wants to measure a salient aspect of the well-being of an area: wealth and sustainable development. The domain must be considered connected to other domains such as Labour, Economic wellbeing, Environment, Infrastructures and mobility.

In this domain two individual indicators are selected:

- Entrepreneurship rate;
- Density of local units.

Table 4.2.7.1 – Correlation matrix

Indicator	TI	DUL
TI	1.000	0.163
DUL	0.163	1.000

The correlation analysis has a very low value (0.163) and shows that the information content of the domain is very high.

Figure 4.2.7.1 – Scatter plot matrix

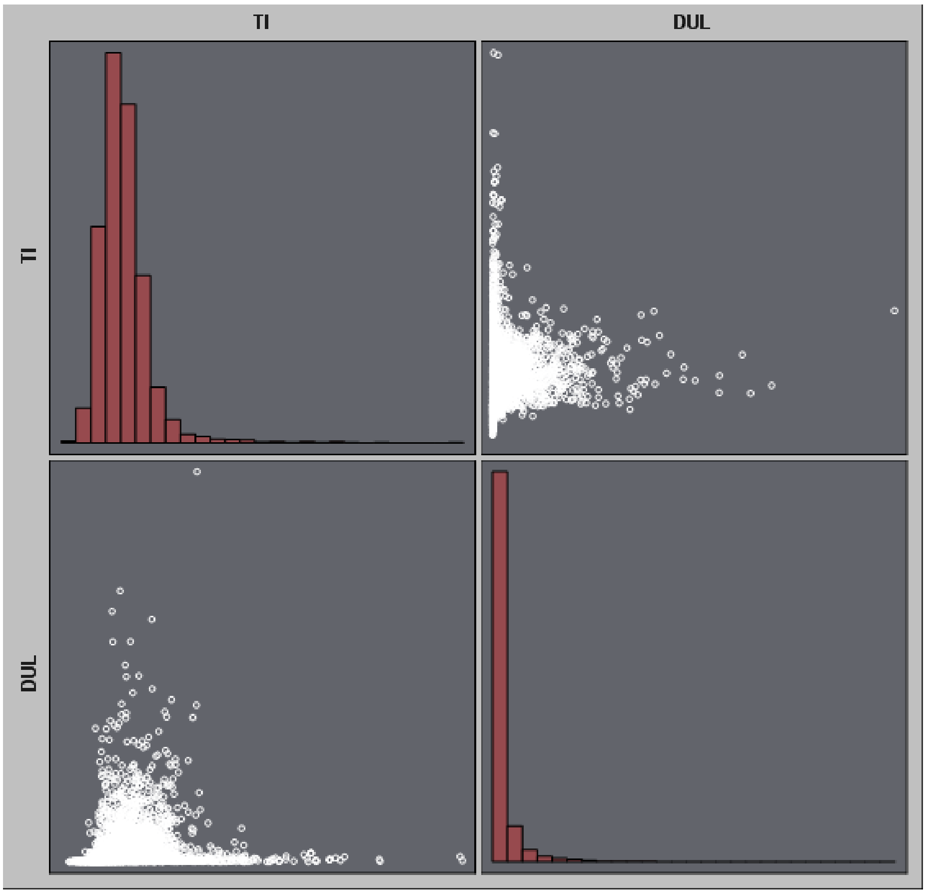
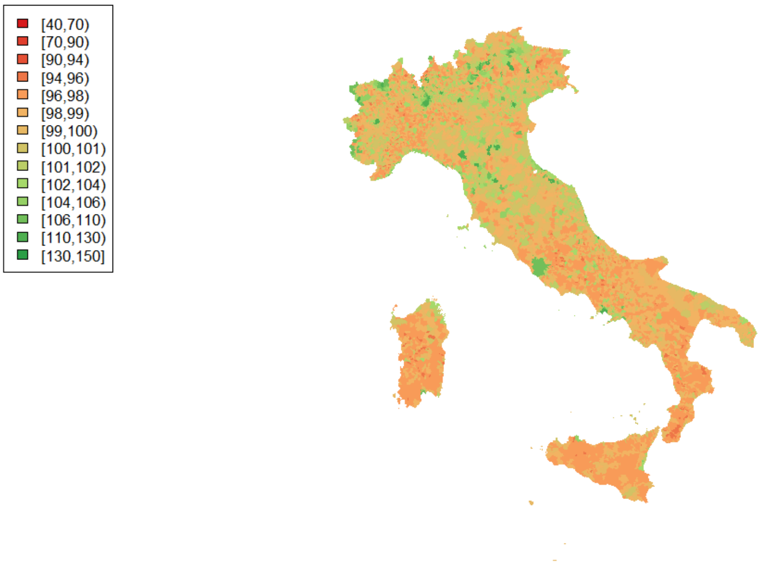


Figure 4.2.7.2 – Map of the domain Economy on territory by AMPI



The map of Italy presents a "patchy" situation in which certainly the north and the centre have a better condition than the south. It seems to emerge such as the Adriatic coast and large areas of Trentino Alto Adige, Lombardy, Piedmont, Emilia-Romagna, Tuscany, Marche, Rome and its hinterland. In the south there are green zones in areas typically tourist such as the Amalfi coast, Salento, Taormina, the Emerald coast in Sardinia.

Figure 4.2.7.3 – Influence analysis by AMPI

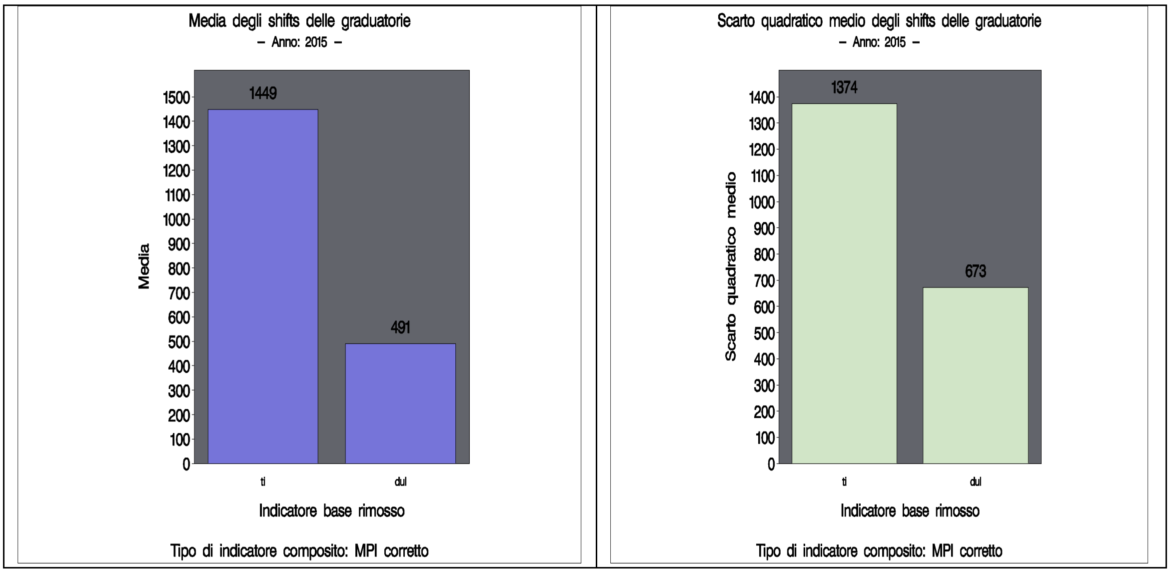


Figure 4.2.7.4 – Influence analysis by Mean (0-1)

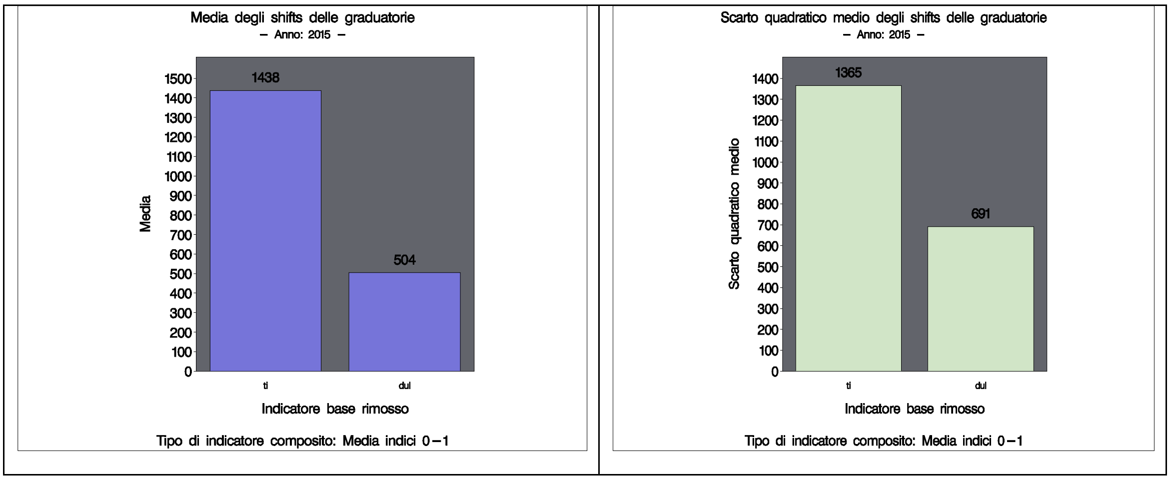
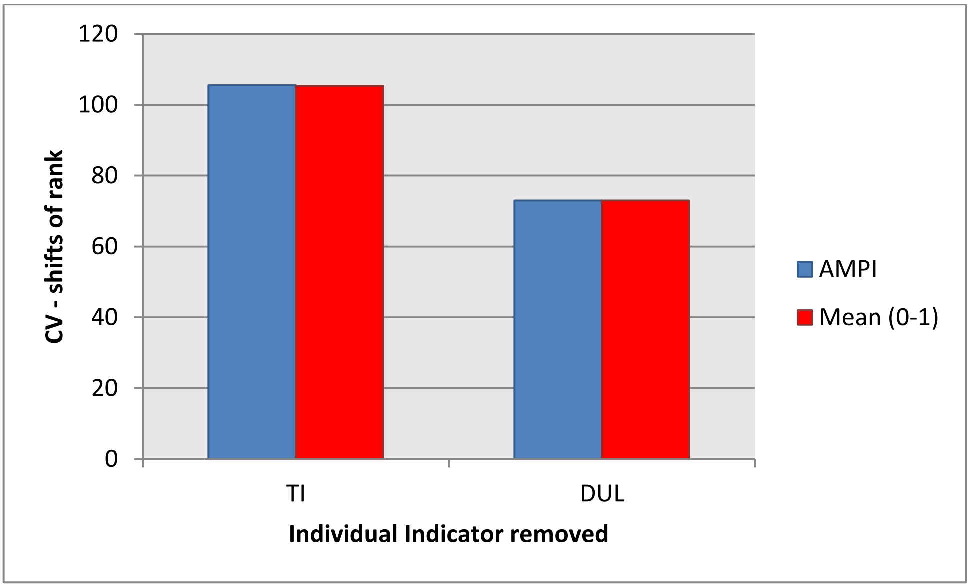
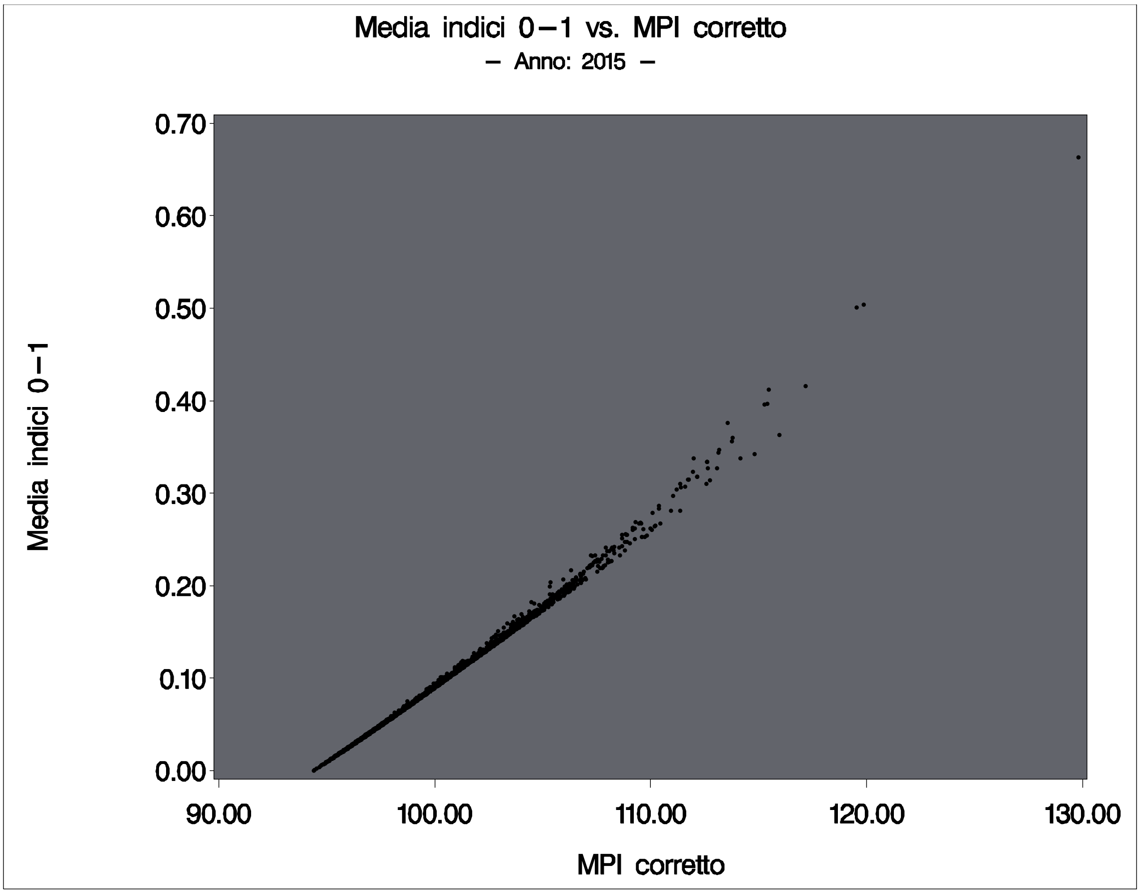


Figure 4.2.7.5 – Influence analysis by CV of shift of rank



The analysis of influence does not present any difference between the two methods compared, in fact they are robust in the same way. The difference in weight between the two selected individual indicators seems more interesting because the rate of entrepreneurship has a triple weight compared to the density of local units.

Figure 4.2.7.6 – Scatter plot between AMPI and Mean (0-1)



The two methods compared do not present substantial differences except for the few municipalities with a higher composite indicator value, i.e. for the most developed municipalities from the point of view of the local economy. In fact, in these cases, the variability between the two individual indicators increases and the penalty effect of the AMPI makes its effect.

4.2.8 Research and innovation

Research and innovation are an indirect determinant of well-being. They are the basis of social and economic progress and make a fundamental contribution to sustainable and lasting development. In the identification of the analysis dimensions, those that most represent the phenomena of research, innovation and high-level professional skills have been privileged. The individual research and innovation indicators chosen refer to distinct dimensions of knowledge: creation, application and dissemination.

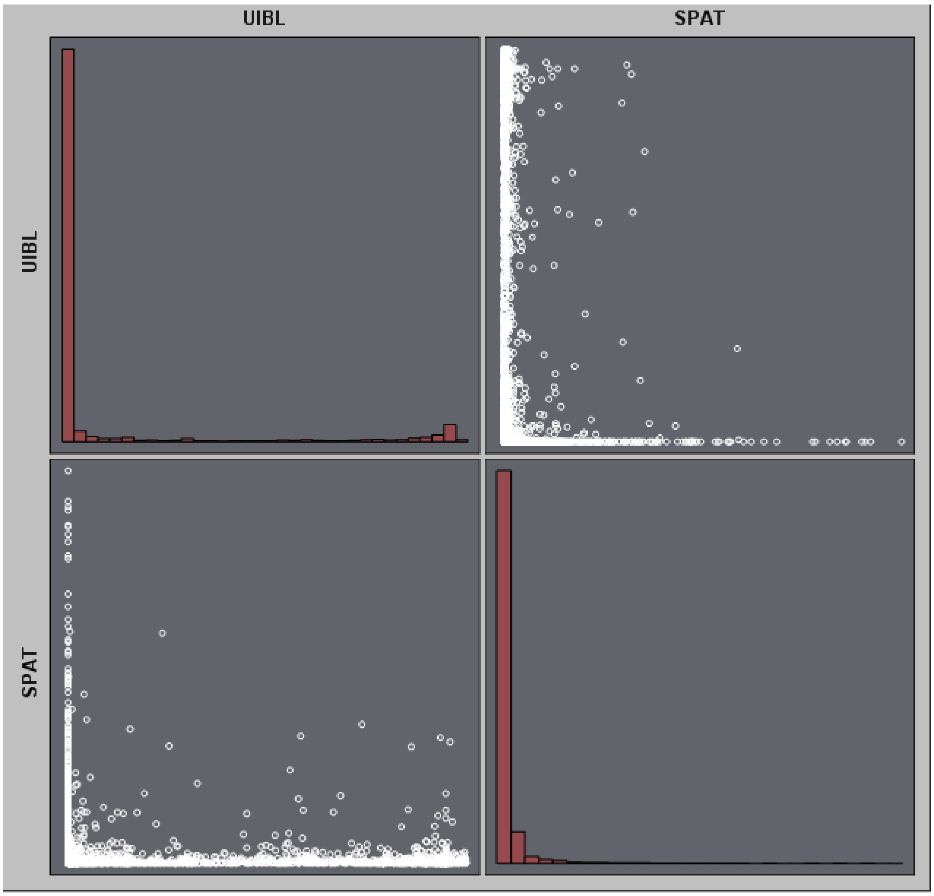
In this domain two individual indicators are selected:

- Real estate units reached by broadband (UIBL);
- Production specialization in high-tech sectors (SPAT).

Table 4.2.8.1 – Correlation matrix

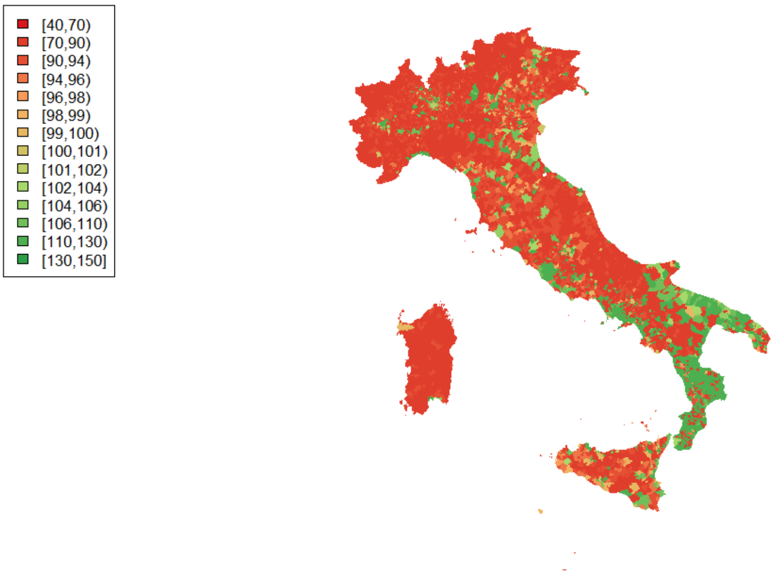
Indicator	UIBL	SPAT
UIBL	1.000	-0.025
SPAT	-0.025	1.000

Figure 4.2.8.1 – Matrix plot



The correlation analysis shows that the two selected individual indicators are absolutely uncorrelated and therefore they are highly informative.

Figure 4.2.8.2 – Map of the domain R & I by AMPI



The map of the composite indicator presents an unexpected situation in which the south has higher values than the north. In particular, in Puglia and Calabria, in recent years, there seem to have been major investments in terms of broadband deployment and the development of advanced technology sectors.

