Alma Mater Studiorum - Università di Bologna

Scuola di Dottorato in Scienze Economiche e Statistiche

Dottorato di Ricerca in:

Metodologia Statistica per la Ricerca Scientifica

XXV Ciclo

Multidimensional Measures of Firm Competitiveness: a Model-Based Approach

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Dipartimento di Scienze Statistiche "Paolo Fortunati"

Gennaio 2013

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Introduction

The concept of competitiveness, for a long time considered as strictly connected to economic and financial performances, evolved, above all in recent years, toward new, wider interpretations disclosing its multidimensional nature.

The diffusion of new world views, implying changes in the theoretical approaches to the analysis of those phenomena governing the growth and development processes, both at a macro and micro level, drove different disciplines toward the consideration of the relevance of the so-called intangible aspects in defining and characterizing concepts that, until that moment, were only considered from a strictly monetary point of view.

Those aspects have been recognized to assume such a relevance in the definition, as well as in the analysis of the phenomenon of competitiveness.

The shift to a multidimensional view of the competitiveness, has excited an intense debate involving theoretical reflections on the features characterizing the competitive phenomenon, as well as methodological considerations on its assessment and measurement.

The present research has a twofold objective: going in depth with the study of tangible and intangible aspects characterizing multidimensional competitive phenomena by assuming a micro-level point of view, and measuring competitiveness through a model-based approach to the construction of composite indicators.

As said before, the growing consensus in favour of including other dimensions, beyond monetary indicators, in analyzing competitiveness is bringing to an increase in the number of empirical studies aiming at assessing and measuring the phenomenon through the use of multidimensional measures. Such a framework is mainly used in macro-level competitiveness analysis approaches. Several studies have in fact been conducted with the aim of identifying composite measures of competitiveness, by starting from a wide interpretation of the phenomenon itself. Micro-level studies, continue instead to identify competitiveness with economic performances and study it by assessing relations with its separately taken into account, tangible and intangible, determinants. In broader terms, micro-level approaches identify competitiveness with profitability measures, only recognizing multidimensionality at the level of factors affecting and determining it.

Our idea is to borrow the macro-level interpretation of the competitiveness concept for assessing the phenomenon from a micro-level point of view. We will thus give micro-level competitiveness a huge connotation, able to include and describe several aspect of the phenomenon under investigation.

This will imply the research of a definition of micro-level competitiveness explaining its multidimensional nature, as well as the in-depth analysis of the economic as well as management theories for the understanding of the main features to be taken into account for an exhaustive analysis of the phenomenon.

Once both the theoretical substratum of the analysis and the dimensions to be used for the measurement of competitiveness have been identified, our focus will be on the methodological choice to be made for the computation of a composite micro-level competitiveness measure.

We propose a Structural Equation Models-based approach to the construction of composite indicators, as it offers methodological tools that may help to overcome controversial questions related to the computation of multidimensional measures.

We will specifically use a non-parametric approach to Structural Equation Models as we believe that it can be helpful in analyzing the micro-level competitiveness framework, for a manifold order of reasons.

Non-parametric Structural Equation Models techniques allow to analyze multidimensional and heterogeneous phenomena, whose study involves several latent aspects to be taken into account (without making any assumption on data distribution), by considering and reducing their inner complexity through a dynamic approach allowing to assess the causality networks among the different dimensions explaining the phenomenon and the phenomenon itself, as well as to understand whether and to what extent each dimension contribute in determining it. Such a technique gives us the chance to conceptualize competitiveness as a huge, latent and heterogeneous phenomenon, hypothesized to be determined by several latent dimensions, in their turn characterized by an inner complexity and multidimensionality that Structural Equation Models allow to take into account.

Moreover, in a composite measures computation perspective Structural Equation Models give the chance to aggregate competitiveness dimensions by endogenously individuating two kinds of optimal weights, those reflecting the internal structure of each competitiveness dimension and the ones measuring the contribution of each dimension in determining the overall micro-level competitiveness measure. It will therefore possible to simultaneously consider the elements influencing micro-level competitiveness and to test not only their significance, but also to what extent they determine it.

We will subsequently use Structural Equation Models tools for the empirical application to the Italian case: we will develop a micro-level model-based competitiveness indicator for the measurement of the phenomenon on a large sample of Italian small and medium enterprises.