Figure 4.2.8.3 – Influence analysis by AMPI

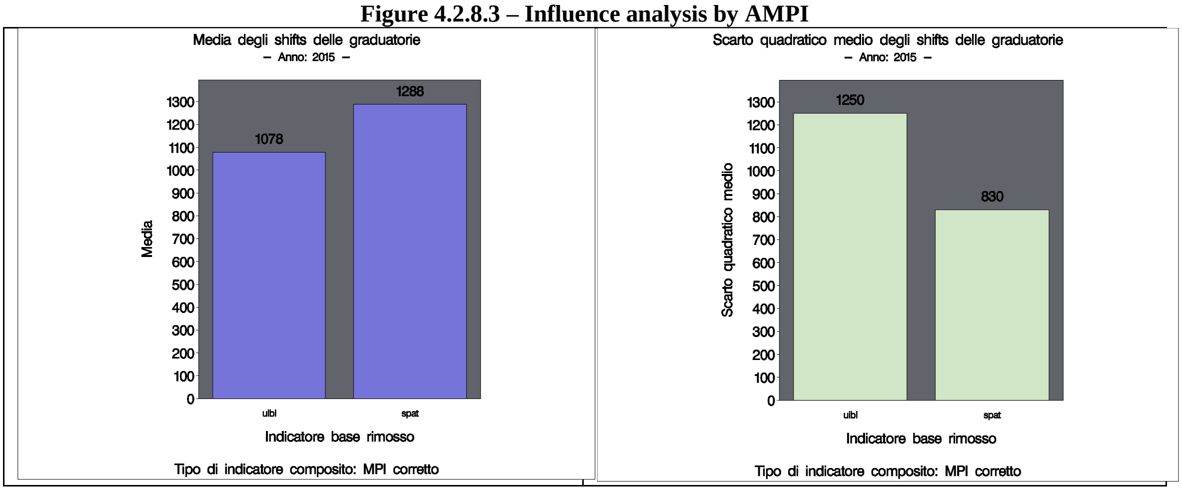


Figure 4.2.8.4 – Influence analysis by Mean (0-1)

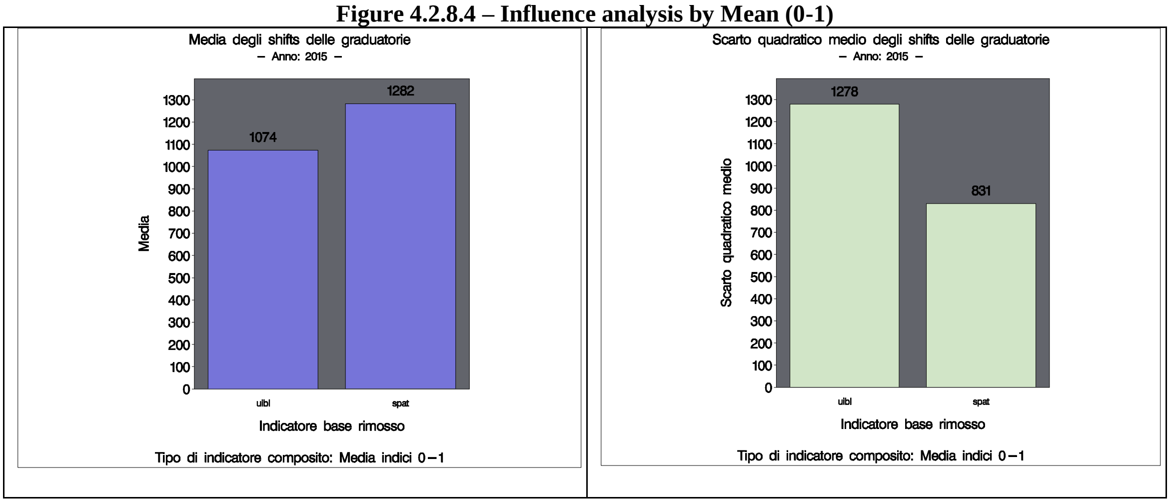
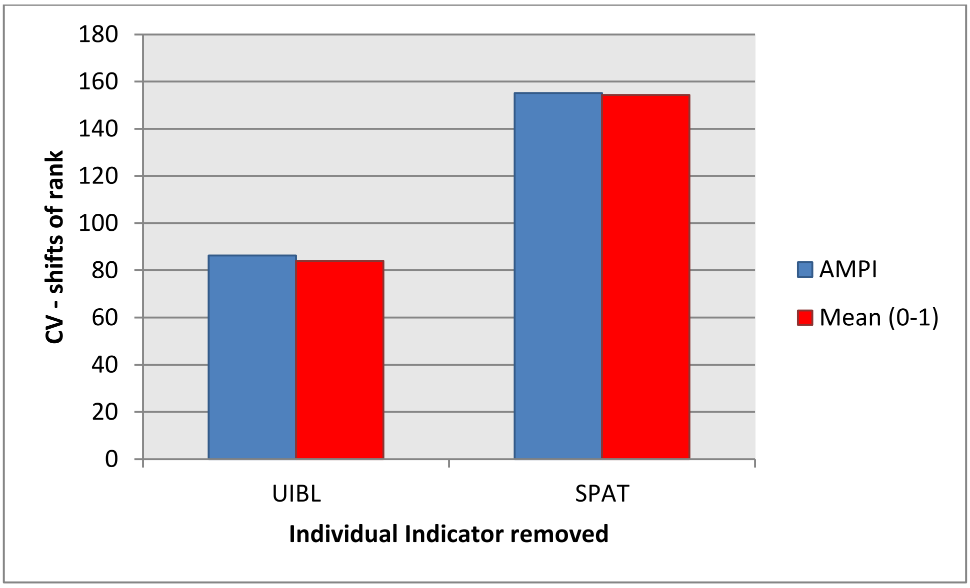
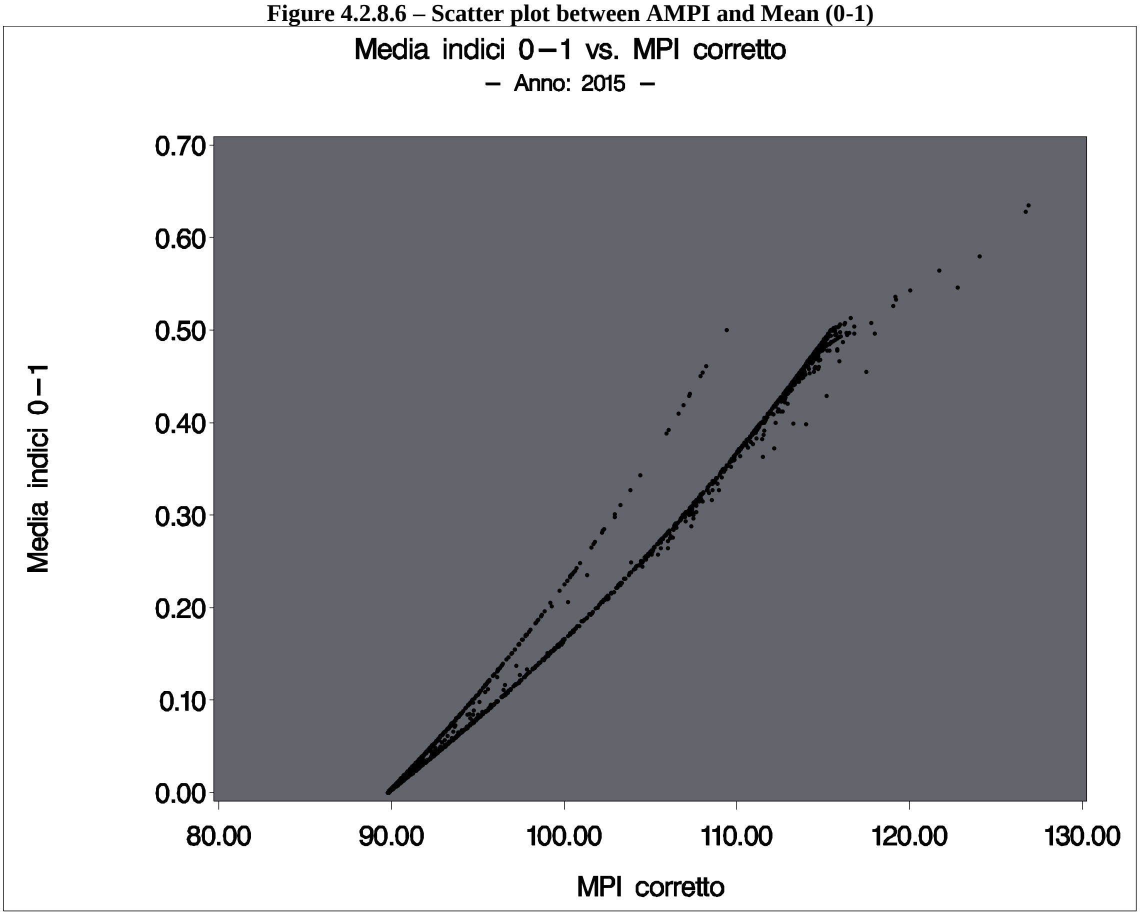


Figure 4.2.8.5 – Influence analysis by CV of shift of rank



The influence analysis demonstrates the equal robustness of the two chosen synthesis methods. The greater weight of the individual indicator “Production specialization in high-tech sectors” is shown with respect to the individual indicator “Real estate units reached by broadband”. This weight is attributable to the greater variability of the phenomenon on the territory.

Figure 4.2.8.6 – Scatter plot between AMPI and Mean (0-1)



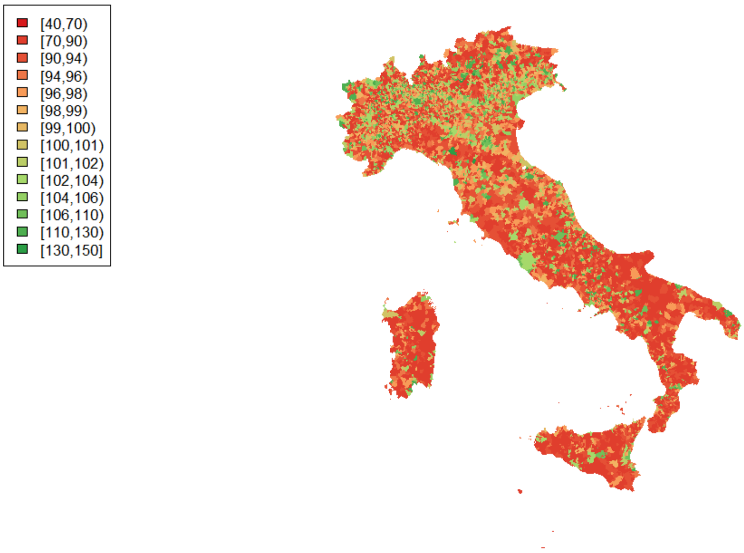
The scatter plot presents a curious "V" shape with many outliers.

4.2.9 Infrastructure and mobility

Widespread access to quality services is a fundamental element for a society that intends to guarantee its citizens a minimum standard of well-being and opens up opportunities to base individual growth paths. The inadequate availability of services particularly affects those who do not have sufficient resources to resort to alternatives and increase the risk of poverty and exclusion. The availability of quality public services is therefore one of the fundamental tools for redistributing and overcoming inequalities. The analysis of services, both public and not goes through the various aspects necessary to guarantee their quality: the infrastructural endowment, a condition often indispensable to the provision, the accessibility of the population and the effectiveness of the services provided in the satisfaction of the needs.

For this reasons, in this domain only one individual indicator is selected: attraction index.

Figure 4.2.9.1 – Map of the domain Infrastructure and Mobility by AMPI



The map of Italy shows a situation in the country similar to a painting by a French Impressionist: a red background with many green points of different width. These points seem to be more concentrated in the North and, later, in the Centre. The South and the Islands are certainly more sparse.

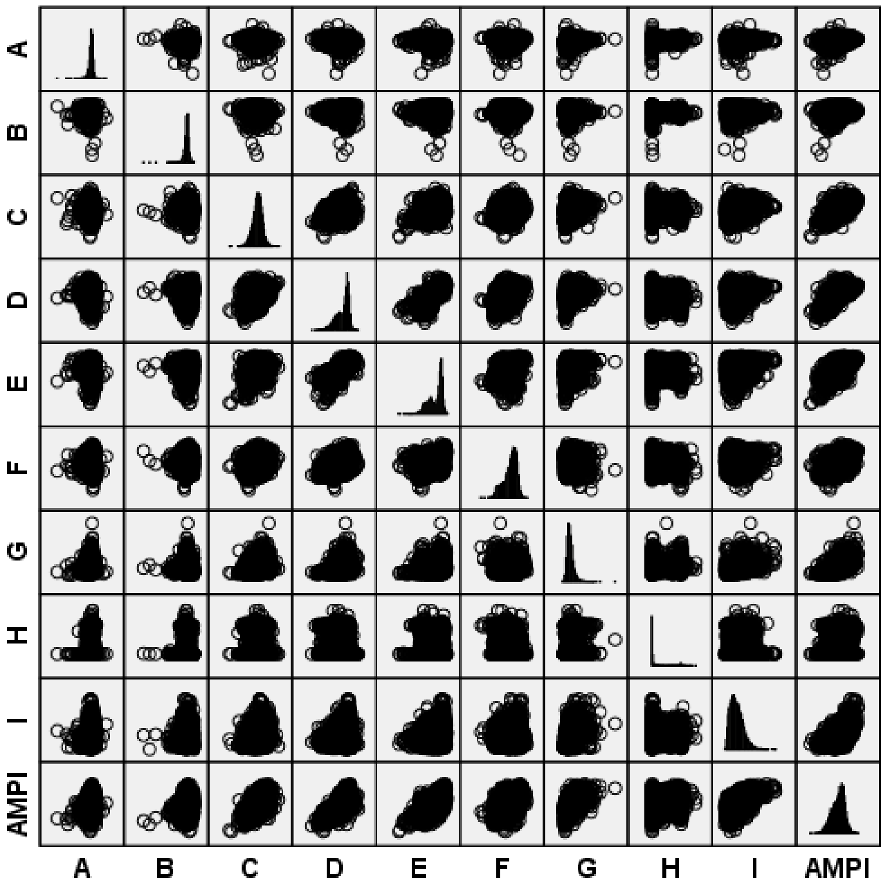
4.3 Analysis of the results

In this section a composite indicator of the 9 composite indicators of the domains is computed and it is the measure of well-being of Italian municipalities. Furthermore, in order to facilitate the reading of the results of the "super index", a classification method of the municipalities is applied: regression trees by CHAID (Chi Square Automatic Interaction Detector). As done in the description of the domains of well-being, the explorative analysis of the matrix 7,998 (municipalities) for 9 (composite indicators of the domains) is calculated.

Table 4.3.1 – Correlation matrix of the 9 plus 1 composite indices

Domain	Population	Health	Education	Labour	Economic WB	Environment	Economy on T	R&I	I&M	AMPI
Population	1,00	0,03	0,03	0,03	-0,01	0,10	0,16	0,13	0,16	0,23
Health	0,03	1,00	0,08	0,08	0,09	0,09	0,07	-0,03	0,05	0,21
Education	0,03	0,08	1,00	0,48	0,43	0,26	0,34	-0,02	0,29	0,63
Labour	0,03	0,08	0,48	1,00	0,88	0,59	0,35	-0,32	0,31	0,79
Economic WB	-0,01	0,09	0,43	0,88	1,00	0,59	0,31	-0,34	0,29	0,76
Environment	0,10	0,09	0,26	0,59	0,59	1,00	0,09	-0,31	0,17	0,62
Economy on T	0,16	0,07	0,34	0,35	0,31	0,09	1,00	0,07	0,55	0,57
R&I	0,13	-0,03	-0,02	-0,32	-0,34	-0,31	0,07	1,00	0,03	0,04
I&M	0,16	0,05	0,29	0,31	0,29	0,17	0,55	0,03	1,00	0,65
AMPI	0,23	0,21	0,63	0,79	0,76	0,62	0,57	0,04	0,65	1,00

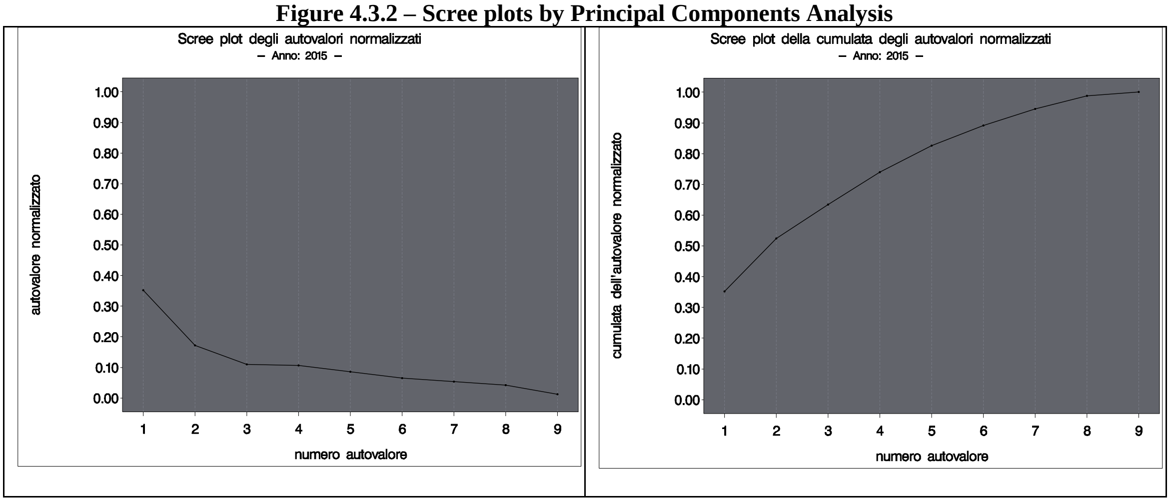
Figure 4.3.1 – Scatter plot matrix of the 9 plus 1 composite indices



The correlation analysis is carried out by studying the reciprocal relationships among the nine well-being composite indices of the Italian municipalities plus the composite indicator that summarizes them (the super index). Population and households and

Health domains have very weak correlations with other domains. The highest correlation value is between Labour and Economic well-being (0.884). The domain environment is positively correlated with Labour (0.586) and with Economic well-being (0.594). The highest negative correlation occurs between Research and Innovation and Economic well-being (-0.340). The Education domain has a good positive correlation with Labour (0.477) and with Economic well-being (0.435). It seems very interesting and important the correlation between Infrastructure and Mobility and Economy on Territory (0.547): this shows how important the level of economic development of an area is so that it attracts resources and people. The correlation between AMPI (the super index) and the nine domains of municipal welfare certifies the weight that each domain has on the final composite indicator. Very high correlations occur with Labour (0.789), Economic well-being (0.762), Infrastructure and mobility (0.649), Education (0.630), Environment (0.617), Economy on the territory (0.566). Very low correlations with Population and households (0.231) and Health (0.214) are presented. Research and Innovation is completely uncorrelated with the super composite indicator.

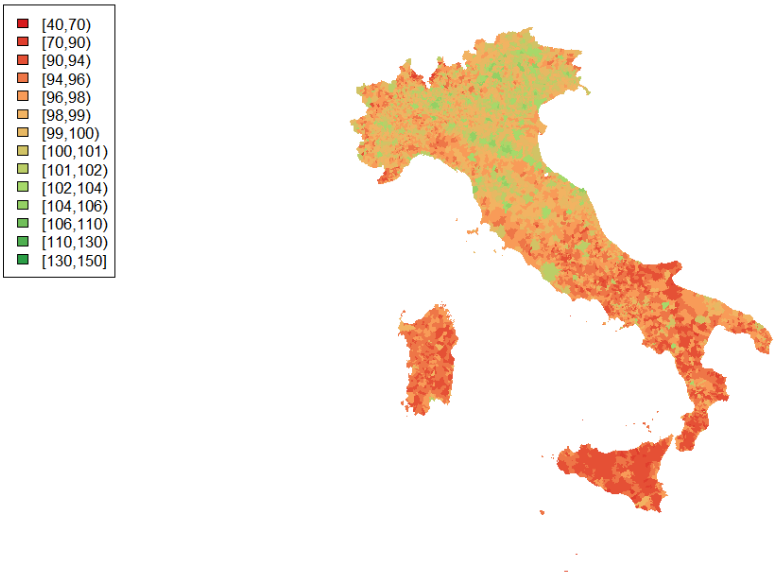
Figure 4.3.2 – Scree plots by Principal Components Analysis



Since in the calculation of the super index we start from a matrix with many indicators (nine), a Principal components analysis (PCA) can be performed (in the domains the number of individual indicators is too small). The PCA allows an extraordinary exploratory analysis of the data. The results, presented in Figure 4.3.2, show that the first two factors explain little more than 50% of the variability (therefore of statistical information). The interesting aspect is that the factors after the second explain roughly the same amount of variability: this means that, as shown in Table

4.3.1, the correlations between the composite indicators of the domains are weak and that, in order to measure well-being, each of the domains has an important weight.

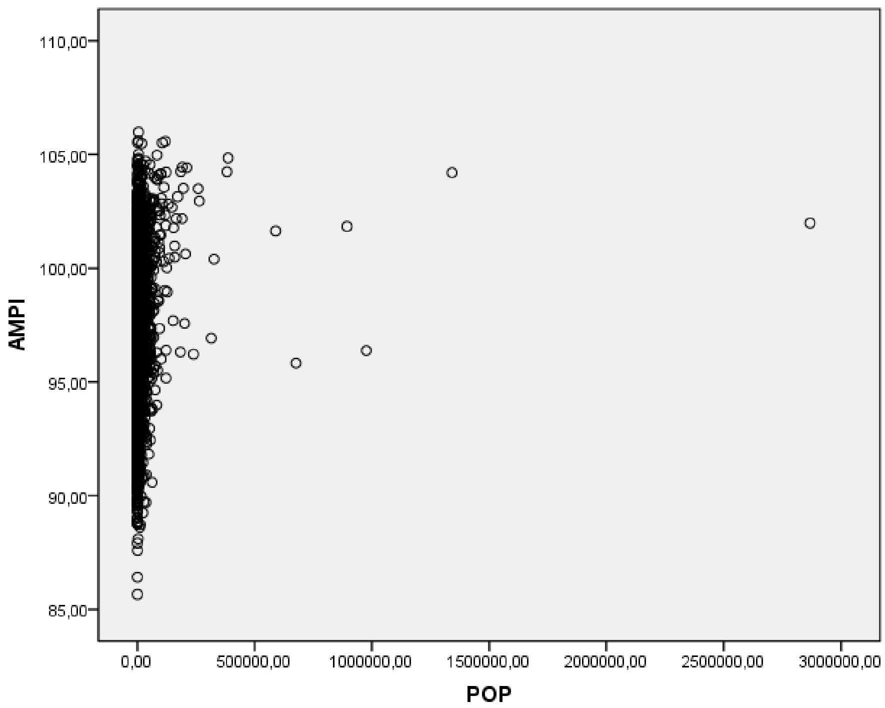
Figure 4.3.3 – Map of Well-being Italian Municipality by AMPI



The composite wealth index of Italian municipalities is characterized by large green areas to the North-East and green areas in Lombardy, Piedmont, north of Tuscany and in the Marche. The municipality of Rome has an excellent performance (please note that the data refer to 2015). In the South the situation is very different with the shades of red very widespread throughout the territory. Sicily seems to present the worst level of well-being.

The composite indicator analysis for all municipalities must be a starting point for both micro-depth studies, but also for macro studies, such as measuring the correlation with other variables/indicators available at this territorial level.

Figure 4.3.4 – Scatter plot between AMPI and Population size



The idea is to correlate the composite indicator of socio-economic condition with the population size of the municipality (Fig.3): the result is surprising since there is full uncorrelation (ρ = 0.101). This means that there is no factor related to the size of the municipality that can determine the socio-economic conditions or the well-being, and vice versa: these two informative contributions do not affect each other. And this is certainly a strength point of the composite indicator that can explain a multidimensional phenomenon that is independent from an important variable, especially in Italy, as the size of the municipality. On the right side of the figure the outliers are visible: they are the biggest cities like Rome, Milan, Naples, Palermo and Turin. As you can see, the points that represent them are located around the reference value (100). This confirms that the population size is not as determinant as the geographical location.

However, the theme should certainly deserve a deepening by trying to do the analysis again with more aggregate territorial areas (regions or macro-regions). In fact, in the next table the correlation between the population size and AMPI is calculated at regional level.

Table 4.3.2 – Correlation between AMPI and population size (regional level)

Italian Region	Correlation coefficient
Piemonte	0,138
Valle d'Aosta	0,284
Liguria	0,218
Lombardia	0,178
Bolzano/Bozen	0,409
Trento	-0,026
Veneto	0,320
Friuli Venezia Giulia	0,274
Emilia Romagna	0,446
Marche	0,508
Toscana	0,460
Umbria	0,532
Lazio	0,213
Campania	0,088
Abruzzo	0,371
Molise	0,440
Puglia	0,342
Basilicata	0,513
Calabria	0,267
Sicilia	0,230
Sardegna	0,434

If the correlation between the composite welfare index and the population size is calculated within each region, the results still show very low values. In central-northern Italy the values are around 0.5: Umbria (0.532), Marche (0.508), Tuscany (0.460) and Emilia-Romagna (0.446). This means that in these regions it is quite true that if the size of the municipality is greater then well-being increases; perhaps because the larger cities "operate" better than the corresponding ones in other regions. In the province of Trento and in the region Campania the two parameters are completely uncorrelated. Probably the reading of this last consideration is very different: in Trento the high level of well-being is widespread throughout the territory, while in Campania unfortunately a low level of well-being is widespread.

The first hundred municipalities sorted by the composite indicator of well-being are concentrated mainly in North-East (sixty) of which seven in the first ten and in North-west (thirty-five). Five municipalities are in the Centre of which four in Tuscany with three provincial capitals: Siena, Firenze e Pisa. The first provincial capital in absolute is Bergamo in third position. The first regional capital is Bologna in ninth position. Milan, in thirty-second position, is the largest in terms of inhabitants. The smallest municipality, in terms of population size, is Bresimo (253 inhabitants) in the province of Trento.

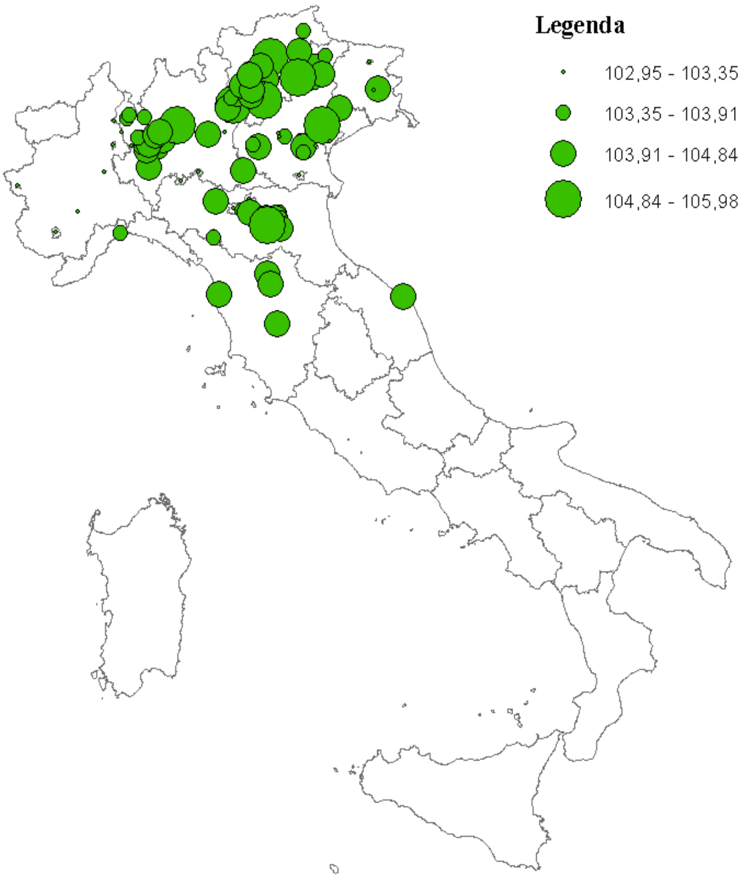
Table 4.3.3 - The first 100 Italian municipalities sorted by well-being

Municipality	Province	Region	Zone	AMPI
Altopiano della Vigolana	Trento	Trentino Alto Adige	North-East	105.983
Agordo	Belluno	Veneto	North-East	105.602
Bergamo	Bergamo	Lombardia	North-West	105.581
Pieve di Bono-Prezzo	Trento	Trentino Alto Adige	North-East	105.521
Bolzano/Bozen	Bolzano/Bozen	Trentino Alto Adige	North-East	105.513
Zola Predosa	Bologna	Emilia Romagna	North-East	105.483
Primiero San Martino di Castrozza	Trento	Trentino Alto Adige	North-East	105.024
Treviso	Treviso	Veneto	North-East	104.973
Bologna	Bologna	Emilia Romagna	North-East	104.844
Vallelaghi	Trento	Trentino Alto Adige	North-East	104.815
Altavalle	Trento	Trentino Alto Adige	North-East	104.802
Borgo Chiese	Trento	Trentino Alto Adige	North-East	104.722
Casalecchio di Reno	Bologna	Emilia Romagna	North-East	104.698
Valfloriana	Trento	Trentino Alto Adige	North-East	104.581
San Martino Buon Albergo	Verona	Veneto	North-East	104.578
Siena	Siena	Toscana	Centre	104.557
Vimercate	Monza e della Brianza	Lombardia	North-West	104.537
Madruzzo	Trento	Trentino Alto Adige	North-East	104.534
Amblar-Don	Trento	Trentino Alto Adige	North-East	104.486
Tre Ville	Trento	Trentino Alto Adige	North-East	104.473
Assago	Milano	Lombardia	North-West	104.461
Parma	Parma	Emilia Romagna	North-East	104.442
Padova	Padova	Veneto	North-East	104.420
Collebeato	Brescia	Lombardia	North-West	104.343
Calenzano	Firenze	Toscana	Centre	104.340
San Lazzaro di Savena	Bologna	Emilia Romagna	North-East	104.304
Ville d'Anaunia	Trento	Trentino Alto Adige	North-East	104.283
Modena	Modena	Emilia Romagna	North-East	104.248
Firenze	Firenze	Toscana	Centre	104.241
Longarone	Belluno	Veneto	North-East	104.228
Monza	Monza e della Brianza	Lombardia	North-West	104.219
Milano	Milano	Lombardia	North-West	104.199
Corvara in Badia/Corvara	Bolzano/Bozen	Trentino Alto Adige	North-East	104.180
Mantova	Mantova	Lombardia	North-West	104.170
Ancona	Ancona	Marche	Centre	104.148
Udine	Udine	Friuli Venezia Giulia	North-East	104.133
Peschiera Borromeo	Milano	Lombardia	North-West	104.125

Pisa	Pisa	Toscana	Centre	104.077
Portobuffolè	Treviso	Veneto	North-East	104.068
Anzola dell'Emilia	Bologna	Emilia Romagna	North-East	104.043
Castel Maggiore	Bologna	Emilia Romagna	North-East	104.025
Gorgonzola	Milano	Lombardia	North-West	104.019
Pavia	Pavia	Lombardia	North-West	104.013
Varese	Varese	Lombardia	North-West	103.912
Borgo Lares	Trento	Trentino Alto Adige	North-East	103.904
Como	Como	Lombardia	North-West	103.901
Galliate Lombardo	Varese	Lombardia	North-West	103.823
Silea	Treviso	Veneto	North-East	103.808
Selva di Val Gardena	Bolzano/Bozen	Trentino Alto Adige	North-East	103.789
Castenaso	Bologna	Emilia Romagna	North-East	103.732
Granarolo dell'Emilia	Bologna	Emilia Romagna	North-East	103.727
Andalo	Trento	Trentino Alto Adige	North-East	103.715
Ventasso	Reggio nell'Emilia	Emilia Romagna	North-East	103.689
Cusago	Milano	Lombardia	North-West	103.672
Sella Giudicarie	Trento	Trentino Alto Adige	North-East	103.665
Albignasego	Padova	Veneto	North-East	103.597
Rubiera	Reggio nell'Emilia	Emilia Romagna	North-East	103.584
Vicenza	Vicenza	Veneto	North-East	103.554
Brescia	Brescia	Lombardia	North-West	103.512
Verona	Verona	Veneto	North-East	103.495
Brunico/Bruneck	Bolzano/Bozen	Trentino Alto Adige	North-East	103.479
Bentivoglio	Bologna	Emilia Romagna	North-East	103.477
Limena	Padova	Veneto	North-East	103.456
Treviolo	Bergamo	Lombardia	North-West	103.432
Nerviano	Milano	Lombardia	North-West	103.397
Dimaro Folgarida	Trento	Trentino Alto Adige	North-East	103.394
Calalzo di Cadore	Belluno	Veneto	North-East	103.374
Arenzano	Genova	Liguria	North-West	103.361
Amaro	Udine	Friuli Venezia Giulia	North-East	103.347
Pomarolo	Trento	Trentino Alto Adige	North-East	103.326
Treviglio	Bergamo	Lombardia	North-West	103.317
Agrate Brianza	Monza e della Brianza	Lombardia	North-West	103.274
Coniolo	Alessandria	Piemonte	North-West	103.225
SEastriere	Torino	Piemonte	North-West	103.218
Argelato	Bologna	Emilia Romagna	North-East	103.193
Cembra Lisignago	Trento	Trentino Alto Adige	North-East	103.177
Segrate	Milano	Lombardia	North-West	103.153
San Pietro Mosezzo	Novara	Piemonte	North-West	103.146
Reggio nell'Emilia	Reggio nell'Emilia	Emilia Romagna	North-East	103.141
Piacenza	Piacenza	Emilia Romagna	North-East	103.071
Cuneo	Cuneo	Piemonte	North-West	103.058

Creazzo	Vicenza	Veneto	North-East	103.057
Saronno	Varese	Lombardia	North-West	103.052
Bresimo	Trento	Trentino Alto Adige	North-East	103.047
Gambugliano	Vicenza	Veneto	North-East	103.043
Verduno	Cuneo	Piemonte	North-West	103.039
Pasian di Prato	Udine	Friuli Venezia Giulia	North-East	103.034
Cremona	Cremona	Lombardia	North-West	103.032
Origgio	Varese	Lombardia	North-West	103.027
Arona	Novara	Piemonte	North-West	103.020
Magenta	Milano	Lombardia	North-West	103.018
Roè Volciano	Brescia	Lombardia	North-West	103.011
Carpi	Modena	Emilia Romagna	North-East	102.982
Rovigo	Rovigo	Veneto	North-East	102.981
Brunello	Varese	Lombardia	North-West	102.978
Perarolo di Cadore	Belluno	Veneto	North-East	102.975
Dolo	Venezia	Veneto	North-East	102.962
Vizzola Ticino	Varese	Lombardia	North-West	102.960
Venezia	Venezia	Veneto	North-East	102.952
San Donato Milanese	Milano	Lombardia	North-West	102.950

Figure 4.3.5 – Map of the first 100 municipalities sorted by well-being



As reported in the Figure 4.3.5, the first 100 municipalities are distributed in North-East with an high concentration in the two provinces of Trento e Bolzano. As you move towards the Centre, the concentration of green dots becomes sparser. A considerable concentration of points is found in the East of Lombardy and along the last stretch of the “via Emilia”.

Table 4.3.4 – The last 100 Italian municipalities sorted by well-being

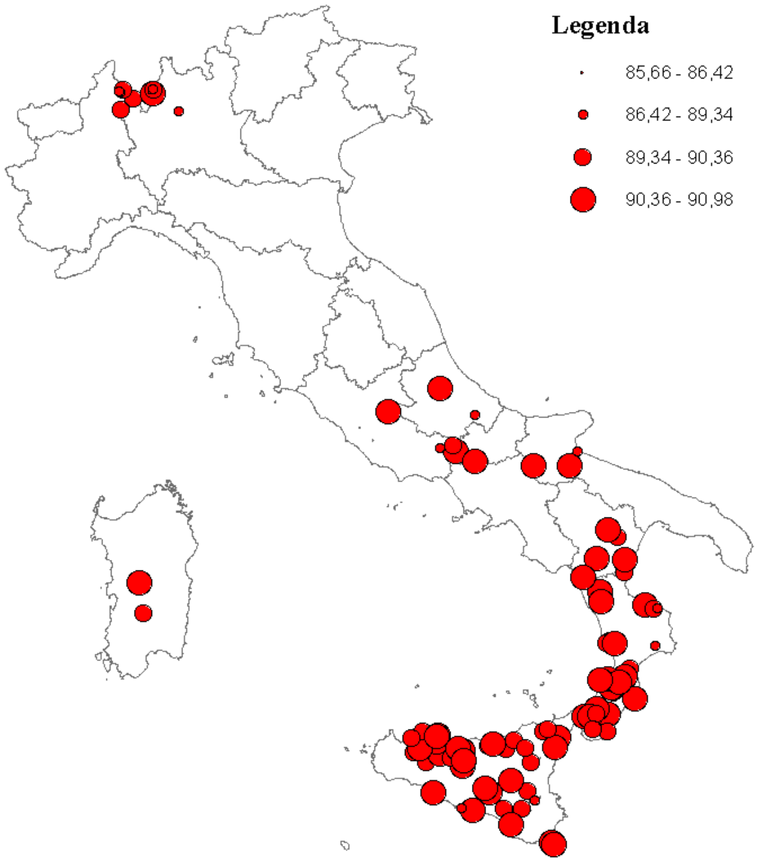
Municipality	Province	Region	Zone	AMPI
Corrido	Como	Lombardia	North-West	90.985
Cerda	Palermo	Sicilia	Islands	90.969
Canna	Cosenza	Calabria	South	90.966
Sorianello	Vibo Valentia	Calabria	South	90.947
Valledolmo	Palermo	Sicilia	Islands	90.946
Ficarazzi	Palermo	Sicilia	Islands	90.939
Raddusa	Catania	Sicilia	Islands	90.931
Licata	Agrigento	Sicilia	Islands	90.921
Pettineo	Messina	Sicilia	Islands	90.919
Caloveto	Cosenza	Calabria	South	90.917
Santa Caterina Albanese	Cosenza	Calabria	South	90.908
San Mauro Forte	Matera	Basilicata	South	90.905
Mezzojuso	Palermo	Sicilia	Islands	90.903
San Cipirello	Palermo	Sicilia	Islands	90.902
Aieta	Cosenza	Calabria	South	90.897
Platì	Reggio di Calabria	Calabria	South	90.887
San Gregorio d'Ippona	Vibo Valentia	Calabria	South	90.884
Zungri	Vibo Valentia	Calabria	South	90.875
Misilmeri	Palermo	Sicilia	Islands	90.860
Pachino	Siracusa	Sicilia	Islands	90.829
Martirano	Catanzaro	Calabria	South	90.814
Portopalo di Capo Passero	Siracusa	Sicilia	Islands	90.799
Acquafondata	Frosinone	Lazio	Centre	90.789
Villabate	Palermo	Sicilia	Islands	90.788
Villa Santa Lucia degli Abruzzi	L'Aquila	Abruzzo	South	90.784
Montallegro	Agrigento	Sicilia	Islands	90.745
Celle di San Vito	Foggia	Puglia	South	90.734
San Roberto	Reggio di Calabria	Calabria	South	90.731
Stignano	Reggio di Calabria	Calabria	South	90.682
Percile	Roma	Lazio	Centre	90.644
San Procopio	Reggio di Calabria	Calabria	South	90.610
Vittoria	Ragusa	Sicilia	Islands	90.585
Barrafranca	Enna	Sicilia	Islands	90.579
Vallelunga Pratameno	Caltanissetta	Sicilia	Islands	90.579
Gaggi	Messina	Sicilia	Islands	90.559
Sciara	Palermo	Sicilia	Islands	90.558

Fiumara	Reggio di Calabria	Calabria	South	90.542
Ulà Tirso	Oristano	Sardegna	Islands	90.536
Dinami	Vibo Valentia	Calabria	South	90.528
Acquaformosa	Cosenza	Calabria	South	90.525
Carbone	Potenza	Basilicata	South	90.491
Stornara	Foggia	Puglia	South	90.483
Casalvecchio Siculo	Messina	Sicilia	Islands	90.483
Valle Agricola	Caserta	Campania	South	90.466
Pietraperzia	Enna	Sicilia	Islands	90.442
Torre di Ruggiero	Catanzaro	Calabria	South	90.431
Las Plassas	Medio Campidano	Sardegna	Islands	90.359
Camini	Reggio di Calabria	Calabria	South	90.351
Torretta	Palermo	Sicilia	Islands	90.334
Cremenaga	Varese	Lombardia	North-West	90.333
Licodia Eubea	Catania	Sicilia	Islands	90.330
Belgirate	Verbano-Cusio-Ossola	Piemonte	North-West	90.323
Camporeale	Palermo	Sicilia	Islands	90.308
Francica	Vibo Valentia	Calabria	South	90.301
Serra d'Aiello	Cosenza	Calabria	South	90.273
Bagaladi	Reggio di Calabria	Calabria	South	90.252
Aiello Calabro	Cosenza	Calabria	South	90.225
Albidona	Cosenza	Calabria	South	90.203
Trappeto	Palermo	Sicilia	Islands	90.184
Campofiorito	Palermo	Sicilia	Islands	90.175
San Pietro di Caridà	Reggio di Calabria	Calabria	South	90.164
Cosoleto	Reggio di Calabria	Calabria	South	90.161
Roccapalumba	Palermo	Sicilia	Islands	90.137
Careri	Reggio di Calabria	Calabria	South	90.055
Palagonia	Catania	Sicilia	Islands	89.983
Staiti	Reggio di Calabria	Calabria	South	89.970
Capizzi	Messina	Sicilia	Islands	89.877
Placanica	Reggio di Calabria	Calabria	South	89.868
San Mauro Castelverde	Palermo	Sicilia	Islands	89.843
Basicò	Messina	Sicilia	Islands	89.784
Sinopoli	Reggio di Calabria	Calabria	South	89.772
Niscemi	Caltanissetta	Sicilia	Islands	89.732
San Fratello	Messina	Sicilia	Islands	89.731
Adrano	Catania	Sicilia	Islands	89.704
Palermiti	Catanzaro	Calabria	South	89.696
San Biagio Saracinisco	Frosinone	Lazio	Centre	89.694
Craco	Matera	Basilicata	South	89.645
San Bartolomeo Val Cavargna	Como	Lombardia	North-West	89.609
Maniace	Catania	Sicilia	Islands	89.586
Mazzarrà Sant'Andrea	Messina	Sicilia	Islands	89.586
Cavaglio-Spoccia	Verbano-Cusio-Ossola	Piemonte	North-West	89.548
Scala Coeli	Cosenza	Calabria	South	89.459

Pizzoni	Vibo Valentia	Calabria	South	89.337
Feroleto della Chiesa	Reggio di Calabria	Calabria	South	89.329
Centrache	Catanzaro	Calabria	South	89.296
Palma di Montechiaro	Agrigento	Sicilia	Islands	89.242
San Nazzaro Val Cavargna	Como	Lombardia	North-West	89.037
Marcedusa	Catanzaro	Calabria	South	89.002
Giffone	Reggio di Calabria	Calabria	South	88.866
Falmenta	Verbano-Cusio-Ossola	Piemonte	North-West	88.849
Montebello sul Sangro	Chieti	Abruzzo	South	88.810
Blello	Bergamo	Lombardia	North-West	88.759
Casalattico	Frosinone	Lazio	Centre	88.752
Francofonte	Siracusa	Sicilia	Islands	88.730
Acate	Ragusa	Sicilia	Islands	88.617
Zapponeta	Foggia	Puglia	South	88.107
Gurro	Verbano-Cusio-Ossola	Piemonte	North-West	87.915
Terravecchia	Cosenza	Calabria	South	87.592
Cavargna	Como	Lombardia	North-West	86.422
Val Rezzo	Como	Lombardia	North-West	85.662

The hundred municipalities with the lowest level of well-being are principally concentrated in Sicily (thirty-eight) and Calabria (thirty-six). Seven municipalities of Lombardy are present and four of Piedmont but they are border municipalities in which the problems of administrative archives are known and already discussed in the previous paragraphs. The number of inhabitants of the "last" one hundred municipalities is very variable and ranges from seventy-two to about sixty-three thousand. There are no provincial capitals.

Figure 4.3.6 - Map of the last 100 municipalities sorted by well-being



In the figure 4.3.6, the map of the last hundred municipalities is presented. As you can see there is a strong concentration in many areas of Calabria and Sicily. The most interesting thing is the highlight of the municipalities in the province of Como where, as explained above, the administrative archives cannot well represent the socio-economic reality because many citizens are cross-border

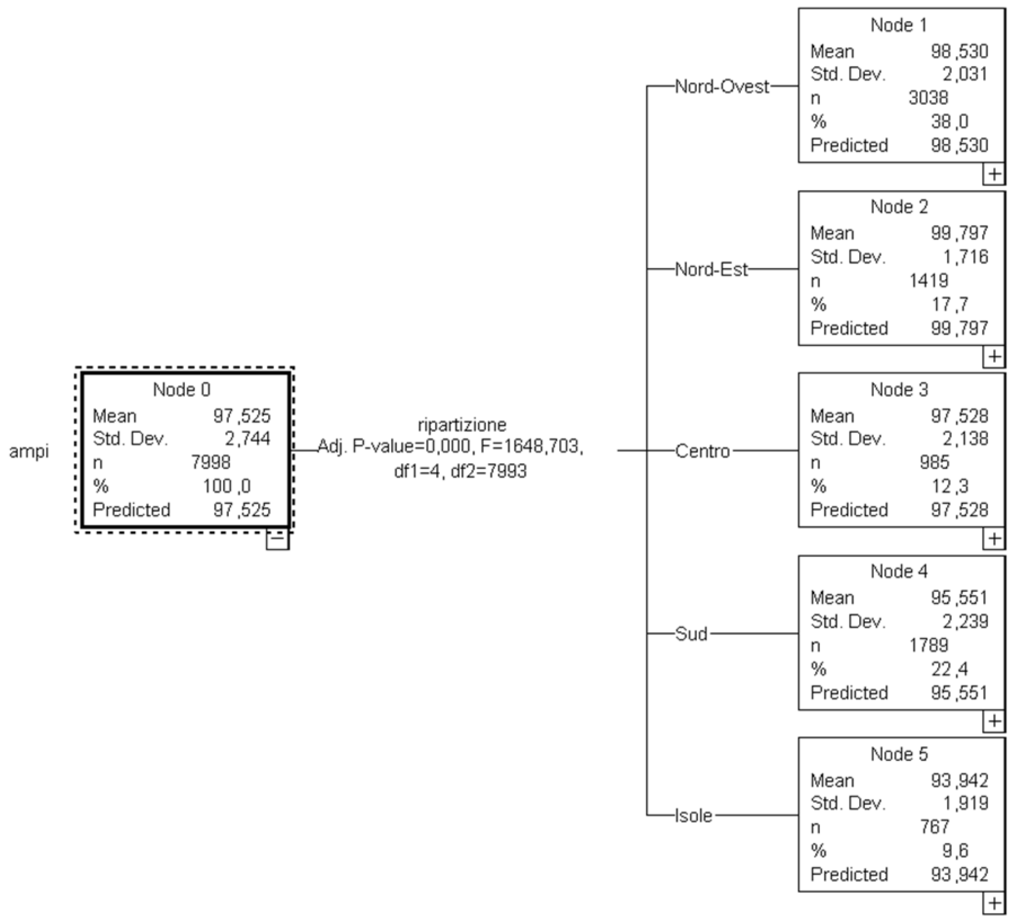
The method of sorting the municipalities by AMPI is interesting and can provide information on the evidence of the phenomenon. However, a more systematic approach is needed that can classify municipalities taking into account the well-being composite indicator as a function of some covariates. In this perspective a good classification method is the regression tree, called CHAID (*Chi*-squared Automatic Interaction Detector). It "builds" non-binary trees (i.e., trees where more than two branches can attach to a single root or node), based on a relatively simple algorithm that is particularly well suited for the analysis of larger datasets because the CHAID algorithm often effectively yields many multi-way frequency tables. In the application of the thesis, the dependent variable is the composite indicator of the well-being of the Italian municipalities; the independent variables are the three territorial levels (Zone, Region and Province) and the population size. In this way the goal is to classify the well-being of the municipalities according to the localization on the territory and the population size.