The dissertation will be structured as follows:

In Chapter 1 a review of economy theories showing the competitiveness historical evolution processes will be presented. Moreover issues related to the definition, the measurement as well as to sources of competitiveness will be discussed, by the use of a classification scheme taking into account different levels of aggregation and different theoretical references.

In Chapter 2 a review of the main approaches to the measurement of multidimensional phenomena will be presented, with the aim to investigate the controversial questions related to the computation of composite indicators, as well as to choose the most suitable tools for the measurement of competitiveness.

In Chapter 3 the methodology proposed in order to construct the model-based composite indicators will be described and discussed. The focus will be on the Structural Equation Models techniques, with particular reference to the non-parametric estimation methods and to the multi-group analysis methodologies.

Chapter 4 contains a review of economic and management theoretical and empirical studies on micro-level competitiveness tangible and intangible features, systematized in order to:

- trace the theoretical substratum to be used to be taken into account during the micro-level competitiveness composite measure computation;
- individuate the variables that should be used in order conduct the empirical study;
- have some information both on the direction and the sign of the relationships between each of the analyzed element and competitiveness;
- know which are the controversial and unsolved question.

In Chapter 5 the results of the empirical application to the Italian case will be displayed and discussed. Specifically, the micro-level model-based competitiveness indicator will first be presented; subsequently the results of the multi-group analyses conducted in order to investigate on the presence of heterogeneous structures inside the disposable sample will be shown and discussed.

Chapter 1: The concept of competitiveness

1.1 THE CONCEPT OF COMPETITIVENESS: BETWEEN CLASSICAL APPROACHES AND EVOLUTIONARY THEORIES. FEATURES OF ITS DETERMINATION

The study of a concept of great importance in the domain of a science cannot prescind from its historical analysis. The historical ground consideration is of fundamental importance if the objective of a study is to reach relevant conclusions both on the relationship between the development of the concept itself and the empirical background which it is connected to, and on its future evolution and perspectives.

This is particularly true for the concept of competitiveness, as the flow of time shed light on different contents and features: from the classic macroeconomic approach, going through the dynamic concept of *creative destruction* of Schumpeter till the growing attention on the research of the components and variables determining its level in an economic system.

The importance of the concept of competitiveness is demonstrated by the fact that there is an increasing interest around the phenomenon at the firm level as well as toward the policies through which governments can enhance national competitiveness.

Most of the time the expression of competitiveness has a quite blurred outline. It would be useful to try to give this concept, often misused and burdened with vague meanings, a more accurate definition and collocation.

That need arises from the fact that the term of competitiveness is, alternatively or jointly, related to a plurality of elements. And, although it is commonly used because considered a key issue for the success of an economic system in the global market, it is not possible to skip a more clear definition of it. However the problem is not only a lexical one, but involves a more profound conceptual collocation issue.

The most relevant theoretical contributions to the topic of competitiveness come from the Neoclassical approach.

As a matter of fact, the Neoclassical theory, influenced by the works of Schumpeter on innovation, had a great impact both on macroeconomic and microeconomic approaches to the study of competitiveness, while classical economist only focused, on an embryonic form, on its macroeconomic aspect.

Let's see it in details. The thought that the processes of nations growth and international trade are strictly related arose with Adams Smith (1776). He systematized the analysis of the concept of market competition carried out by a series of authors before him and his specific contribution has been to bring the concept of competition to a general organizing principle of economic society. After Smith’s great achievement, the concept of competition became quite literally the *sine qua non* condition of economic reasoning.

Smith strongly highlighted the importance of the capacity of a nation to operate in broader markets and based his theory on the concept of division of labour, that was thought to provide for economies of scale and differences in productivity across nations as well as to give “value to the *surplus*”, which otherwise should have caused overproduction problems and a non-adequately valued use of labour itself.

For Smith, investment in capital (improved machinery) and trade (increasing the size of the market) could facilitate nations specialization and raise productivity and output growth. Moreover, growth itself could be reinforced, since increasing outputs permits further division of labour and hence further growth.

As far as the Smith’s theory on international trade is concerned, he asserted that nations had to be careful in not wasting their scarce resources on producing the commodities which they could obtain from abroad at a lesser cost.

A nation should divert its resources only to the production of commodities in which they have greatest efficiency and trade for those products which they cannot produce in an efficient way. This way it is possible to make the wealth of a country growing.