The population size is divided in 18 classes as used in the Population Census and as reported in the table below.

Table 4.3.5 – Classes of population size

Class	Population size	Class	Population size
1	<=500	10	20,001-30,000
2	501-1,000	11	30,001-40,000
3	1,001-2,000	12	40,001-50,000
4	2,001-3,000	13	50,001-65,000
5	3,001-4,000	14	65,001-80,000
6	4,001-5,000	15	80,001-100,000
7	5,001-10,000	16	100,001-250,000
8	10,001-15,000	17	250,001-500,000
9	**15,001-20,000**	**18**	**>=500,001**

Figure 4.3.7 – Regression tree (Node 0 and first partition)



In the node 0 it is possible to individuate the mean of the well-being composite indicator (97.525) and the standard deviation (2.744); the number of observations is 7,998 (the municipalities) that is the total of units considered in the analysis (100%). The first partition (that is the most important, in statistical terms because it presents the highest value of F) is characterized by the Zone (North-West, Nord-East, Centre, South and Islands). The highest level of well-being is present in the node 2 (North-East), in fact the value of the mean computed on the well-being composite indicator (99.797) of 1,419 municipalities is close to the reference value. Furthermore, the standard deviation is low (1.716), demonstrating a level of poor dispersion. Follow the values of North-West (Mean equal to 98.530 and standard deviation equal to 2.031), Centre (97.528, 2.138), South (95.551, 2.239) and Islands (93.942, 1.919).

Table 4.3.5 – Gain Summary for nodes

Node	N	Percent	Mean
57	107	1,30%	101,576
48	114	1,40%	101,239
59	72	0,90%	100,884
55	274	3,40%	100,269
51	156	2,00%	100,244
47	59	0,70%	100,227
58	89	1,10%	99,988
19	96	1,20%	99,857
12	111	1,40%	99,847
56	121	1,50%	99,710
46	401	5,00%	99,614
52	218	2,70%	99,611
62	128	1,60%	99,550
49	125	1,60%	99,530
43	119	1,50%	99,296
53	95	1,20%	99,194
10	222	2,80%	99,168
45	141	1,80%	99,052
41	169	2,10%	98,839
9	345	4,30%	98,830
38	142	1,80%	98,691
61	78	1,00%	98,629
42	156	2,00%	98,293
37	192	2,40%	98,043
54	94	1,20%	97,959
20	129	1,60%	97,942
26	88	1,10%	97,617
60	115	1,40%	97,612
44	134	1,70%	97,578
39	58	0,70%	97,514
34	365	4,60%	97,443
50	68	0,90%	97,295
69	61	0,80%	97,259
64	100	1,30%	97,162
21	61	0,80%	97,014
72	83	1,00%	97,002
27	104	1,30%	96,802
76	66	0,80%	96,669
40	126	1,60%	96,551
74	115	1,40%	96,527
36	93	1,20%	96,466
71	163	2,00%	96,435
68	148	1,90%	96,000

70	196	2,50%	95,969
80	106	1,30%	95,947
66	110	1,40%	95,928
63	114	1,40%	95,609
67	199	2,50%	95,041
35	91	1,10%	95,014
79	271	3,40%	94,407
65	54	0,70%	94,398
75	96	1,20%	94,262
29	138	1,70%	94,119
73	235	2,90%	93,907
78	213	2,70%	93,569
31	97	1,20%	93,424
77	177	2,20%	92,478

Table 4.3.5 shows the characteristics of all the nodes generated by the regression tree. At the node the corresponding number of municipalities (also as a percentage of the total) and the average value of the well-being composite indicator are associated.

As reported in the Figure 4.3.8, the node 57 is composed by a group of municipalities (107) whose composite indicator average is 101,576 and the standard deviation is equal to 1.5: it is important to analyse the path to get to node 57. The node 2 is partitioned for the population class; node 17 represents all the municipalities with a population greater than 10,000; node 17, in turn, is partitioned according to the variable province. Thus it appears that the best node in Italy (node 57) contains municipalities in the provinces of Bolzano, Verona, Belluno, Treviso, Padua and Bologna.

Figure 4.3.9 shows the path that leads to the worst node (77): node 5 is partitioned into two nodes (32 is Sicily and 33 is Sardinia) by the variable region. Sicily is partitioned into two nodes by class of population size. Node 77 gathers 177 municipalities of Sicily with a population of less than 4,000 inhabitants.

The other nodes are shown in the Annex I.

Figure 4.3.8 – The "best" node (57) of the regression tree

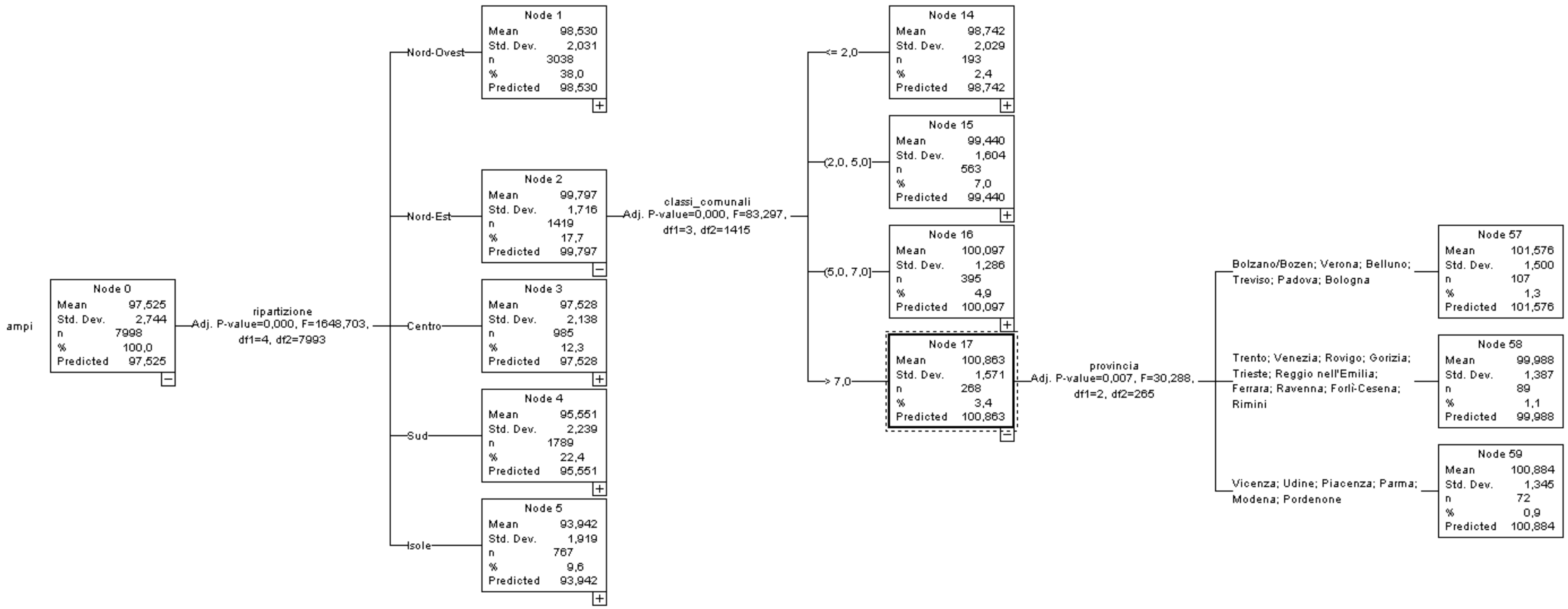
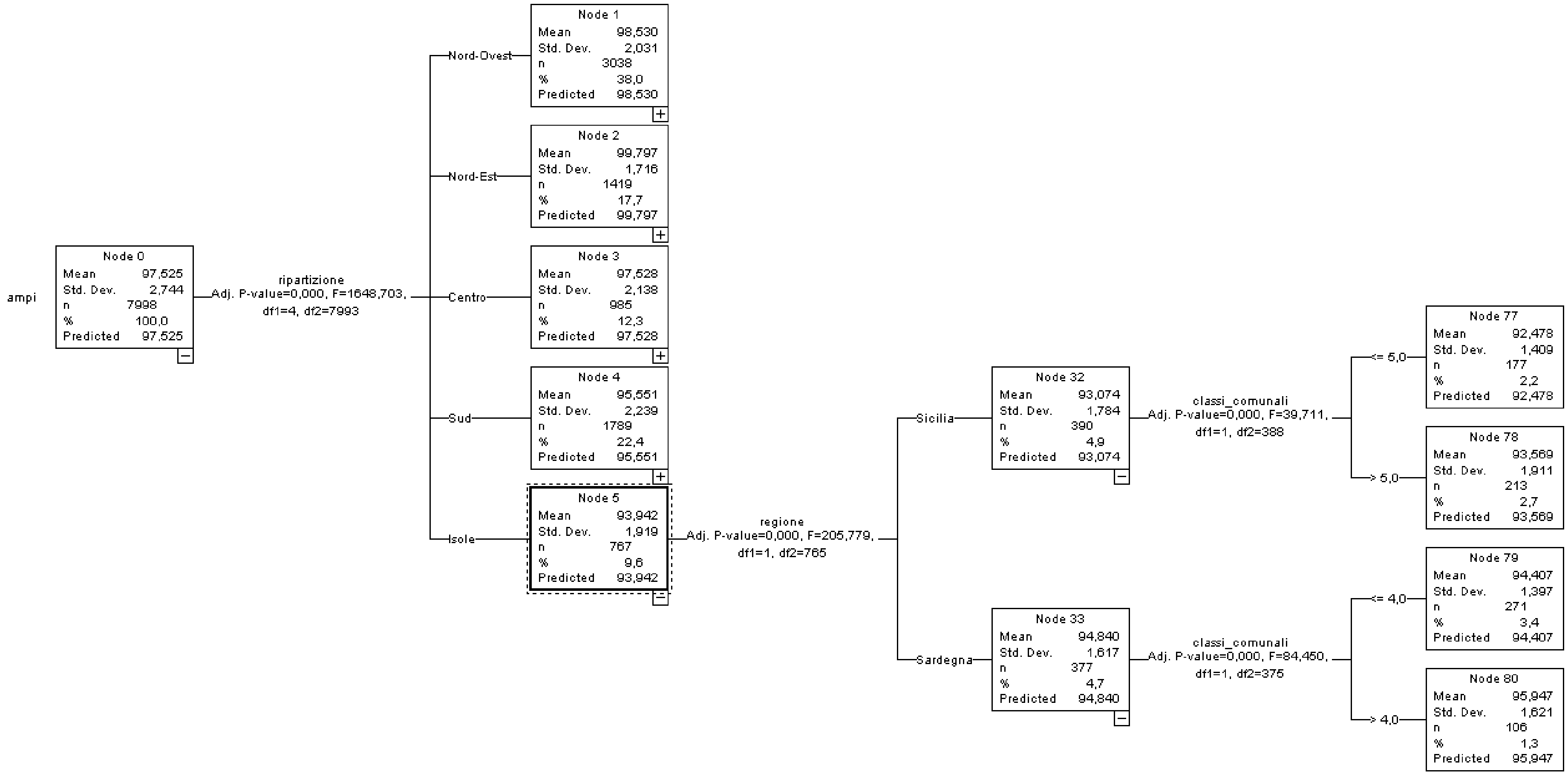


Figure 4.3.9 – The "worst" node (77) of the regression tree



Conclusions

The publication of the last three reports on Equitable and Sustainable Well-being (BES) by Istat is a central experience of study and socio-economic analysis for the entire international scientific community: composite indicators are calculated at regional level and over time for each of the nine outcome domains by creating a unique precedent in the official statistics at international level. Probably this very stimulating innovation has attracted the interest of policy makers at national and local level; hence several reflections were made not only in scientific journals but mostly on traditional media. The discussion is focused both on purely definitional aspects about the well-being of citizens and on methodological issues, more specifically the use of a set of individual indicators (dashboard) or on the application of composite indicators, because the scientific community is in agreement for supporting the multidimensionality of the phenomenon in a view "Beyond GDP" (Maggino, 2014). All this is even more relevant since the performance of well-being indicators have entered, by law, within the national budget and therefore public accounts (the reform of the budget law was approved by the parliament on July 28, 2016).

In this context, it seems important to provide high-quality statistics for the smallest territorial detail. Where traditional surveys cannot be of help because they are characterized by too small sample size, then it is necessary to use administrative sources and/or big data. The research proposed in this thesis is based on the selection of domains from the BES (the total is twelve) that represent the socio-economic conditions of the citizens on the municipalities. From each of the nine selected domains, individual indicators are extracted so that, based on a formative model (Diamantopoulos, 2008; Mazziotta and Pareto, 2017), they could well represent the multidimensional phenomenon well-being. The nine domains and the twenty socio-economic individual indicators are available at level of Italian municipality (7,998) from an integrated system of administrative sources (collected in ARCHIMEDE). Composite indicators, obtained by AMPI, are calculated into the domains and among the domains in order to measure well-being of the 7,998 municipalities, so that for each of them a single measure is provided (to make multidimensional reality one-dimensional). This "exercise of democracy" has a double objective: in fact, these values can be very useful for the evaluation of the intervention's policies by local administrators and for the assessment of the administrators themselves by the citizens (OECD, 2008). This means that one of the most important phases of the research is the best practice for publishing these results so that everyone can have easy access in order to better understand the socio-economic context and decide independently through data recognized as impartial by the Community.

The experimentation on the data of nine domains seems to achieve satisfactory results both methodologically and theoretically. Preliminary data analysis shows that the correlations among the indicators have a correct polarity and that some indicators are almost orthogonal to each other and therefore they are very informative from a statistical point of view: so, the goodness of the choice of indicators is also confirmed by an objective approach (a formative model is adopted, therefore, theoretically, correlations should not be relevant to the selection of the indicators). The composite indicator calculated on all Italian municipalities draws a well-known geography of social and economic conditions. In fact, the peninsula seems to be divided into three parts with the conditions getting worse going south. The North-east seems to be better than the North-west and the Centre-north better than the Centre.

The composite indicator and demographic amplitude are basically uncorrelated and this means that there is no link between well-being of the municipality and its population size: rather there is a relation with localization in the Italian territory. In fact the analysis of the results, conducted with descriptive techniques and more complex classification methods (regression trees based on CHAID), shows a very precise geography in which about 800 medium sized municipalities located mainly in the North-East have a level of well-being decidedly superior to the rest Italy. At the same time, there are about 700 small-sized municipalities concentrated in Sicily, Sardinia and Calabria with a lower level of well-being than other municipalities. And most of the municipalities that are around a satisfactory average level of well-being are the majority. And this seems a very important aspect to consider.

However, these conclusions do not appear to be the relevant aspects that emerge from the thesis. The fact that Italy is divided into three parts, that their distances are increasing and that the velocities are very different, are concepts known in the literature. In fact, the goal of the thesis is not this. The most important conclusion of the thesis is that the statistical analyses confirm this assumption by introducing innovative elements and original ideas:

- the socio-economic indicators at the municipal level from the administrative sources are calculable and the level of quality is high;
- it is possible to represent and read complex phenomena through the use of composite indicators;
- the regression tree is a classification method suitable for use of municipal data;
- socio-economic indicators and composite indicators must enter the political debate;
- the economic planning of the territory (municipal and sub-municipal) can exploit these disaggregated databases published in Istat web-site in August 2018.

However, the type of data available would require the analysis to be made for details of particular smaller areas as Local Labour Systems (LLS), neighbourhoods of large cities or special sub-populations such as people with disabilities, homeless, people detained in prison, etc. In fact, the main objective is to use this data for the evaluation of public policies and to provide an objective set of available social and economic measures to thematic experts and ordinary citizens in order to assess the performance of actions on the territory. The research in this scientific field is making great strides. Nevertheless, it seems necessary that the use of administrative sources and big data (such as mobile data, scanner data and others) is associated with sample surveys that can, for example, collect types of subjective variables. This new scenario could change radically, on the one hand, the production of official statistics, and other, the analyses of socio-economic phenomena.

The thesis shows how important it is to define a theoretical framework that is a basic concept that supports all the following, methodological and not only, actions. The "scientific path" of measuring well-being places Italy and Istat at the forefront of the world both from a definitional and a methodological point of view. In fact the BES project is a unique case in international literature and, in any case, is an example for other Statistic Institutes that tried to calculate composite indicators for the measurement of well-being (Portugal and Mexico). The choice of the methods for constructing composite indicators is not independent from the definition of the theoretical framework. The description of the statistical methodologies of normalization and aggregation of the individual indicators aims to demonstrate that the researcher's ability is to associate the best methodology with the theory. This can be done for any type of indicator, over time, and for any territorial disaggregation.

References

Bandura, R. (2008). A *Survey of Composite Indices Measuring Country Performance: 2008 Update*. A UNDP/ODS Working Paper, New York.

Bleys, B. (2012). Beyond GDP: Classifying Alternative Measures for Progress. *Social Indicators Research*, 109, 355-376.

Boarini, R., Kolev, A., & McGregor, A. (2014). Measuring well-being and progress in countries at different stages of development: Towards a more universal conceptual framework. Working Paper No. 325. OECD Development Centre.

Booysen, F. (2002). An overview and evaluation of composite indices of development. *Social Indicators Research*, 59, 115-151.

Casadio Tarabusi, E., Guarini, G. (2013). An Unbalance Adjustment Method for Development Indicators. *Social Indicators Research*, 112, 19-45.

Ciommi M. T., Gentili A., Ermini B., Gigliarano C., Chelli F. M., Gallegati M. (2016). Have Your Cake and Eat it Too: The Well-Being of Italians (1861-2011). Social Indicators Research, DOI 10.1007/s11205-016-1450-y. Springer.

Coltman, T., Devinney, T. M., Midgley, D. F., & Venaik, S. (2008). Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business Research*, 61, 1250-1262.

De Muro, Pasquale, Matteo Mazziotta, and Adriano Pareto. 2011. “Composite Indices of Development and Poverty: An Application to MDGs”. Social Indicators Research 104: 1-18.

Diamantopoulos, Adamantios, Petra Riefler, and Katharina Roth. 2008. “Advancing formative measurement models.” Journal of Business Research 61: 1203–1218.

Diamantopoulos, A., Winklhofer, H. M. (2001). Index Construction with Formative Indicators: An Alternative to Scale Development. *Journal of Marketing Research*, 38, 269-277.

Dunteman, G. H. (1989). Principal Components Analysis. Newbury Park: Sage Publications

Easterlin R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. Nations and households in economic growth, 89, 89-125.

European Commission (2009). Comunicazione della Commissione al Consiglio e al Parlamento europeo. Non solo PIL. Misurare il progresso in un mondo in cambiamento. Bruxelles, 20 agosto 2009

Freudenberg, M. (2003). *Composite indicators of country performance: a critical assessment*. OECD, DSTI/IND, 5, Paris.

Garofalo, Giuseppe. 2014. “Il progetto ARCHIMEDE: obiettivi e risultati sperimentali.” Istat Working Paper 9. Rome: Istat.

Giovannini, E. (2011). Misurare il benessere delle persone e della società: una sfida per la statistica e la politica. Le Conversazioni dell’AREL.

Giovannini, E., Rondinella, T. (2012). Measuring Equitable and Sustainable Well-Being in Italy. In: F. Maggino, G. Nuvolati (eds.), *Quality of Life in Italy: Research and Reflections* (pp. 27-40). Springer, New York.

Giudici, P., Avrini, F. (2002). Modelli statistici per la costruzione di indicatori della qualità della vita: aspetti metodologici. *Rivista di statistica ufficiale*, 1, 61-80.

Gnesi, C., Segre, E., Villa, A. (2010). *Come si vive in Italia? Rapporto QUARS 2010 – Indice di qualità regionale dello sviluppo*. www.sbilanciamoci.org.

Guilford, J. P. (1954). *Psychometric methods*. McGraw-Hill, New York-London.

Jacobs, R., Smith, P., Goddard, M. (2004). Measuring performance: An examination of composite performance indicators. The University of York, CHE Technical Paper Series, 29, York.

Hall, J.C., Crowley G.R., Sobel R. S. (2010). Institutions, Capital, and Growth. Southern Economic Journal. Volume 77, Issue 2, pp. 385-405. Wiley.

Harbison, F. H., Maruhnic, J., Resnick, J. R. (1970). *Quantitative Analyses of. Modernization and Development*. Princeton University Press, New Jersey.

Hotelling, H. (1933). Analysis of a Complex of Statistical Variables Into Principal Components. *Journal of Educational Psychology*, 24, 417-441.

Istat. (2017). Rapporto sul benessere equo e sostenibile.

Istat. (2015). Rapporto sul benessere equo e sostenibile.

Istat. (2016). Rapporto sul benessere equo e sostenibile.

Jarvis, C. B., Mackenzie, S. B., & Podsakoff, P. M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research*, 30, 199-218.

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society*, A 374: 20150202. http://dx.doi.org/10.1098/rsta.2015.0202

Maggino F. (2006). *Gli indicatori statistici: concetti, metodi e applicazioni*. Firenze: University Press, Archivio E-Prints. (da citare nel testo)

Maggino, Filomena. 2014. "Indicator Development and Construction." Pp. 3190-3197 in Encyclopedia of Quality of Life and Well-Being Research, edited by A. C. Michalos. Dordrecht: Springer.

Maggino, F. (2017). Developing Indicators and Managing the Complexity. In: F. Maggino (Eds.), *Complexity in Society: From Indicators Construction to their Synthesis* (pp. 87-114). Social Indicators Research Series, vol. 70. Springer, Cham.

Maggino, F., & Zumbo, B. D. (2012). Measuring the Quality of Life and the Construction of Social Indicators. In: Kenneth C. Land, Alex C. Michalos, & M. Joseph Sirgy (Eds.), *Handbook of Social Indicators and Quality-of-Life Research*, (pp. 201-238). Dordrecht, Netherlands: Springer Publishers.

Mazziotta M., Pareto A., 2013. Methods for Constructing Composite Indices: One for all or all for one, *Rivista Italiana di Economia Demografia e Statistica*, Vol. LXVII, n. 2, pp. 67-80.

Mazziotta, Claudio, Matteo Mazziotta, Adriano Pareto, Francesco Vidoli. 2010. “La sintesi di indicatori territoriali di dotazione infrastrutturale: metodi di costruzione e procedure di ponderazione a confronto”, Rivista di Economia e Statistica del Territorio (Review of Economics and Statistics for Regional Studies): n. 1.

Mazziotta, Matteo and Adriano Pareto. 2011. “Un indice sintetico non compensativo per la misura della dotazione infrastrutturale: un’applicazione in ambito sanitario”. Rivista di Statistica Ufficiale 1: 63-79.

Mazziotta, Matteo and Adriano Pareto. 2013. "Methods for Constructing Composite Indices: One for all or all for one” in Rivista Italiana di Economia Demografia e Statistica LXVII (2): 67-80.

Mazziotta, M., Pareto, A. (2015). Comparing Two Non-Compensatory Composite Indices to Measure Changes over Time: a Case Study. *Statistika*, 95, 44-53.

Mazziotta, Matteo and Adriano Pareto. 2016. “On a Generalized Non-compensatory Composite indicator for Measuring Socio-economic Phenomena”. Social Indicators Research 127 (3): 983-1003.

Mazziotta, Matteo, Adriano Pareto. 2017. “Synthesis of indicators: the composite indicators approach”. In: “Complexity in Society: From Indicators Construction to their Synthesis”, Filomena Maggino Editors. Social Indicators Research Series: 159-191. Springer.

Mazziotta, Matteo. 2017. “Well-Being Composite Indicators for Italian Municipalities: Case Study of Basilicata”. Working papers Series n.1/2017. Department of Social Sciences and Economics, Sapienza University of Rome.

Michalos, A. C. (2014). *Encyclopedia of Quality of Life and Well-Being Research*. Dordrecht, Netherlands: Springer.

Mishra, S. K. (2007). *A Comparative Study of Various Inclusive Indices and the Index Constructed by the Principal Components Analysis*. MPRA Paper, 3377. Available at: http://mpra.ub.uni-muenchen.de/3377.

Munda, G., Nardo, M. (2009). Non-compensatory/non-linear composite indicators for ranking countries: A defensible setting. *Applied Economics,* 41, 1513-1523.

Nahman, A., Mahumani, B. K., & De Lange W. J. (2016). Beyond GDP: Towards a Green Economy Index. *Development Southern Africa*, DOI: 10.1080/0376835X.2015.1120649.

Nordaus, W. D., Tobin, J. (1972). Is Growth Obsolete? In: National Bureau of Economic Research, *Economic Research: Retrospect and Prospect* (pp. 1-80). Columbia University Press, New York

OECD (2004). The OECD-JRC Handbook on Practices for Developing Composite Indicators. Paper presented at the OECD Committee on Statistics, 7-8 June 2004, OECD, Paris.

OECD (2015*). How's Life? 2015: Measuring Well-being*. Paris: OECD Publishing.

OECD (2011). *Compendium of OECD Well-being Indicators*. OECD, Paris.

OECD-JRC (2008). *Handbook on constructing composite indicators: Methodology and user guide*. Paris: OECD.

Rinaldi A., Zelli R., 2014. Misurare il benessere. La sfida degli indicatori alternativi al Pil. Roma: Donzelli Editore.

Saisana, M., Tarantola, S. (2002). *State-of-the-art report on current methodologies and practices for composite indicator development*. European Commission-JRC, EUR 20408 EN, Ispra.

Saisana, M., Tarantola, S., Saltelli, A. (2005). Uncertainty and sensitivity techniques as tools for the analysis and validation of composite indicators. *Journal of the Royal Statistical Society A*, 168, 307-323.

Saltelli, A. (2007). Composite Indicators between analysis and advocacy. *Social Indicators Research*, 81, 65-77.

Salzman, Julia. 2003. Methodological Choices Encountered in the Construction of Composite Indices of Economic and Social Well-Being. Ottawa: Centre for the Study of Living Standards.

Sen, A. K. (1985). *Commodities and capabilities*. Amsterdam: North Holland Publishing Company.

Silvio-Pomenta, J. F. (1973). *Typological study using the Wroclaw Taxonomic Method (A study of regional disprities in Venezuela)*. SHC/WS/316, UNESCO, Paris.

Simonetto, A. (2012). Formative and reflective models: State of the art. *Electronic Journal of Applied Statistical Analysis*, 5, 452-457.

Stiglitz J.E., Sen A. & Fitoussi J.P. (2009). Report by the commission on the measurement of economic performance and social progress. Paris: Commission on the Measurement of Economic Performance and Social Progress.

Tarantola, S. (2008). *European Innovation Scoreboard: strategies to measure country progress over time*. JRC Scientific and Technical Reports, EUR 23526 EN, Luxembourg.

UNDP (1990). *Human Development Report 1990: Concept and Measurement of Human Development.* Oxford University Press, Oxford.

UNDP (2001). *Human Development Report 2001*. Oxford University Press, New York.

UNDP (2010). *Human Development Report 2010*. Palgrave Macmillan, New York.

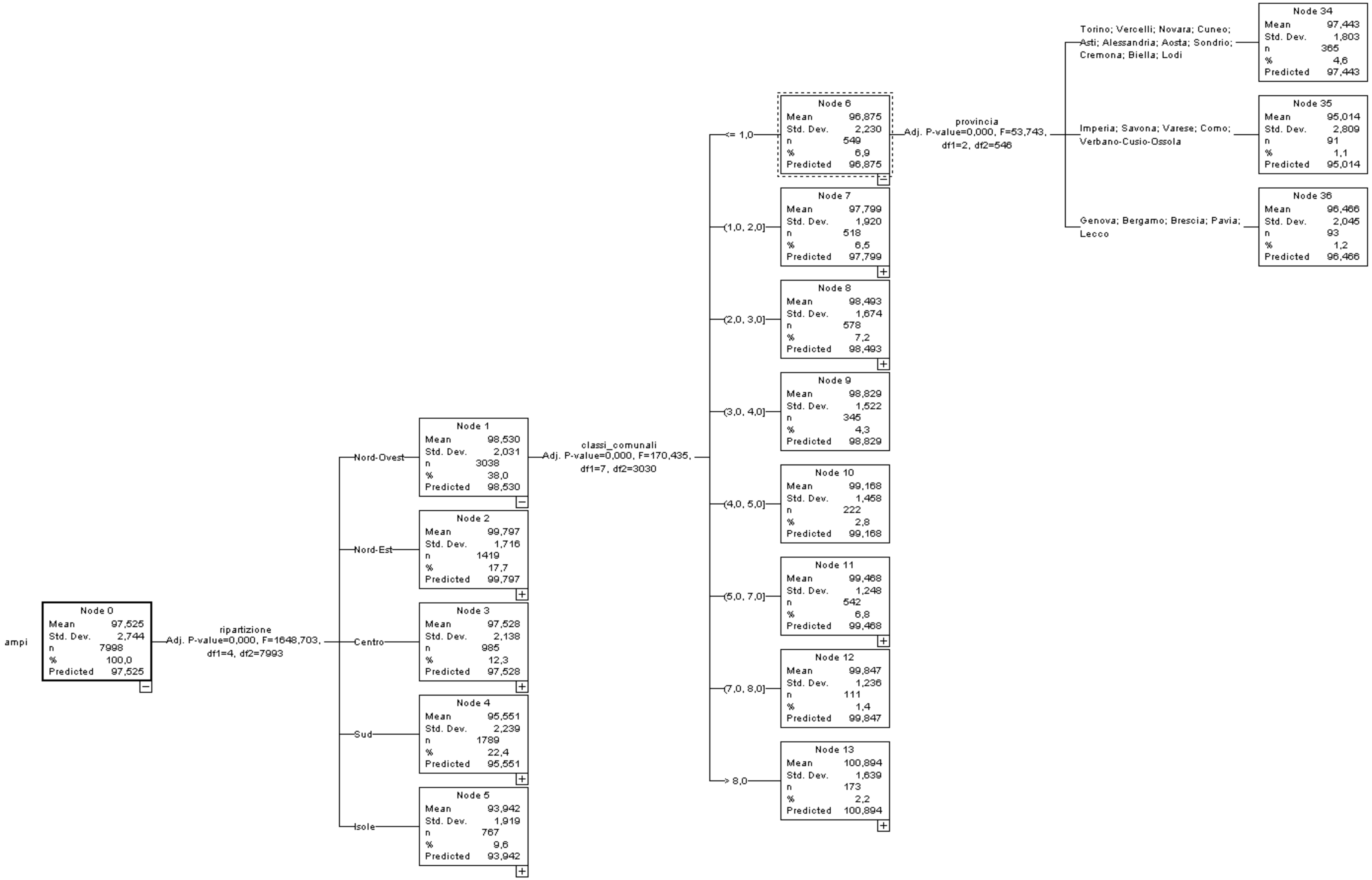
USAID (2014). *Design and Use of Composite Indices in Assessments of Climate Change Vulnerability and Resilience*. U.S. Agency for International Development, Washington.

Van Beuningen, J., Van der Houwen, K., & Moonen, L. (2014). Measuring well-being. An analysis of different response scales. Discussion Paper, 3. Statistics Netherlands.

Veenhoven, R. (1996). Happy Life-Expectancy. A Comprehensive Measure of Quality of Life in Nations. *Social Indicators Research*, 39, 1-58.

ANNEX I – The Regression Trees

North-West



ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
Nord-Ovest
Nord-Est
Centro
Sud
Isole
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=170,435, df1=7, df2=3030
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n 549
% 6,9
Predicted 96,875
Node 7
Mean 97,799
Std. Dev. 1,920
n 518
% 6,5
Predicted 97,799
Node 8
Mean 98,493
Std. Dev. 1,674
n 578
% 7,2
Predicted 98,493
Node 9
Mean 98,829
Std. Dev. 1,522
n 345
% 4,3
Predicted 98,829
Node 10
Mean 99,168
Std. Dev. 1,458
n 222
% 2,8
Predicted 99,168
Node 11
Mean 99,468
Std. Dev. 1,248
n 542
% 6,8
Predicted 99,468
Node 12
Mean 99,847
Std. Dev. 1,236
n 111
% 1,4
Predicted 99,847
Node 13
Mean 100,894
Std. Dev. 1,639
n 173
% 2,2
Predicted 100,894
provincia
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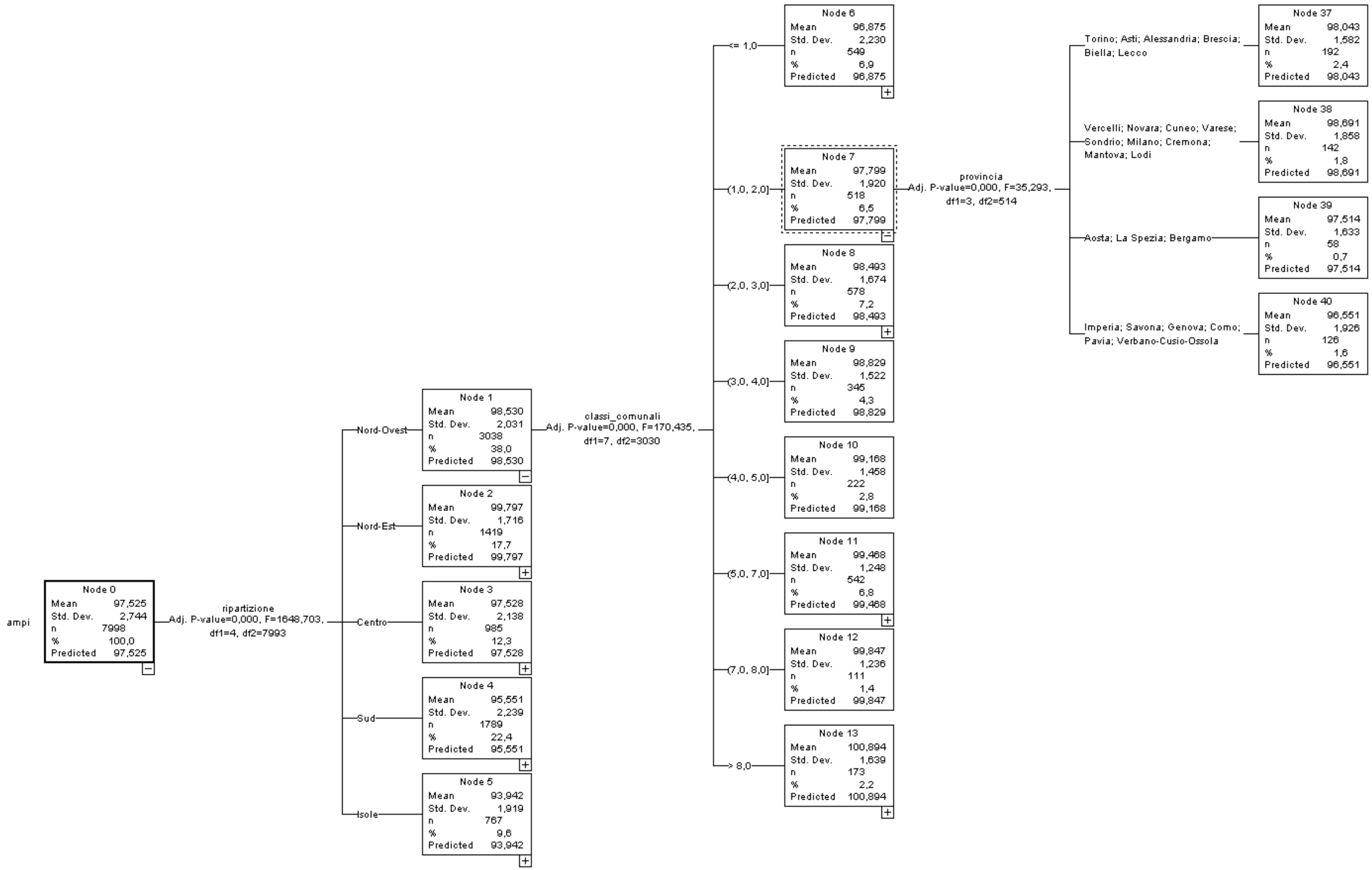
Torino; Vercelli; Novara; Cuneo; Asti; Alessandria; Aosta; Sondrio; Cremona; Biella; Lodi
Imperia; Savona; Varese; Como; Verbano-Cusio-Ossola
Genova; Bergamo; Brescia; Pavia; Lecco
Node 34
Mean 97,443
Std. Dev. 1,803
n 365
% 4,6
Predicted 97,443
Node 35
Mean 95,014
Std. Dev. 2,809
n 91
% 1,1
Predicted 95,014
Node 36
Mean 96,466
Std. Dev. 2,045
n 93
% 1,2
Predicted 96,466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Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
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Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
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Sud
Isole
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
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Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
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Adj. P-value=0,000, F=170,435,
df1=7, df2=3030
<= 1,0
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(5,0, 7,0]
(7,0, 8,0]
> 8,0
Node 6
Mean 96,875
Std. Dev. 2,230
n 549
% 6,9
Predicted 96,875
Node 7
Mean 97,799
Std. Dev. 1,920
n 518
% 6,5
Predicted 97,799
Node 8
Mean 98,493
Std. Dev. 1,674
n 578
% 7,2
Predicted 98,493
Node 9
Mean 98,829
Std. Dev. 1,522
n 345
% 4,3
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Mean 99,168
Std. Dev. 1,458
n 222
% 2,8
Predicted 99,168
Node 11
Mean 99,468
Std. Dev. 1,248
n 542
% 6,8
Predicted 99,468
Node 12
Mean 99,847
Std. Dev. 1,236
n 111
% 1,4
Predicted 99,847
Node 13
Mean 100,894
Std. Dev. 1,639
n 173
% 2,2
Predicted 100,894
provincia
Adj. P-value=0,000, F=35,293,
df1=3, df2=514
Torino; Asti; Alessandria; Brescia; Biella; Lecco
Vercelli; Novara; Cuneo; Varese; Sondrio; Milano; Cremona; Mantova; Lodi
Aosta; La Spezia; Bergamo
Imperia; Savona; Genova; Como; Pavia; Verbano-Cusio-Ossola
Node 37
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Std. Dev. 1,582
n 192
% 2,4
Predicted 98,043
Node 38
Mean 98,691
Std. Dev. 1,858
n 142
% 1,8
Predicted 98,691
Node 39
Mean 97,514
Std. Dev. 1,633
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% 0,7
Predicted 97,514
Node 40
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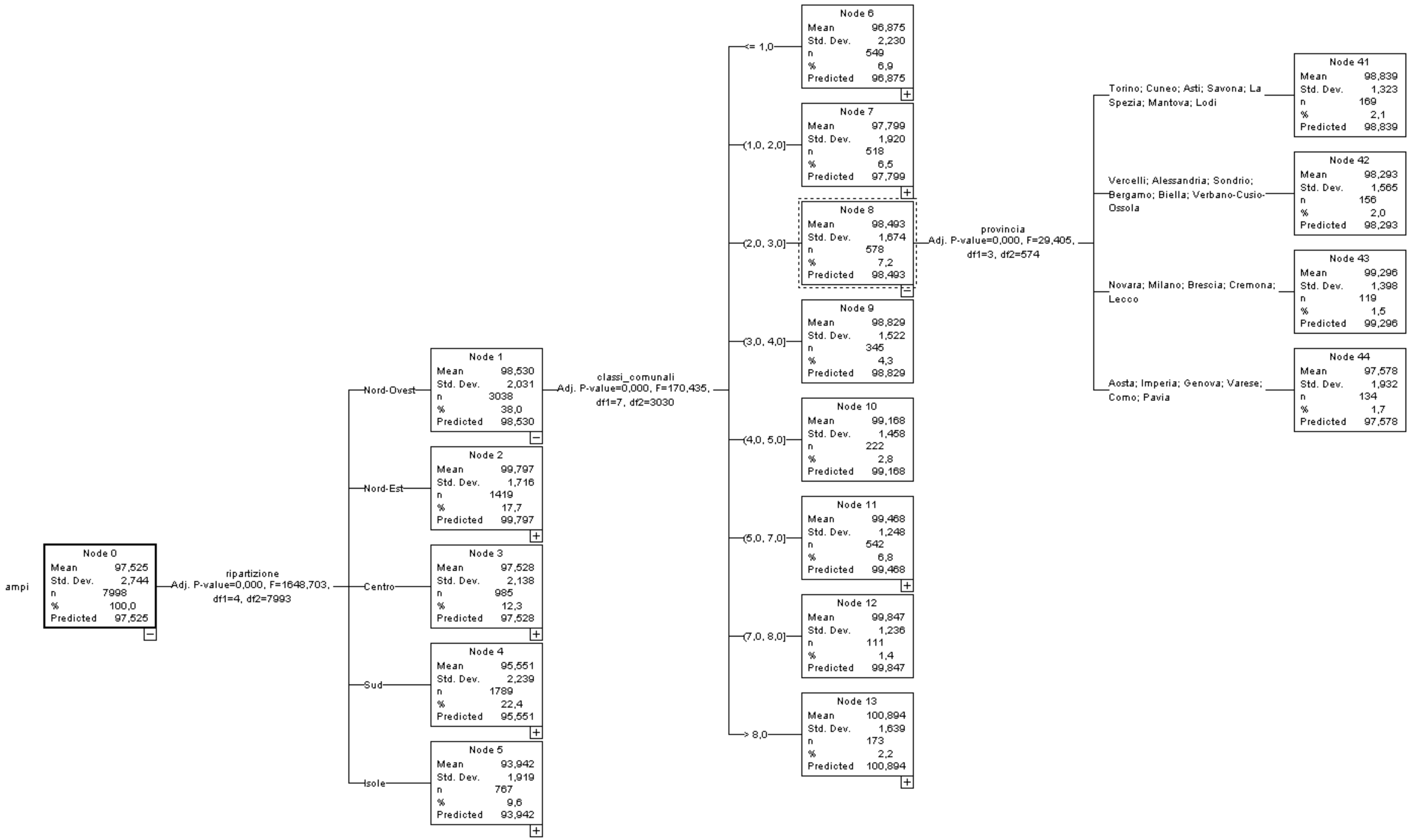
n 126
% 1,6
Predicted 96,551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Node 0
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Std. Dev. 2,744
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Predicted 97,525
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Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
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Std. Dev. 2,031
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Mean 99,797
Std. Dev. 1,716
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% 17,7
Predicted 99,797
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Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=170,435, df1=7, df2=3030
<= 1,0
(1,0, 2,0]
(2,0, 3,0]
(3,0, 4,0]
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(5,0, 7,0]
(7,0, 8,0]
> 8,0
Node 6
Mean 96,875
Std. Dev. 2,230
n 549
% 6,9
Predicted 96,875
Node 7
Mean 97,799
Std. Dev. 1,920
n 518
% 6,5
Predicted 97,799
Node 8
Mean 98,493
Std. Dev. 1,674
n 578
% 7,2
Predicted 98,493
Node 9
Mean 98,829
Std. Dev. 1,522
n 345
% 4,3
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Node 10
Mean 99,168
Std. Dev. 1,458
n 222
% 2,8
Predicted 99,168
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Mean 99,468
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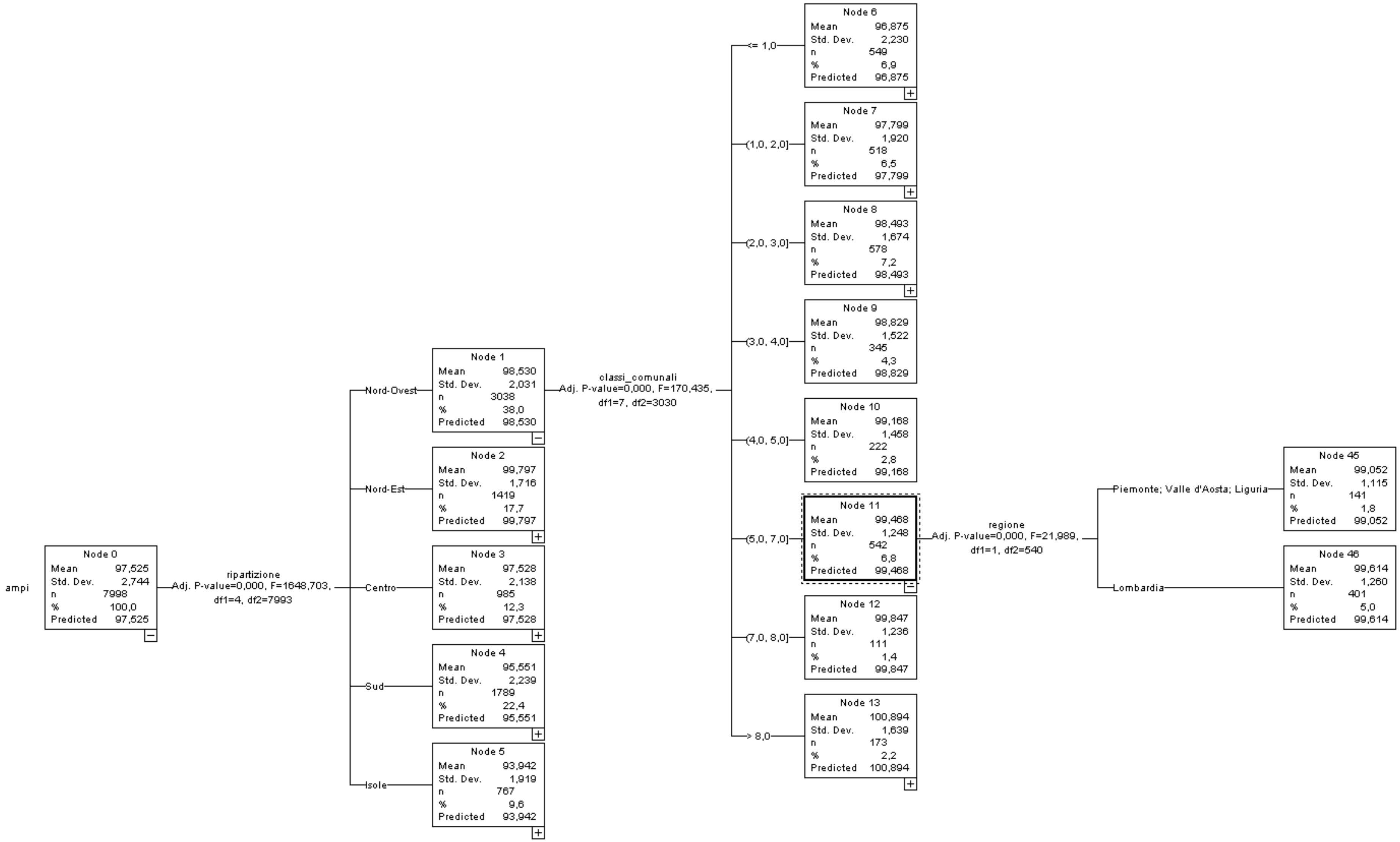
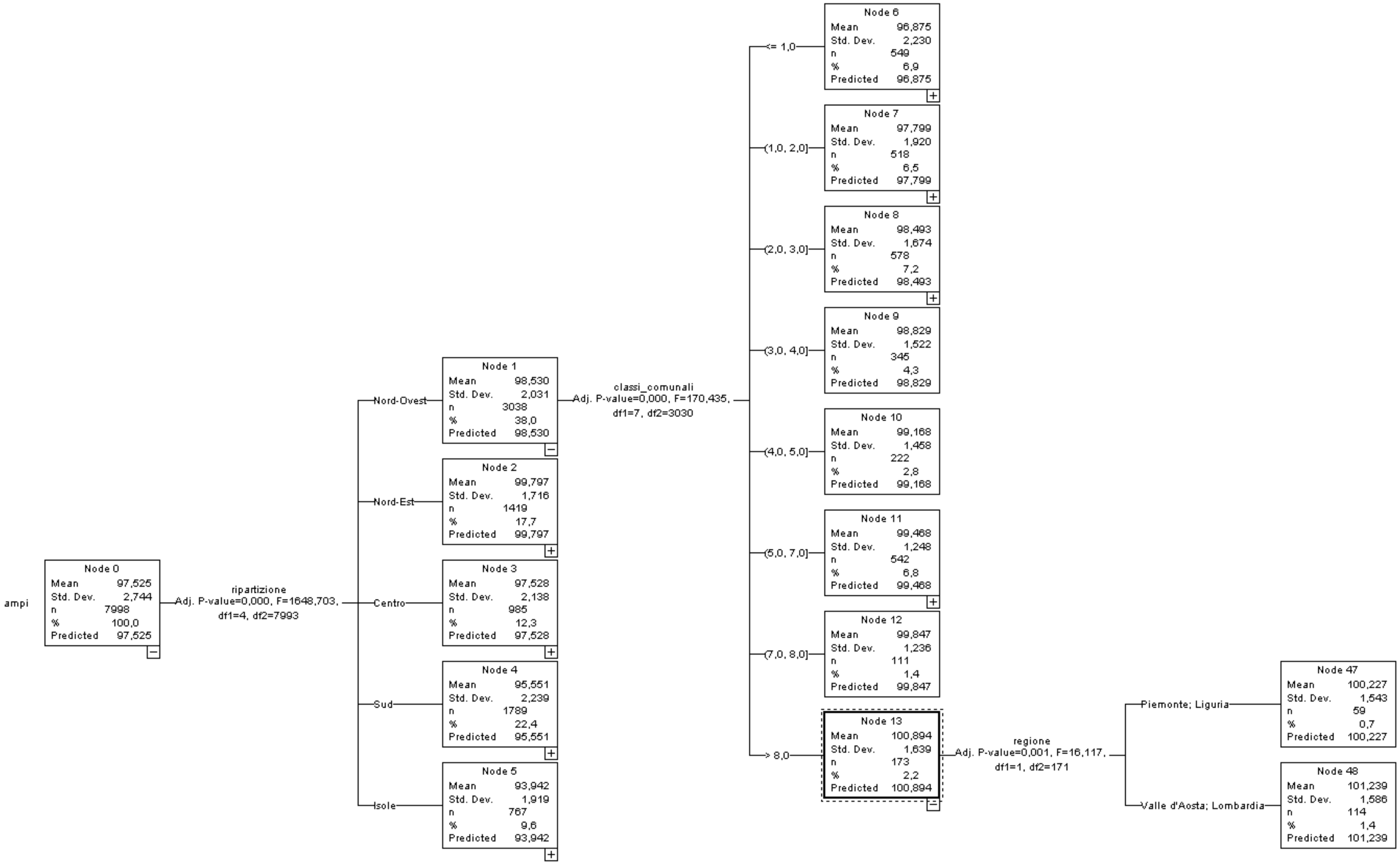
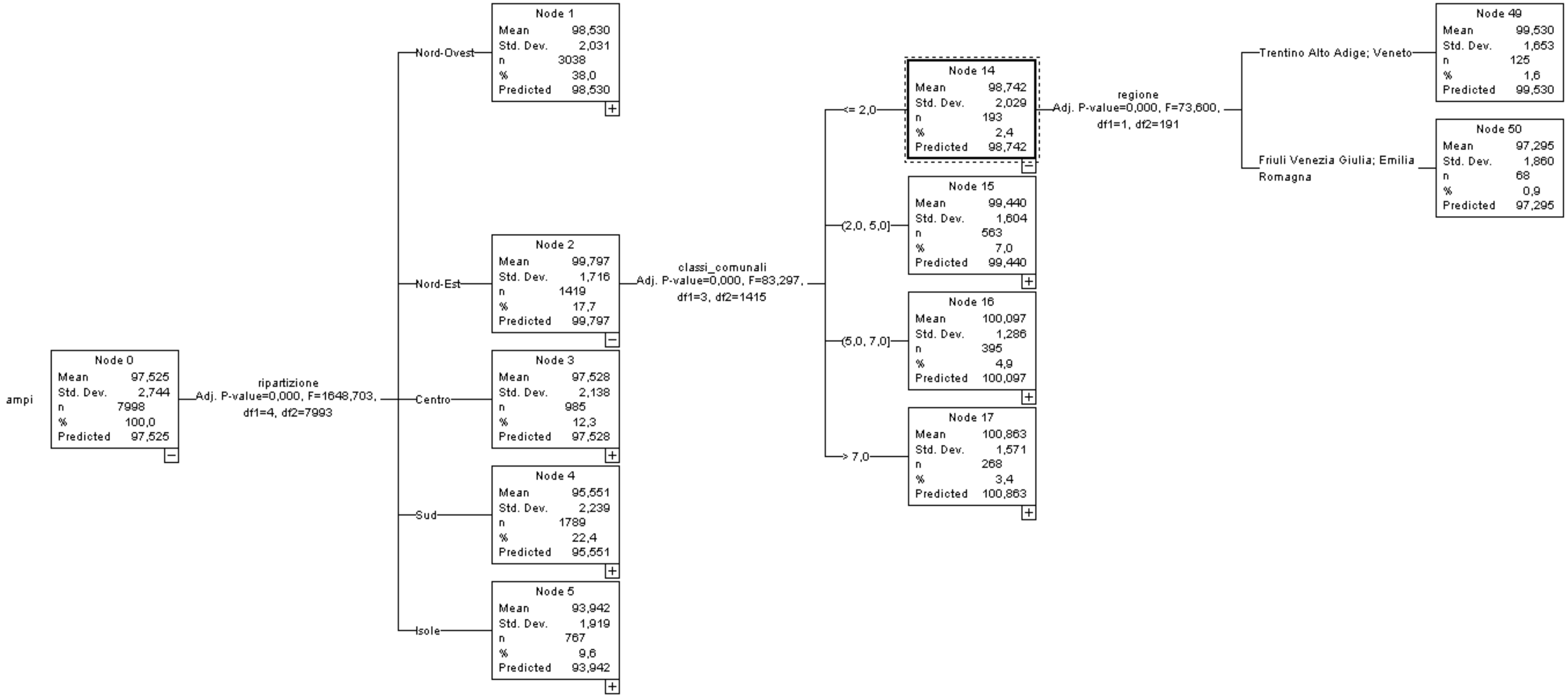
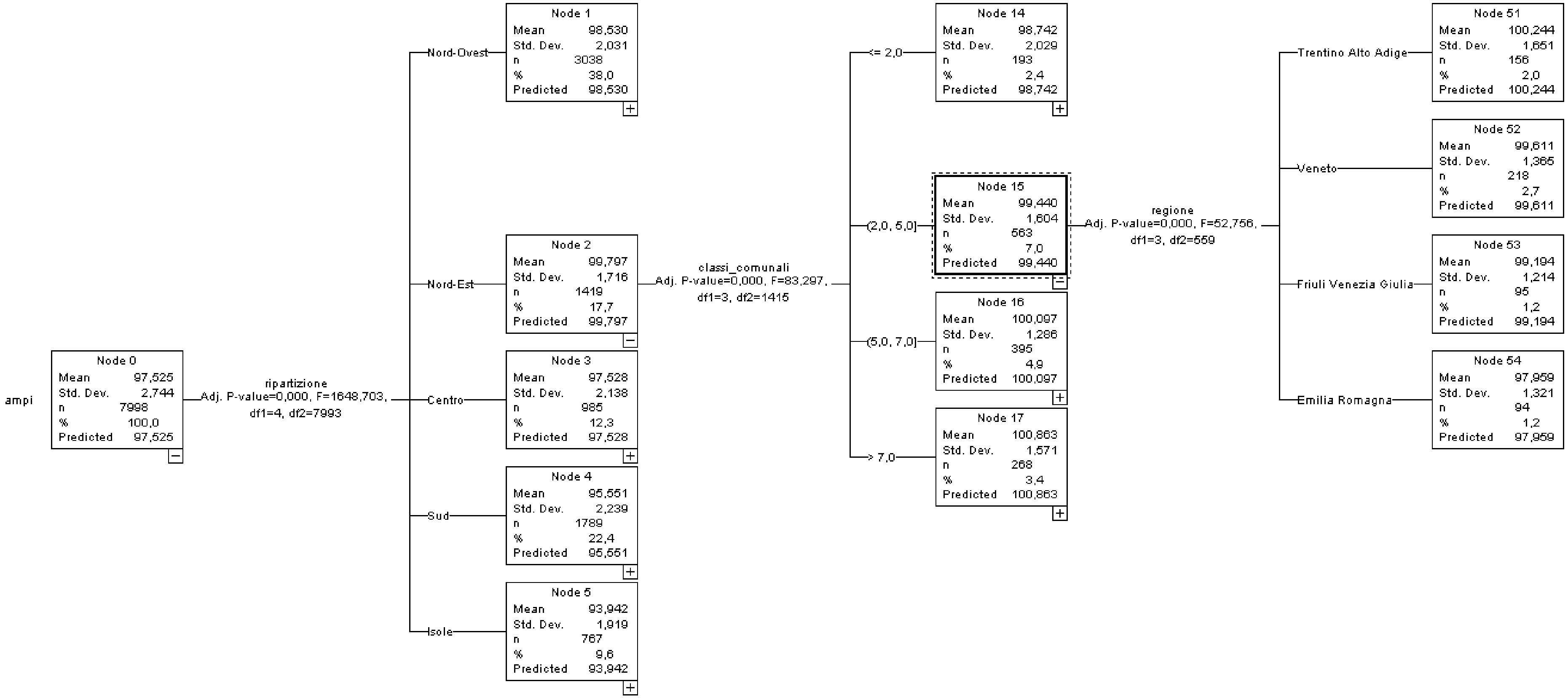
Node 12
Mean 99,847
Std. Dev. 1,236
n 111
% 1,4
Predicted 99,847
Node 13
Mean 100,894
Std. Dev. 1,639
n 173
% 2,2
Predicted 100,894
provincia
Adj. P-value=0,000, F=29,405, df1=3, df2=574
Torino; Cuneo; Asti; Savona; La Spezia; Mantova; Lodi
Vercelli; Alessandria; Sondrio; Bergamo; Biella; Verbano-Cusio-Ossola
Novara; Milano; Brescia; Cremona; Lecco
Aosta; Imperia; Genova; Varese; Como; Pavia
Node 41
Mean 98,839
Std. Dev. 1,323
n 169
% 2,1
Predicted 98,839
Node 42
Mean 98,293
Std. Dev. 1,565
n 156
% 2,0
Predicted 98,293
Node 43
Mean 99,296
Std. Dev. 1,398
n 119
% 1,5
Predicted 99,296
Node 44
Mean 97,578
Std. Dev. 1,932
n 134
% 1,7
Predicted 97,578