If one country can produce goods using less inputs (labour) in production then it will have an absolute advantage and should export the good; or alternatively countries should import goods that others can produce using fewer inputs (i.e. where they are produced most cheaply). Trade is attributed to differences in productivity.

This theory contains an embryonic approach to the topic of competitiveness related to the concept of absolute advantage and it is discussed from a static point of view, as if each component of the system is independent and disconnected with the others.

It was David Ricardo (1817) who began thinking to a possible interdependence between the components of the market, as well as to the fact that technological differences between nations are fundamental factors in the explanation of the commerce and international specialization models.

He based his theory on the concept of comparative advantage, that refers to the ability of a nation to produce a particular good or service at a lower marginal and opportunity cost over another. Even if a country is more efficient in the production of all goods (absolute advantage in all goods) than the others, both countries will gain by trading with each other, as long as they have different relative efficiencies.

Necessary condition for the international trade is the existence of a difference in the comparative costs, reflecting differences in the production methods of the trading countries (comparative costs postulate that trade is beneficial between countries even if one country is more efficient in every sector because of the difference in internal production costs). Sufficient condition is that the terms of international trade lie between the comparative costs of the trading countries, and never equals none of the two. When both the condition are satisfied, every country will produce its commodities for the production of which it is most suited in terms of its natural endowments, climate, quality of soil, means of transport, capital, etc. It will produce these commodities in excess with respect to its own requirements and will exchange the surplus with the imports of goods from other countries for the production of which it is not well suited or which it cannot produce at all. Thus all countries produce and export those commodities in which they have cost advantages and import those commodities in which they have cost disadvantages.

The conclusions of the above mentioned theory seems to be logical and faultless, since it is referred to countries having no absolute advantages in term of production of both goods, and since there are not situations of international trade implying bilateral advantages.

For a considerable period the theory of comparative costs formulated by David Ricardo was the most acceptable explanation of the international trade. However, it was subjected to number of criticisms.

The most important issue is that the classical theory on international trade does not takes into account several elements characterizing the productive specialization of a country, in particular capital and raw materials: in the theory of Ricardo only labour productivity determines trade pattern.

Moreover, the technological degrees differences characterizing the production processes and related to the organizational side of firms development, even if having a considerable influence on trade, are not taken into consideration by the classical economic theory of comparative costs. Another problem is that the theory neglects the starting economic, social and political conditions of the analyzed countries, instead assuming full employment, equal size economies, perfect mobility of factors of production within countries, immobility of factors of production between countries, perfect competition.

The weak points of the theory of Ricardo are its static nature and its abstractness: the theory would have an empirical confirmation only if the countries taking part to international trade had the same degrees of economic development, equal levels of technological progress, the same firm production structure. Such an hypothesis seems to be quite utopian and it is not difficult to understand that these conditions does not hold in the real trade dynamics.

With the assumption of equality in the level of technology and of both the homogeneity of production inputs and the specialization of production, the competitiveness is merely linked to the productive resources of each nation.

Concluding, in the classic economic theory the degree of international competition is not determined by economic policies, as the competitive advantage depends on the starting availability of the production factors, that are non-modifiable because of the immobility of factors of production. Furthermore possible improvements of the comparative advantages do not depend on the technological progress that, as assumed for hypothesis, is an exogenous element and for this reason constant. So, it is not possible to think about the disadvantage of the less competitive countries resulting from the existing difference in the transformation rates of traded goods.

The assumption that the market forces are able, by themselves, to bring the system to a long run equilibrium state with a rational allocation of resources, is the less persuasive way of analyzing the dynamic process of competitiveness.

From the beginning of the twentieth century the economy started to be studied from a dynamic point of view. A fundamental contribute in this sense comes from the works of Schumpeter (1912). He ascribed to classical authors the fault of neglecting the substantial role of science, technology and human capital during the analysis of the different growth rate of nations.

Although the contribute of Schumpeter is mostly oriented in the field of cyclical development and innovation, it is not possible to ignore how much he has influenced the future theories on competitiveness.

Schumpeter stated that development is a peculiar feature of a dynamic capitalistic economy. The driving forces taking a system from an equilibrium state to development and growth are non-economic, and they are to be found in the institutional structure of the society. The most important figure in the theory of Schumpeter is the one of the innovative entrepreneur: he aims for profit, and profit cannot exist in a stationary equilibrium state, it can only be set up by innovation.

Therefore, economic growth is fostered by an institutional environment that rewards and encourages the activities of entrepreneurs; early capitalism, with its private property and laissez-faire government, is ideally suited to economic growth.