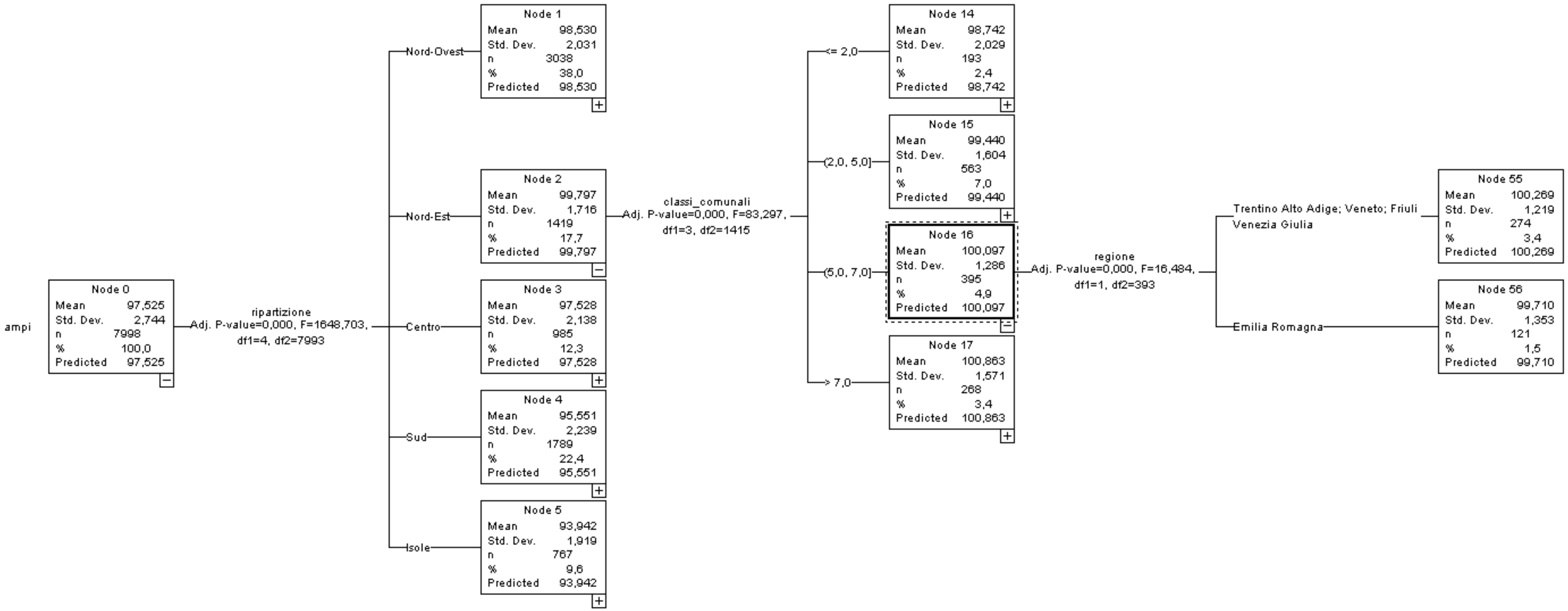

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Nord-Est
Centro
Sud
Isole
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=170,435,
df1=7, df2=3030
<= 1,0
(1,0, 2,0]
(2,0, 3,0]
(3,0, 4,0]
(4,0, 5,0]
(5,0, 7,0]
(7,0, 8,0]
> 8,0
Node 6
Mean 96,875
Std. Dev. 2,230
n 549
% 6,9
Predicted 96,875
Node 7
Mean 97,799
Std. Dev. 1,920
n 518
% 6,5
Predicted 97,799
Node 8
Mean 98,493
Std. Dev. 1,674
n 578
% 7,2
Predicted 98,493
Node 9
Mean 98,829
Std. Dev. 1,522
n 345
% 4,3
Predicted 98,829
Node 10
Mean 99,168
Std. Dev. 1,458
n 222
% 2,8
Predicted 99,168
Node 11
Mean 99,468
Std. Dev. 1,248
n 542
% 6,8
Predicted 99,468
Node 12
Mean 99,847
Std. Dev. 1,236
n 111
% 1,4
Predicted 99,847
Node 13
Mean 100,894
Std. Dev. 1,639
n 173
% 2,2
Predicted 100,894
regione
Adj. P-value=0,000, F=21,989,
df1=1, df2=540
Piemonte; Valle d'Aosta; Liguria
Lombardia
Node 45
Mean 99,052
Std. Dev. 1,115
n 141
% 1,8
Predicted 99,052
Node 46
Mean 99,614
Std. Dev. 1,260
n 401
% 5,0
Predicted 99,614

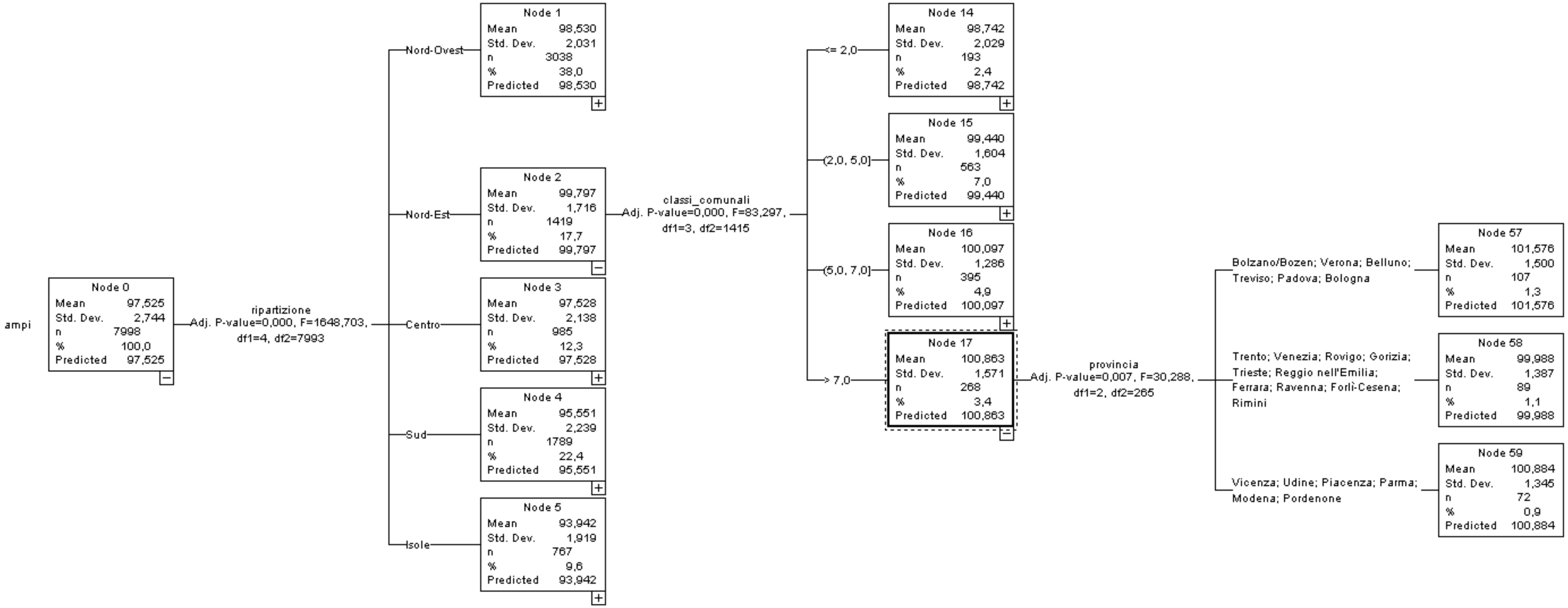

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Nord-Est
Centro
Sud
Isole
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=170,435,
df1=7, df2=3030
<= 1,0
(1,0, 2,0]
(2,0, 3,0]
(3,0, 4,0]
(4,0, 5,0]
(5,0, 7,0]
(7,0, 8,0]
> 8,0
Node 6
Mean 96,875
Std. Dev. 2,230
n 549
% 6,9
Predicted 96,875
Node 7
Mean 97,799
Std. Dev. 1,920
n 518
% 6,5
Predicted 97,799
Node 8
Mean 98,493
Std. Dev. 1,674
n 578
% 7,2
Predicted 98,493
Node 9
Mean 98,829
Std. Dev. 1,522
n 345
% 4,3
Predicted 98,829
Node 10
Mean 99,168
Std. Dev. 1,458
n 222
% 2,8
Predicted 99,168
Node 11
Mean 99,468
Std. Dev. 1,248
n 542
% 6,8
Predicted 99,468
Node 12
Mean 99,847
Std. Dev. 1,236
n 111
% 1,4
Predicted 99,847
Node 13
Mean 100,894
Std. Dev. 1,639
n 173
% 2,2
Predicted 100,894
regione
Adj. P-value=0,001, F=16,117,
df1=1, df2=171
Piemonte; Liguria
Valle d'Aosta; Lombardia
Node 47
Mean 100,227
Std. Dev. 1,543
n 59
% 0,7
Predicted 100,227
Node 48
Mean 101,239
Std. Dev. 1,586
n 114
% 1,4
Predicted 101,239