Schumpeter identified innovation as the critical dimension of economic change. He argued that economic change revolves around innovation, entrepreneurial activities and market power, and tried to prove that innovation-originated market power can provide better results than the invisible hand and price competition. Technological innovation often creates temporary monopolies, allowing abnormal profits that would soon be competed away by rivals and imitators. He said that these temporary monopolies were necessary to provide the incentive for firms to develop new products and processes.

Schumpeter vividly characterized innovation as industrial mutation, which incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. This process of *creative destruction* is the essential element determining growth and development.

Change is the only constant in the evolution of capitalist economies. Schumpeterian competition drives innovation, but it also begets imitators, swarms of which copy their rival's innovation, attracting investment, and leading to an outbreak. When the original innovator's profit advantage is eliminated, investment moves elsewhere, and the sector may even shrink, until the next disruptive innovation, which restarts the cycle.

Although the theory of Schumpeter is mainly grounded on microeconomic considerations and assumption, it has been for a long time considered fundamental for the explanation of the growth processes at macro-level.

Only at the beginning of the seventies a new, dynamic interpretive key of international trade has been theorized: the new economic system is considered to be susceptible to transformation for effect of competition, it is described in a dynamical way and it is characterized by discontinuous development processes; interactions between financial players are the result of self-regulating processes.

It's the Neo-Schumpeterian approach, also known as Evolutionary approach. It brings about a change in the perspective of analysis. The evolutionary theory considers economy as an ever-changing system, whose mechanisms are necessary to be analyzed and understood. The economic dynamics are interpreted as evolutionary processes, determined on the one hand by learning processes and of competence construction, and on the other hand by economic, social and political selective mechanisms: there is no existence of univocal optimum solutions.

Markets are no more perfectly competitive, technological change is an endogenous factor of the economic models, the system reveals different degrees of uncertainty.

The sector of research and development is not considered as a common good which all firms can accede to, it is instead a good for the possession of which firms have to invest part of their resources. Moreover there is a change in the consideration of the concept of competitive advantage: it is no more the exclusive result of the initial supply of production factors, but it is dependent on the action and strategies the countries implement in order to increase their productivity. Great importance is also given to the innovative activity of countries as it influences their returns in terms of exportation; the theory of evolution asserts that the competitiveness of a nation depends on its innovation system and that each change on the technological variables influences the trade performance of a country.

Another element of novelty is the introduction of variables, used for the explanation of the theories on international trade, never taken into account before (infrastructures, education, institutional features): aspects representing the environmental, political and social contest in which firms act. The objective is to understand if firms as well as the economic system are influenced by elements considered to be, since that time, exogenous and for this reason not so crucial.

The increasing attention to the technological progress as endogenous variable brings to the development of the theory of the endogenous growth also known as New Growth Theory. Variables such as human capital, common goods, R&D, public institution wealth are firmly introduced in economic models in which the productivity growth is considered an internal unavoidable element of each economic system.

This new approach not only concerns the new idea of technological progress, but also the different consideration of the concepts of comparative advantages and specialization models in term of intentionally reproducible factors.

The most important exponents of the theory of endogenous growth are Grossman, Helpman, Krugman, Lucas. Each of them tickles the issue of economic growth by different perspectives, using different approaches.

Grossman and Helpman analyze the technological progress as the result of the resources allocation in the R&D sector, Krugman and Lucas focus on the link between innovation and the principle of learning by doing.

The above mentioned dichotomy emerges with respect to the analysis of the effects of technological innovation on productive sectors.

The former authors state that the most utilized practice characterizing production processes is the imitation of the new technologies, with the consequence of the erosion of the competitive advantage of the firms introducing the innovation.

The latter assert that the phenomenon of appropriation of new technologies by a few number of firms is dominant, in this case the competitive advantage results from a systematic research activity that increase the innovation success probability. For this reason investments in R&D have a key role for the economic growth of the most industrialized economies.

Independently from the different approaches, it is possible to see that the key assumption of endogenous growth theory is that accumulation of knowledge generates increasing returns. Another important contribution of the endogenous growth theory is the formalization of the importance of human capital: the hypothesis is that highly skilled workers are more productive and innovative and represent therefore and element of crucial relevance to both companies and economies.

It is necessary to remember that the contributions of the theory of the endogenous growth are an answer to a theory that revolutionized the concept of economic and productive growth: the neo-classical growth theory of Solow[1].

[1] The neoclassical theory influenced the ones coming later, both from a macroeconomic and microeconomic point of view.
If the most important macroeconomic approaches come from the works of Solow, for the understanding of the microeconomic approach it is necessary to take into account the contribution of economists and mathematics such as Arrow and Von Hayek.
Arrow is considered one of the most important authors of the innovation theory, through the theory of competition that is consider an incentive to innovation.
Technological innovation is the key element, the force driving to economic growth. The innovative boost originate from competitiveness as the innovative product gives to the firm the chance to have a greater market power.
Von Hayek considers competition as a never-ending discovery process during which firms search for unemployed resources and capabilities in way of developing technical knowledge. He also tries to explain the

Neoclassical growth models attempted to explain long run economic growth by looking at productivity, capital accumulation, population growth, and technical progress. The starting hypothesis of Solow's theory is that the saving and accumulation mechanism of nation should have only guarantee, in the long run, the constant retention of per capita product: if a nation's saving rate growths, the country can only temporarily enjoy a growth of the per capita income, but in the long run this effect disappears. In spite of the starting hypothesis, Solow observational studies showed that the per capita income continue increasing at a quite constant rate. It demonstrated that the above mentioned growth was the result of the improved production methods and processes and gave that driving force the name of technological progress, consisting in a set of innovation, techniques and improvements that make the labour processes more productive.

The paradox of the theory of Solow is that technological progress, considered to be the most powerful force determining economic growth, was still an exogenous phenomenon, not yet explained by economic models.

As said before, it is only at the beginning of the twentieth century that some economists such as Grossman, Helpman and Aghion, propose a most coherent innovation theory. Their intuition has been that incentives moving most of technological and economic processes toward progress have economic nature, and that new ideas are potential sources of future incomes only if they guarantee the chance to product new goods with new techniques.

Theories considering technology an endogenous element of economic growth processes aimed at explaining the difference in the countries rate of per capita production growth. They stated that in a non-perfectly competitive markets, the monopolistic advantage perspectives make firms to undertake innovative activities, as they know that each success in the field of research and innovation will generate competitive advantages in the marketplace. Their conclusions are that the difference in the growth rate of countries is ascribable to their different degrees of technological advancement.

reason why different levels of competitiveness exists, by analyzing the relationship between technical progress and economic growth; its conclusion is that the boost toward innovation, and therefore competitiveness, lies in and depends on the special needs of firms.

The new theoretical system leaves the principles of laissez-faire and takes into account heterogeneous perspectives with respect to the adoption of geo-economic strategies, aiming at improving and favoring potential competitive situations for each country.

The brief review of the economic theories involving reflections on competitiveness gave us the chance to understand how the concept evolved over time and to confirm the hypothesis on its multidimensional nature.

1.2 DEFINITION ISSUES

Definition of the concept of competitiveness is characterized by a scientific debate which has been going on for several decades, and still continues; define the concept of competitive is, itself, a research question.

Although it has always been central to the economic and social thinking it has taken on a great number of interpretations, many of them vague; as a matter of fact the definition of competitiveness appears to be straightforward and such construct is often used in different and somewhat ambiguous meanings.

Economic literature examines competitiveness along two different levels: competitiveness of national economies (macroeconomic level) and competitiveness of firms/industries (microeconomic level).

It is noteworthy, firstly, that the definition of national competitiveness varies according to the degree of economic development in the countries taken into account. Competitiveness in industrialized countries represents their ability to reach a leading role in the global economy through focusing on improving the technological sector (in terms of invention, innovation, introduction of new businesses) and working to continuously maximize the economic benefits and returns under the competition resulting from openness and globalization, while acting for guarantying sustainable development structures.

The definition of national competitiveness of the emerging industrialized countries centers on how to maintain the progress and leading positions, achieved in the world of middle and high technological industries through framing those countries' comparative advantages in some areas (such as low wages, abundant raw materials, geographical location, etc.), and on working to increase the sectors in which they can occupy a leading position.

For developing countries with closed economies, which are trying to integrate into the global economy, competitiveness is defined as the ability of a country to progress and get a foothold on the global race course of development and advancement through occupying leading positions in some sectors and areas where the country has an opportunity to convert its comparative advantages into competitive advantages through adopting a series of structural reforms and economic policies in order to face the challenges of globalization and integration into the global economy.