North-East

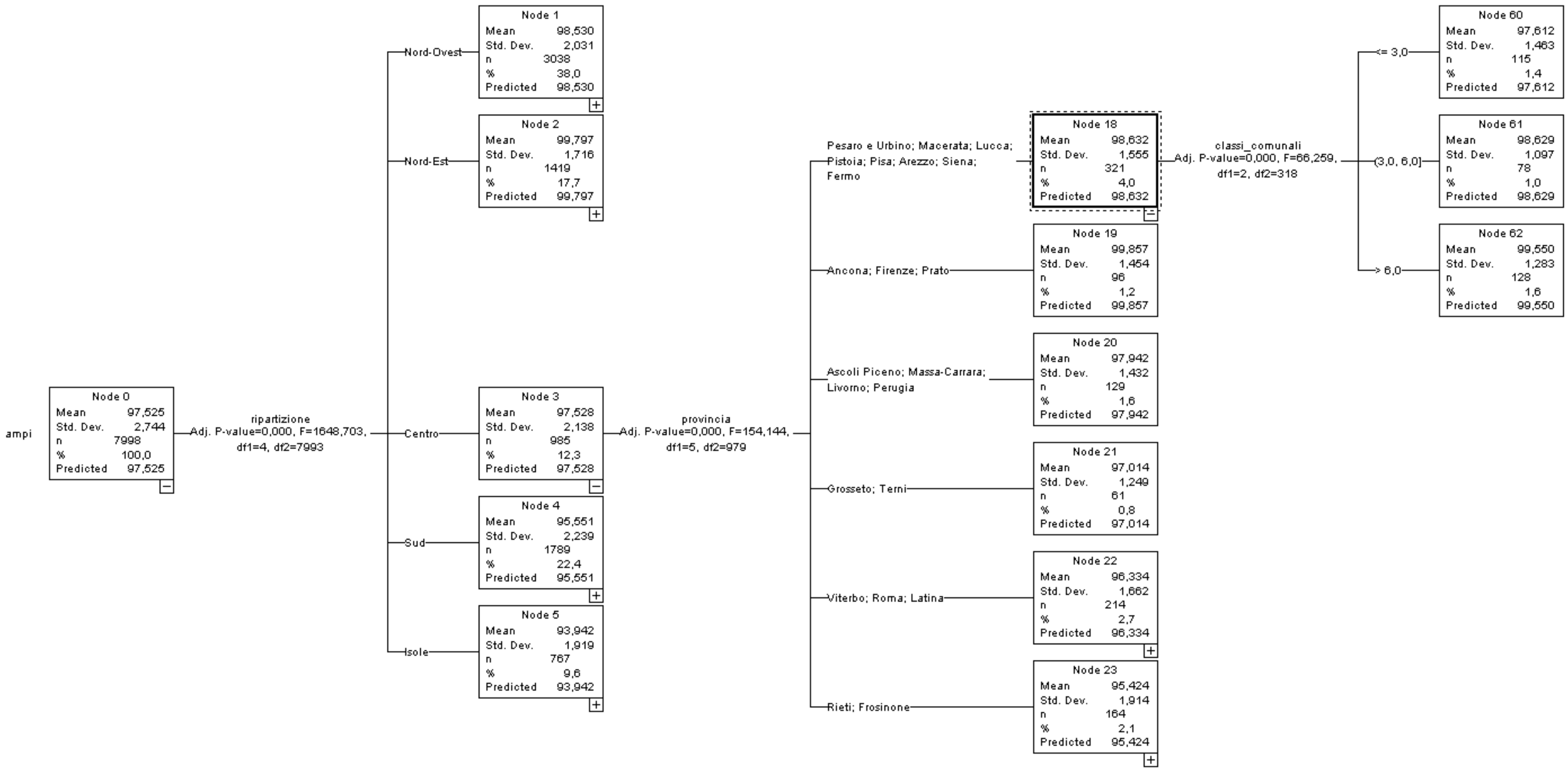

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=83,297, df1=3, df2=1415
<= 2,0
Node 14
Mean 98,742
Std. Dev. 2,029
n 193
% 2,4
Predicted 98,742
(2,0, 5,0]
Node 15
Mean 99,440
Std. Dev. 1,604
n 563
% 7,0
Predicted 99,440
(5,0, 7,0]
Node 16
Mean 100,097
Std. Dev. 1,286
n 395
% 4,9
Predicted 100,097
> 7,0
Node 17
Mean 100,863
Std. Dev. 1,571
n 268
% 3,4
Predicted 100,863
regione
Adj. P-value=0,000, F=73,600, df1=1, df2=191
Trentino Alto Adige; Veneto
Node 49
Mean 99,530
Std. Dev. 1,653
n 125
% 1,6
Predicted 99,530
Friuli Venezia Giulia; Emilia Romagna
Node 50
Mean 97,295
Std. Dev. 1,860
n 68
% 0,9
Predicted 97,295

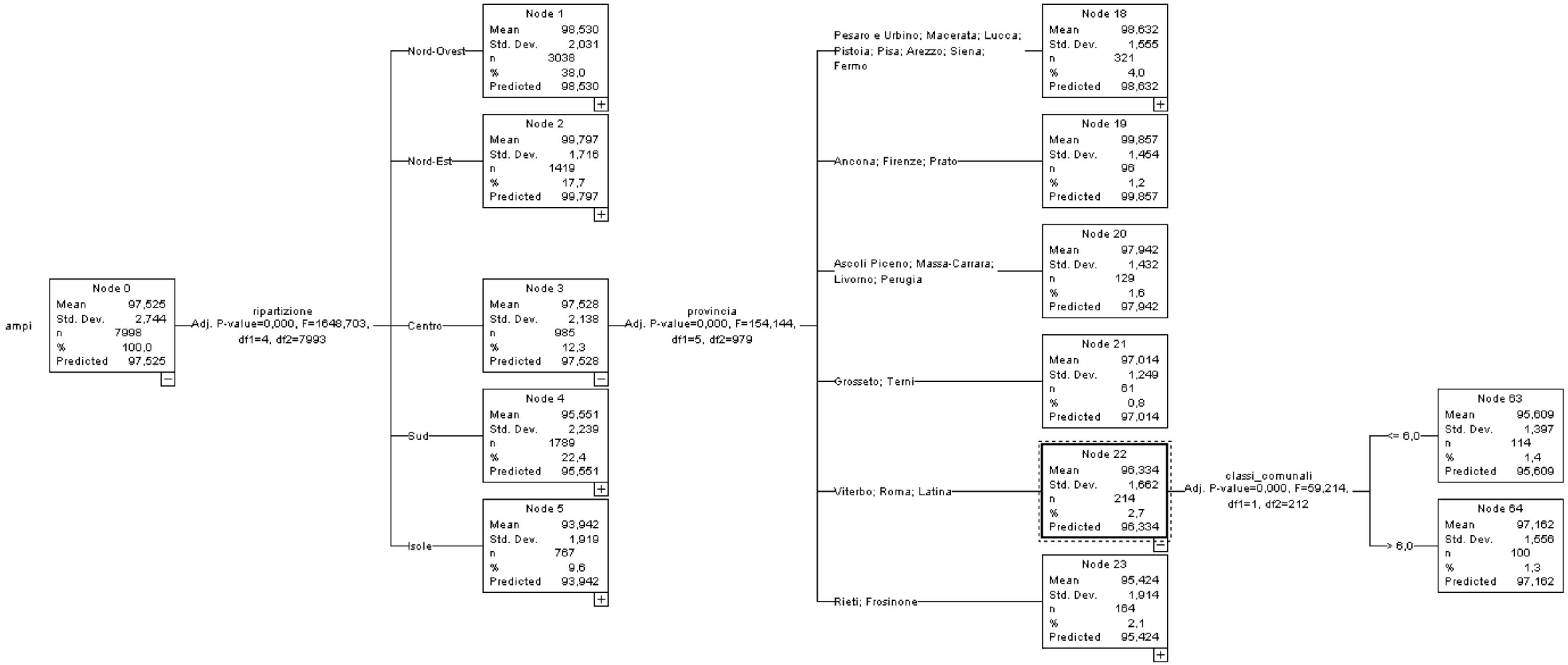

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Nord-Est
Centro
Sud
Isole
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=83,297,
df1=3, df2=1415
<= 2,0
(2,0, 5,0]
(5,0, 7,0]
> 7,0
Node 14
Mean 98,742
Std. Dev. 2,029
n 193
% 2,4
Predicted 98,742
Node 15
Mean 99,440
Std. Dev. 1,604
n 563
% 7,0
Predicted 99,440
Node 16
Mean 100,097
Std. Dev. 1,286
n 395
% 4,9
Predicted 100,097
Node 17
Mean 100,863
Std. Dev. 1,571
n 268
% 3,4
Predicted 100,863
regione
Adj. P-value=0,000, F=52,756,
df1=3, df2=559
Trentino Alto Adige
Veneto
Friuli Venezia Giulia
Emilia Romagna
Node 51
Mean 100,244
Std. Dev. 1,651
n 156
% 2,0
Predicted 100,244
Node 52
Mean 99,611
Std. Dev. 1,365
n 218
% 2,7
Predicted 99,611
Node 53
Mean 99,194
Std. Dev. 1,214
n 95
% 1,2
Predicted 99,194
Node 54
Mean 97,959
Std. Dev. 1,321
n 94
% 1,2
Predicted 97,959

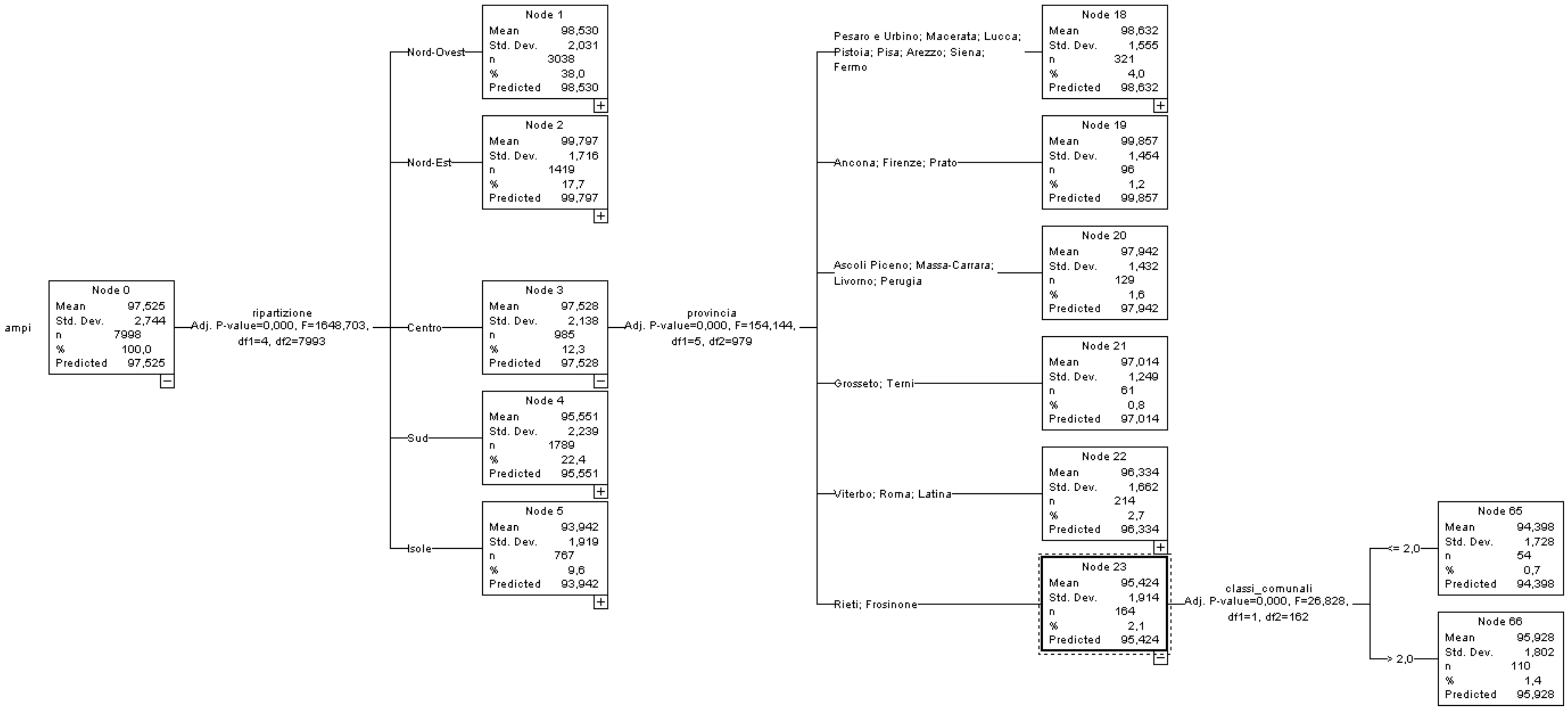

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=83,297, df1=3, df2=1415
<= 2,0
Node 14
Mean 98,742
Std. Dev. 2,029
n 193
% 2,4
Predicted 98,742
(2,0, 5,0]
Node 15
Mean 99,440
Std. Dev. 1,604
n 563
% 7,0
Predicted 99,440
(5,0, 7,0]
Node 16
Mean 100,097
Std. Dev. 1,286
n 395
% 4,9
Predicted 100,097
> 7,0
Node 17
Mean 100,863
Std. Dev. 1,571
n 268
% 3,4
Predicted 100,863
regione
Adj. P-value=0,000, F=16,484, df1=1, df2=393
Trentino Alto Adige; Veneto; Friuli Venezia Giulia
Node 55
Mean 100,269
Std. Dev. 1,219
n 274
% 3,4
Predicted 100,269
Emilia Romagna
Node 56
Mean 99,710
Std. Dev. 1,353
n 121
% 1,5
Predicted 99,710


ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
classi_comunali
Adj. P-value=0,000, F=83,297, df1=3, df2=1415
<= 2,0
Node 14
Mean 98,742
Std. Dev. 2,029
n 193
% 2,4
Predicted 98,742
(2,0, 5,0]
Node 15
Mean 99,440
Std. Dev. 1,604
n 563
% 7,0
Predicted 99,440
(5,0, 7,0]
Node 16
Mean 100,097
Std. Dev. 1,286
n 395
% 4,9
Predicted 100,097
> 7,0
Node 17
Mean 100,863
Std. Dev. 1,571
n 268
% 3,4
Predicted 100,863
provincia
Adj. P-value=0,007, F=30,288, df1=2, df2=265
Bolzano/Bozen; Verona; Belluno; Treviso; Padova; Bologna
Node 57
Mean 101,576
Std. Dev. 1,500
n 107
% 1,3
Predicted 101,576
Trento; Venezia; Rovigo; Gorizia; Trieste; Reggio nell'Emilia; Ferrara; Ravenna; Forlì-Cesena; Rimini
Node 58
Mean 99,988
Std. Dev. 1,387
n 89
% 1,1
Predicted 99,988
Vicenza; Udine; Piacenza; Parma; Modena; Pordenone
Node 59
Mean 100,884
Std. Dev. 1,345
n 72
% 0,9
Predicted 100,884

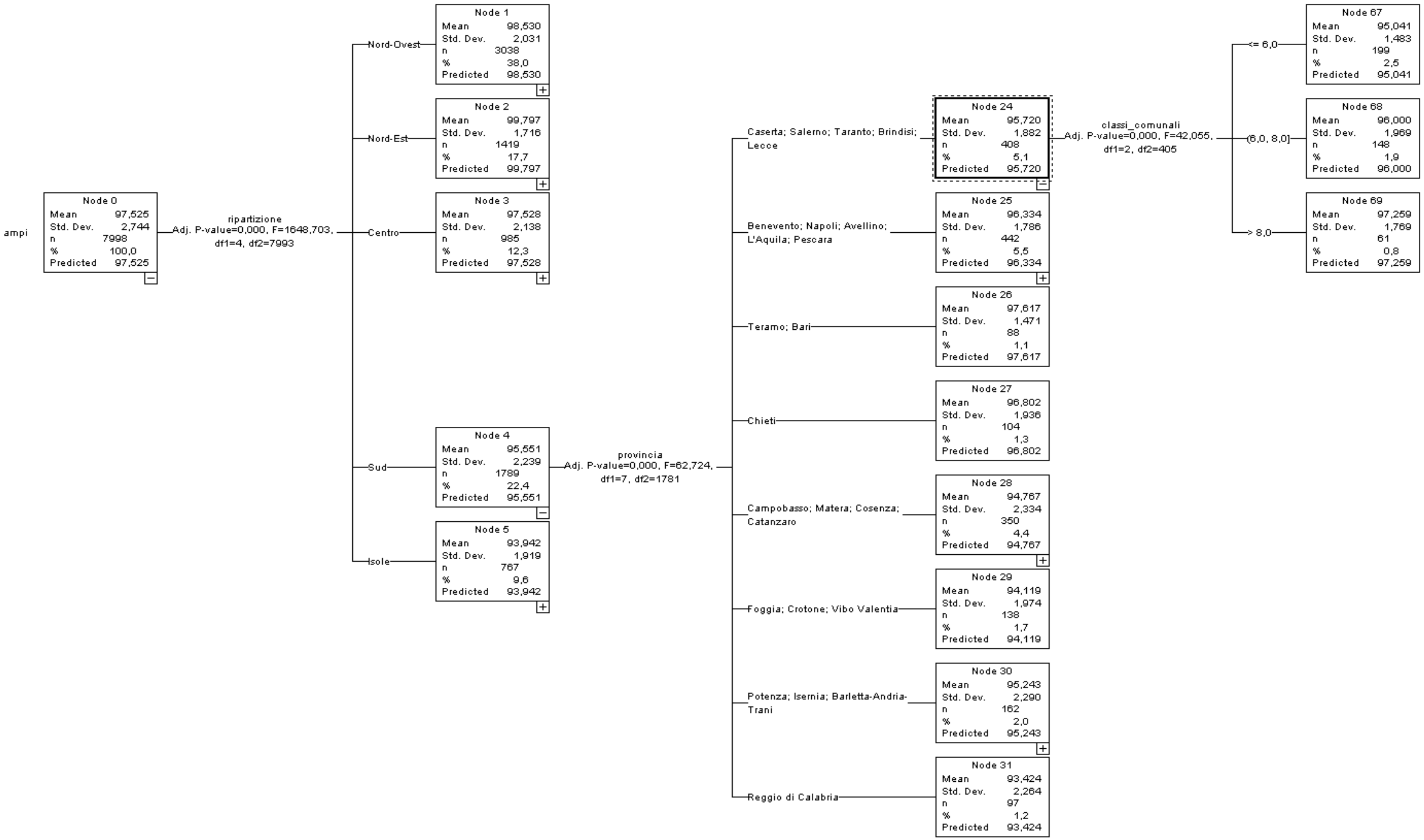
Centre

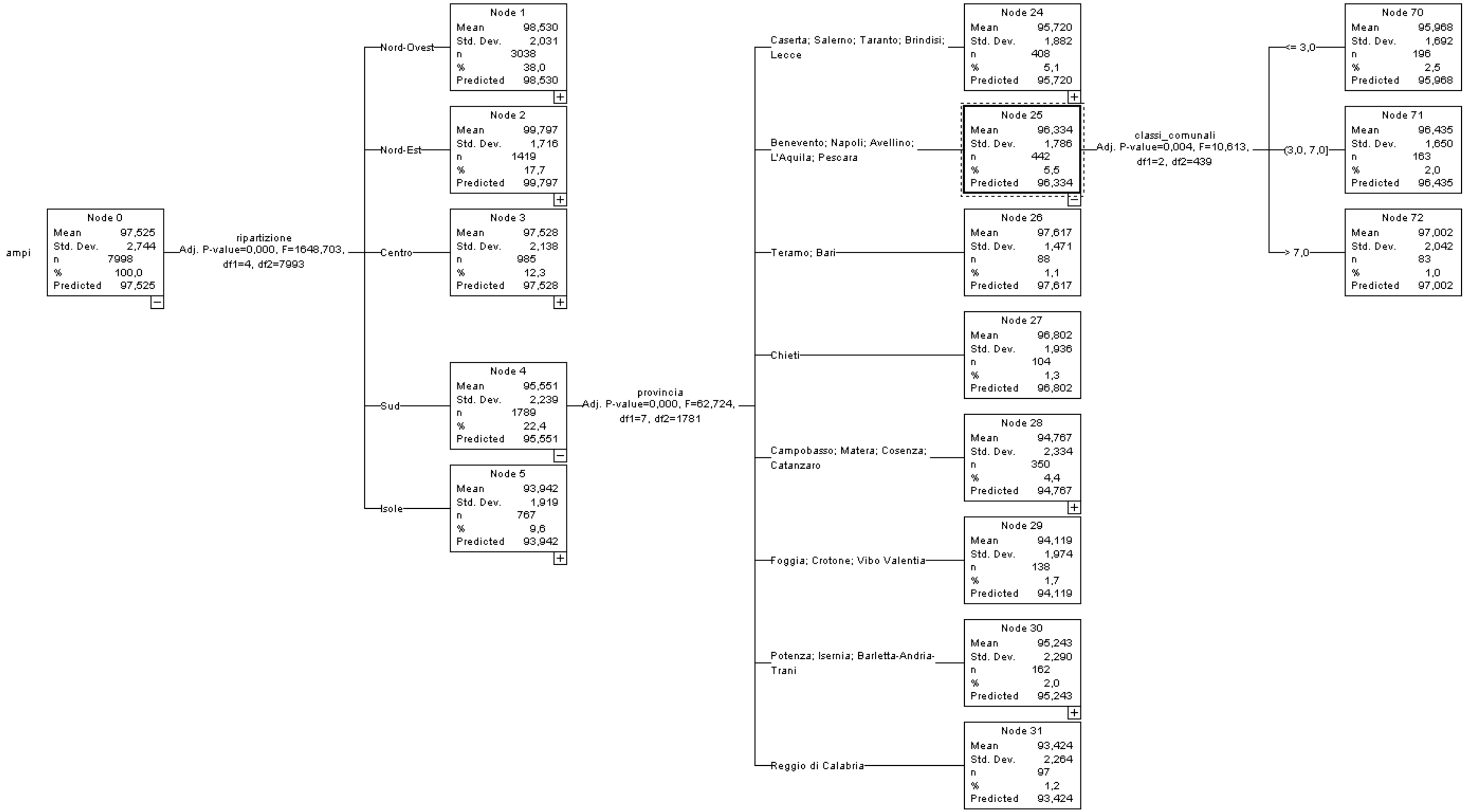

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=154,144, df1=5, df2=979
Pesaro e Urbino; Macerata; Lucca; Pistoia; Pisa; Arezzo; Siena; Fermo
Node 18
Mean 98,632
Std. Dev. 1,555
n 321
% 4,0
Predicted 98,632
Ancona; Firenze; Prato
Node 19
Mean 99,857
Std. Dev. 1,454
n 96
% 1,2
Predicted 99,857
Ascoli Piceno; Massa-Carrara; Livorno; Perugia
Node 20
Mean 97,942
Std. Dev. 1,432
n 129
% 1,6
Predicted 97,942
Grosseto; Terni
Node 21
Mean 97,014
Std. Dev. 1,249
n 61
% 0,8
Predicted 97,014
Viterbo; Roma; Latina
Node 22
Mean 96,334
Std. Dev. 1,662
n 214
% 2,7
Predicted 96,334
Rieti; Frosinone
Node 23
Mean 95,424
Std. Dev. 1,914
n 164
% 2,1
Predicted 95,424
classi_comunali
Adj. P-value=0,000, F=66,259, df1=2, df2=318
<= 3,0
Node 60
Mean 97,612
Std. Dev. 1,463
n 115
% 1,4
Predicted 97,612
(3,0, 6,0]
Node 61
Mean 98,629
Std. Dev. 1,097
n 78
% 1,0
Predicted 98,629
> 6,0
Node 62
Mean 99,550
Std. Dev. 1,283
n 128
% 1,6
Predicted 99,550