Finally, competitiveness for poor countries is the ability to survive through maximizing the potential use of the available natural resources and minimizing the negative consequences of the integration process into the global economy.

Writers and economists, as well as international organizations and agencies, have paid more attention to the definition of competitiveness at the level of countries than at the level of enterprises and activities sectors. Accordingly, there exists a variety of definitions which differ depending on the perspective from which competitiveness is viewed.

Following are some of the most important of these definitions.

The American Council defines competitiveness as "the State's ability to produce goods and services that compete on international markets and, at the same time, achieve continuous improvement in the standards of living in the long-term".

In its Barcelona meeting (2000), the European Council defined a nation's competitiveness as "the ability to constantly improve its citizens' standards of living and to provide high employment level and social cohesion. It covers a wide range and includes economic policies".

The Organization for Economic Cooperation and Development (OECD) defines competitiveness as "the degree to which a nation can, under free and fair market conditions, produce goods and services which compete on international markets while, simultaneously, expanding the real income of its people in the long-term”.

More specific definitions include the one of the United Nation Conference of Trade and Development (UNCTAD, 2002) of international competitiveness “from meaning simply higher exports growth over time, upgrading the technological and skill content of export activity, to expanding the base of domestic companies able to compete globally”.

According to the International Institute for Management Development (IMD), "Competitiveness is the ability of a country to create added values, and then increase national wealth through managing assets and processes by attractiveness, aggressiveness, globalization, and proximity". Thus, the IMD defines global competitiveness within the economic theory as a set of policies that constitute the nation's ability to create and secure an environment that enables enterprises to create values on a sustainable basis, and realize prosperity for the people. Competitiveness depends on the mechanism adopted by countries and enterprises in managing their competitive components to realize further prosperity.

The Word Economic Forum (WEF) defines Competitiveness as “the ability to secure a suitable environment to achieve high and sustainable growth rate”. Moreover the WEF introduced a new definition in the Global Competitiveness Report of 2007-2008: "Competitiveness is a set of factors, policies, and institutions that determines the level of productivity in economy, which, in turn, determines the level of prosperity that can be achieved from the increased rates of return on investment in the economy, and thus achieving sustainable and higher growth in the medium term”.

It is possible to notice that most of the above mentioned definitions have a number common elements. Competitiveness is considered as the capacity to penetrate foreign markets with high quality products at minimum costs and to consequently improve GDP, which in its turn reflects positively on improving citizens living conditions and guarantying fair distributions of wealth.

Competitiveness is, thus, created and improved through a set of policies and measures adopted by nations to help creating an empowering environment in order to turn their comparative advantages to competitive advantages.

The issue of the interpretation of the concept of micro-level competitiveness as excited, above all in recent years, increasing interest, especially after the publication of Porter's work on microeconomic foundations of competitiveness in which he highlights that firms which compete with one another in the market, not nations, and the wealth of a nation is strictly related to the one of its firms.

Economy-wide conditions such as business-friendly economic policies, productivity and high levels of education might have profound impact on the competitiveness of firms. Competitive firms are those producing services or products of superior quality and lower costs than their domestic and international competitors; competitiveness is synonymous with a firm's long-run profit performance and its ability to compensate its employees and provide superior returns to its owners (Buckley et al. 1988).

Enterprise competitiveness is the ability to provide consumers with products and services at a higher level of efficiency and effectiveness compared with other competitors, both on the international and on the local market, in the absence of government support and protection. This can be achieved through raising the productivity of the factors employed in the production process (labour, capital, and technology) and through welcoming international competition. Enterprise competitiveness is no longer determined by reducing costs, but by its success with respect to several criteria, most important of which are productivity, profitability, excellence, and the market share.

According to Freebairn (1986) competitiveness is “an indicator of the ability to supply good and services in the location and form at the time they are sought by buyers, at prices that are good as or better than those of other potential suppliers, while earning at least the opportunity cost of return on resources employed”.

The above definition seems to be widely accepted in the microeconomic literature. Its main advantage lies in the conceptualization of two types of competition. First, the competition on domestic and international product markets and thus the ability to gain and maintain market shares, and second, the competition in factor markets, where factors employed in the productivity processes have to earn at least the opportunity costs.