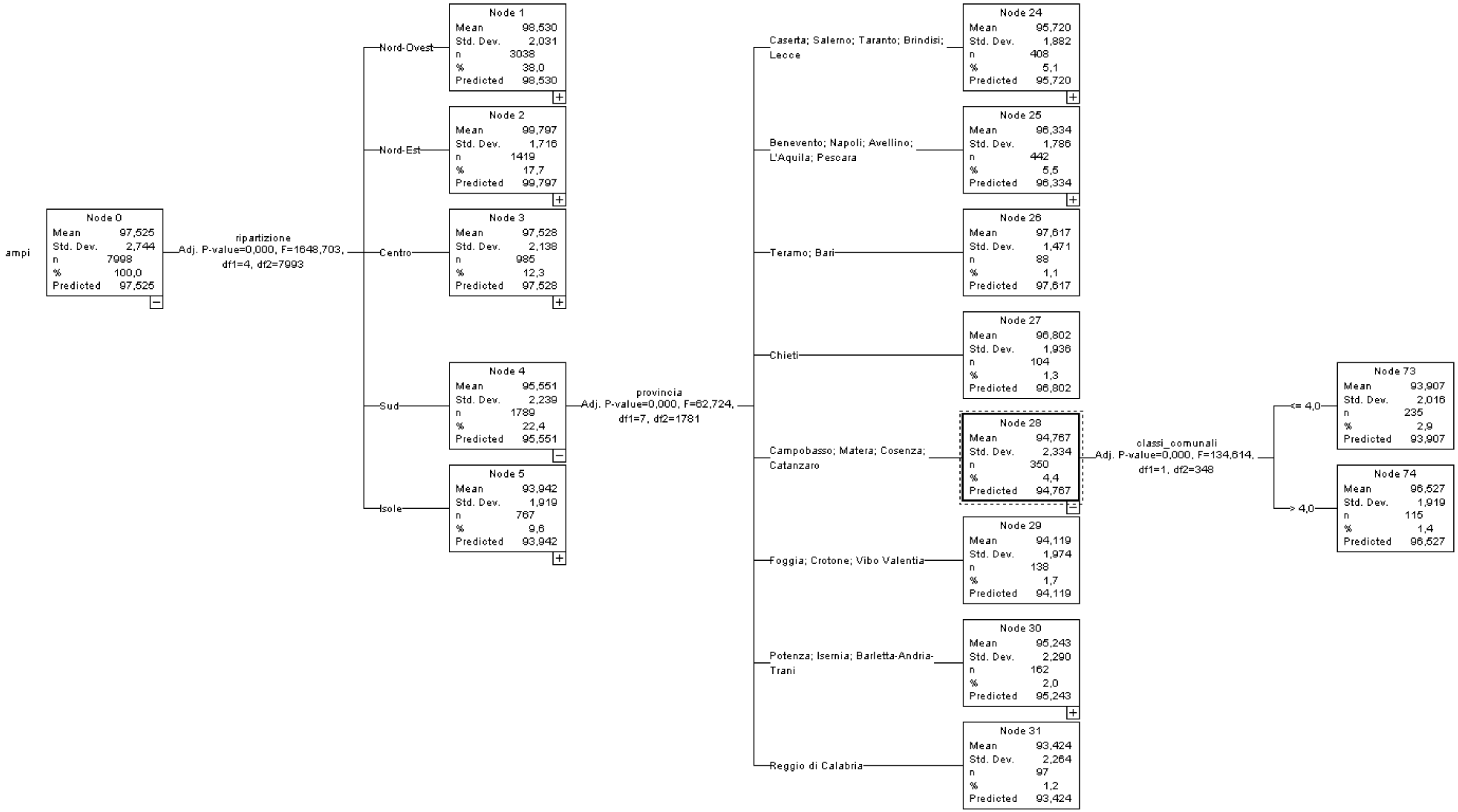

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=154,144,
df1=5, df2=979
Pesaro e Urbino; Macerata; Lucca;
Pistoia; Pisa; Arezzo; Siena;
Fermo
Node 18
Mean 98,632
Std. Dev. 1,555
n 321
% 4,0
Predicted 98,632
Ancona; Firenze; Prato
Node 19
Mean 99,857
Std. Dev. 1,454
n 96
% 1,2
Predicted 99,857
Ascoli Piceno; Massa-Carrara;
Livorno; Perugia
Node 20
Mean 97,942
Std. Dev. 1,432
n 129
% 1,6
Predicted 97,942
Grosseto; Terni
Node 21
Mean 97,014
Std. Dev. 1,249
n 61
% 0,8
Predicted 97,014
Viterbo; Roma; Latina
Node 22
Mean 96,334
Std. Dev. 1,662
n 214
% 2,7
Predicted 96,334
Rieti; Frosinone
Node 23
Mean 95,424
Std. Dev. 1,914
n 164
% 2,1
Predicted 95,424
classi_comunali
Adj. P-value=0,000, F=59,214,
df1=1, df2=212
<= 6,0
Node 63
Mean 95,609
Std. Dev. 1,397
n 114
% 1,4
Predicted 95,609
> 6,0
Node 64
Mean 97,162
Std. Dev. 1,556
n 100
% 1,3
Predicted 97,162

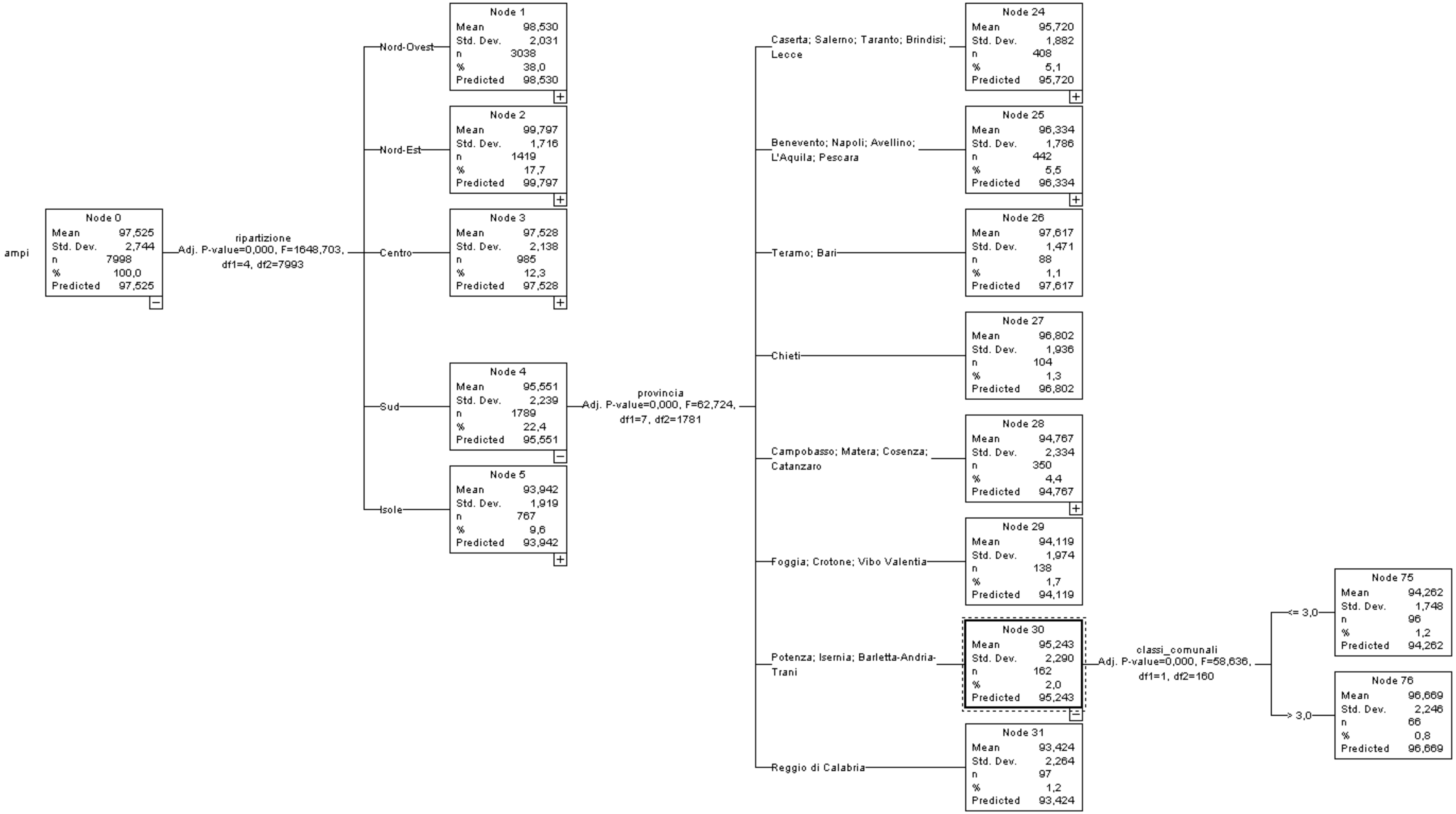

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=154,144,
df1=5, df2=979
Pesaro e Urbino; Macerata; Lucca;
Pistoia; Pisa; Arezzo; Siena;
Fermo
Node 18
Mean 98,632
Std. Dev. 1,555
n 321
% 4,0
Predicted 98,632
Ancona; Firenze; Prato
Node 19
Mean 99,857
Std. Dev. 1,454
n 96
% 1,2
Predicted 99,857
Ascoli Piceno; Massa-Carrara;
Livorno; Perugia
Node 20
Mean 97,942
Std. Dev. 1,432
n 129
% 1,6
Predicted 97,942
Grosseto; Terni
Node 21
Mean 97,014
Std. Dev. 1,249
n 61
% 0,8
Predicted 97,014
Viterbo; Roma; Latina
Node 22
Mean 96,334
Std. Dev. 1,662
n 214
% 2,7
Predicted 96,334
Rieti; Frosinone
Node 23
Mean 95,424
Std. Dev. 1,914
n 164
% 2,1
Predicted 95,424
classi_comunali
Adj. P-value=0,000, F=26,828,
df1=1, df2=162
<= 2,0
Node 65
Mean 94,398
Std. Dev. 1,728
n 54
% 0,7
Predicted 94,398
> 2,0
Node 66
Mean 95,928
Std. Dev. 1,802
n 110
% 1,4
Predicted 95,928

South

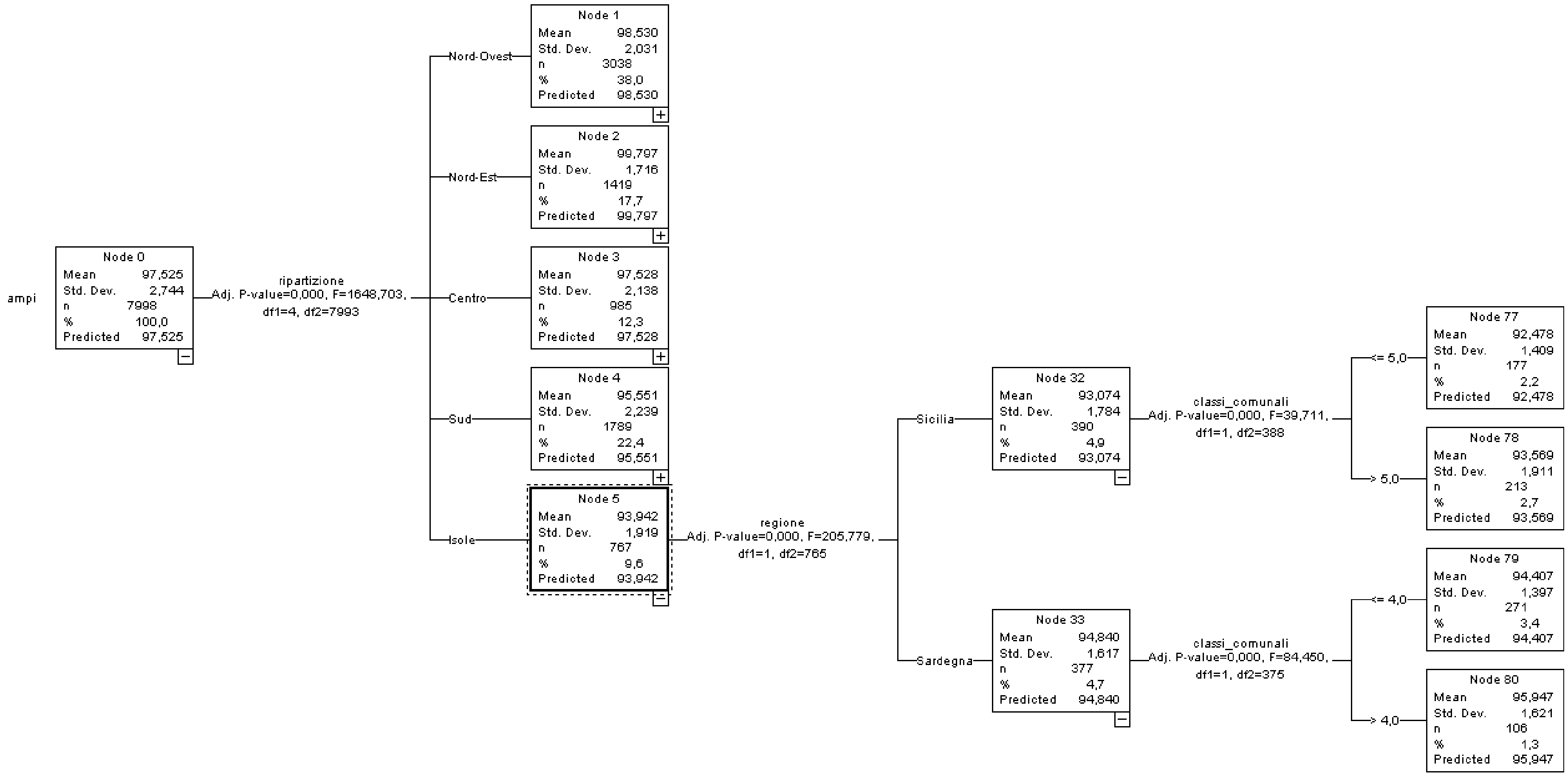

ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703, df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=62,724, df1=7, df2=1781
Caserta; Salerno; Taranto; Brindisi; Lecce
Node 24
Mean 95,720
Std. Dev. 1,882
n 408
% 5,1
Predicted 95,720
Benevento; Napoli; Avellino; L'Aquila; Pescara
Node 25
Mean 96,334
Std. Dev. 1,786
n 442
% 5,5
Predicted 96,334
Teramo; Bari
Node 26
Mean 97,617
Std. Dev. 1,471
n 88
% 1,1
Predicted 97,617
Chieti
Node 27
Mean 96,802
Std. Dev. 1,936
n 104
% 1,3
Predicted 96,802
Campobasso; Matera; Cosenza; Catanzaro
Node 28
Mean 94,767
Std. Dev. 2,334
n 350
% 4,4
Predicted 94,767
Foggia; Crotone; Vibo Valentia
Node 29
Mean 94,119
Std. Dev. 1,974
n 138
% 1,7
Predicted 94,119
Potenza; Isernia; Barletta-Andria-Trani
Node 30
Mean 95,243
Std. Dev. 2,290
n 162
% 2,0
Predicted 95,243
Reggio di Calabria
Node 31
Mean 93,424
Std. Dev. 2,264
n 97
% 1,2
Predicted 93,424
classi_comunali
Adj. P-value=0,000, F=42,055, df1=2, df2=405
<= 6,0
Node 67
Mean 95,041
Std. Dev. 1,483
n 199
% 2,5
Predicted 95,041
(6,0, 8,0]
Node 68
Mean 96,000
Std. Dev. 1,969
n 148
% 1,9
Predicted 96,000
> 8,0
Node 69
Mean 97,259
Std. Dev. 1,769
n 61
% 0,8
Predicted 97,259


ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Nord-Est
Centro
Sud
Isole
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=62,724,
df1=7, df2=1781
Caserta; Salerno; Taranto; Brindisi; Lecce
Benevento; Napoli; Avellino; L'Aquila; Pescara
Teramo; Bari
Chieti
Campobasso; Matera; Cosenza; Catanzaro
Foggia; Crotone; Vibo Valentia
Potenza; Isernia; Barletta-Andria-Trani
Reggio di Calabria
Node 24
Mean 95,720
Std. Dev. 1,882
n 408
% 5,1
Predicted 95,720
Node 25
Mean 96,334
Std. Dev. 1,786
n 442
% 5,5
Predicted 96,334
Node 26
Mean 97,617
Std. Dev. 1,471
n 88
% 1,1
Predicted 97,617
Node 27
Mean 96,802
Std. Dev. 1,936
n 104
% 1,3
Predicted 96,802
Node 28
Mean 94,767
Std. Dev. 2,334
n 350
% 4,4
Predicted 94,767
Node 29
Mean 94,119
Std. Dev. 1,974
n 138
% 1,7
Predicted 94,119
Node 30
Mean 95,243
Std. Dev. 2,290
n 162
% 2,0
Predicted 95,243
Node 31
Mean 93,424
Std. Dev. 2,264
n 97
% 1,2
Predicted 93,424
classi_comunali
Adj. P-value=0,004, F=10,613,
df1=2, df2=439
<= 3,0
(3,0, 7,0]
> 7,0
Node 70
Mean 95,968
Std. Dev. 1,692
n 196
% 2,5
Predicted 95,968
Node 71
Mean 96,435
Std. Dev. 1,650
n 163
% 2,0
Predicted 96,435
Node 72
Mean 97,002
Std. Dev. 2,042
n 83
% 1,0
Predicted 97,002


ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=62,724,
df1=7, df2=1781
Caserta; Salerno; Taranto; Brindisi;
Lecce
Node 24
Mean 95,720
Std. Dev. 1,882
n 408
% 5,1
Predicted 95,720
Benevento; Napoli; Avellino;
L'Aquila; Pescara
Node 25
Mean 96,334
Std. Dev. 1,786
n 442
% 5,5
Predicted 96,334
Teramo; Bari
Node 26
Mean 97,617
Std. Dev. 1,471
n 88
% 1,1
Predicted 97,617
Chieti
Node 27
Mean 96,802
Std. Dev. 1,936
n 104
% 1,3
Predicted 96,802
Campobasso; Matera; Cosenza;
Catanzaro
Node 28
Mean 94,767
Std. Dev. 2,334
n 350
% 4,4
Predicted 94,767
Foggia; Crotone; Vibo Valentia
Node 29
Mean 94,119
Std. Dev. 1,974
n 138
% 1,7
Predicted 94,119
Potenza; Isernia; Barletta-Andria-
Trani
Node 30
Mean 95,243
Std. Dev. 2,290
n 162
% 2,0
Predicted 95,243
Reggio di Calabria
Node 31
Mean 93,424
Std. Dev. 2,264
n 97
% 1,2
Predicted 93,424
classi_comunali
Adj. P-value=0,000, F=134,614,
df1=1, df2=348
<= 4,0
Node 73
Mean 93,907
Std. Dev. 2,016
n 235
% 2,9
Predicted 93,907
> 4,0
Node 74
Mean 96,527
Std. Dev. 1,919
n 115
% 1,4
Predicted 96,527


ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
Predicted 99,797
Centro
Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
provincia
Adj. P-value=0,000, F=62,724,
df1=7, df2=1781
Caserta; Salerno; Taranto; Brindisi;
Lecce
Node 24
Mean 95,720
Std. Dev. 1,882
n 408
% 5,1
Predicted 95,720
Benevento; Napoli; Avellino;
L'Aquila; Pescara
Node 25
Mean 96,334
Std. Dev. 1,786
n 442
% 5,5
Predicted 96,334
Teramo; Bari
Node 26
Mean 97,617
Std. Dev. 1,471
n 88
% 1,1
Predicted 97,617
Chieti
Node 27
Mean 96,802
Std. Dev. 1,936
n 104
% 1,3
Predicted 96,802
Campobasso; Matera; Cosenza;
Catanzaro
Node 28
Mean 94,767
Std. Dev. 2,334
n 350
% 4,4
Predicted 94,767
Foggia; Crotone; Vibo Valentia
Node 29
Mean 94,119
Std. Dev. 1,974
n 138
% 1,7
Predicted 94,119
Potenza; Isernia; Barletta-Andria-
Trani
Node 30
Mean 95,243
Std. Dev. 2,290
n 162
% 2,0
Predicted 95,243
Reggio di Calabria
Node 31
Mean 93,424
Std. Dev. 2,264
n 97
% 1,2
Predicted 93,424
classi_comunali
Adj. P-value=0,000, F=58,636,
df1=1, df2=160
<= 3,0
Node 75
Mean 94,262
Std. Dev. 1,748
n 96
% 1,2
Predicted 94,262
> 3,0
Node 76
Mean 96,669
Std. Dev. 2,246
n 66
% 0,8
Predicted 96,669

Islands


ampi
Node 0
Mean 97,525
Std. Dev. 2,744
n 7998
% 100,0
Predicted 97,525
ripartizione
Adj. P-value=0,000, F=1648,703,
df1=4, df2=7993
Nord-Ovest
Node 1
Mean 98,530
Std. Dev. 2,031
n 3038
% 38,0
Predicted 98,530
Nord-Est
Node 2
Mean 99,797
Std. Dev. 1,716
n 1419
% 17,7
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Node 3
Mean 97,528
Std. Dev. 2,138
n 985
% 12,3
Predicted 97,528
Sud
Node 4
Mean 95,551
Std. Dev. 2,239
n 1789
% 22,4
Predicted 95,551
Isole
Node 5
Mean 93,942
Std. Dev. 1,919
n 767
% 9,6
Predicted 93,942
regione
Adj. P-value=0,000, F=205,779,
df1=1, df2=765
Sicilia
Node 32
Mean 93,074
Std. Dev. 1,784
n 390
% 4,9
Predicted 93,074
classi_comunali
Adj. P-value=0,000, F=39,711,
df1=1, df2=388
<= 5,0
Node 77
Mean 92,478
Std. Dev. 1,409
n 177
% 2,2
Predicted 92,478
> 5,0
Node 78
Mean 93,569
Std. Dev. 1,911
n 213
% 2,7
Predicted 93,569
Sardegna
Node 33
Mean 94,840
Std. Dev. 1,617
n 377
% 4,7
Predicted 94,840
classi_comunali
Adj. P-value=0,000, F=84,460,
df1=1, df2=375
<= 4,0
Node 79
Mean 94,407
Std. Dev. 1,397
n 271
% 3,4
Predicted 94,407
> 4,0
Node 80
Mean 95,947
Std. Dev. 1,621
n 106
% 1,3
Predicted 95,947