The competitiveness of an enterprise (Cuervo, 1993) can be measured by its capacity to produce goods and services for the open market, and at the same time, to create value, i.e., obtaining profit from invested capital equal to or higher than its opportunity cost. In an open market (Gallardo et al. 2003), a firm is considered to be competitive if it is capable of offering its products while remunerating the factors of production, at least at the marketing remunerating level. Therefore one way of studying the competitiveness of a firm is to analyze whether it is capable of enhancing business efficiency, which is the basis of profitability. In term of efficiency improvement, besides most important other things, development of productivity, unit labour costs, the level of used technology, utilization capacity and flexibility of production system are to be investigated. Moreover, competitiveness can be interpreted as the ability of firms to cope with structural changes: formation of strategy and the ability of its implementation have become the essential features of competitive business, being the fundamental condition and means of adaptation to the dynamically changing environment.

The above listed definitions of micro-level competitiveness have a common feature: they give competitiveness a strictly financial and economic characterization.

A different approach to the definition of competitiveness is the one developed in the context of Corporate Social Responsibility[2] and asserting that

2 The goal of CSR is to embrace responsibility for the company's actions and encourage a positive impact through its activities on the environment, consumers, employees, communities, stakeholders and all other members of the public sphere.
As corporations pursue growth through globalization, they have encountered new challenges that impose limits to their growth and potential profits. Government regulations, tariffs, environmental restrictions and varying standards of what constitutes "labour exploitation" are problems that can cost organizations millions of dollars.
Some view ethical issues as simply a costly hindrance, while some companies use CSR methodologies as a strategic tactic to gain public support for their presence in global markets,

competitiveness in industrial activities means developing relative efficiency along with sustainable growth (Lall, 2001). Such a definition of competitiveness if grounded on the hypothesis that the success of a firm is determined not only by monetary aspect, but also by different, sometimes intangibles, elements.

In conclusion, the definition of the Research Centre for Competitiveness is, in my view, the most complete definition found in literature, able to explain its multidimensional nature: "Business competitiveness, in our perception, is the company's ability to permanently offer consumers products and services, which are in compliance with the standards of social responsibility, and for which they are willing to pay more than for the competitors' products, ensuring profitable conditions for the company. Condition of this competitiveness is that the company should be able to detect changes in the environment and within the company, by performing permanent better market competition criteria compared to the competitors" (Chikan, 2008).

1.3 APPROACHES TO THE STUDY OF THE COMPETITIVE PHENOMENON

The phenomenon of competitiveness has been studied by researchers from a variety of perspectives and through the use of several, different approaches.

Our aim is to try to develop a systematic review of the research works that directly or indirectly relate to the topic of competitiveness, through a framework that organizes mainstreams of literature, by considering the way competitiveness is intended.

Competitiveness can be treated as a dependent or independent variable: the first approach looks at competitiveness as driver of a firm's performance, the second one considers competitiveness as outcome of a firm's competitive advantages; such a distinction can also be expressed as the difference between competitiveness *ex ante* and competitiveness *ex post* approaches.

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helping them sustain a competitive advantage by using their social contributions to provide a subconscious level of advertising.

The research contributions about the sources of a firm's competitive advantage can be included within the view of competitiveness *ex ante*.

In this context, the main classification of the sources of a firm's competitiveness distinguishes between internal sources (sources that arise from a firm), and external ones (industry- and country-based factors).

Internal sources can be classified as tangible or intangible, and employee-related or firm-related (Cater, 2005).

Internal intangible firm-related sources mostly include organizational resources, transformational and output-based capabilities (Lado et al., 1992) and the knowledge of the firm as a whole; internal intangible employee-related sources mostly include a firm's strategies, human resources, managerial capabilities, and the knowledge of individuals; internal tangible firm-related sources include physical and financial resources and input-based and some functional capabilities.

On the other hand, external industry-related sources include all the variables related to the industry structure and competition, such as for example weak bargaining power of suppliers and buyers, low rivalry among existing firms in the industry, low threats of substitution and new entrants (Porter, 1980).

Finally, external national-economy-related sources encompass variables representing the characteristics of the national economy.

Moreover, internal sources of competitive advantages can be analyzed by either a static or a dynamic approach: the former focuses on the resources and assets at the basis of a firm's competitiveness; resource-based view studies[3] fall within this domain. The latter refers to management processes that transform and deploy those assets so as to achieve performance.

Specifically, the competence-based approach emphasizes the dynamic component of the competitiveness construct. Whereas resources are the basis of

3 Resources-based view emerged as a dominant paradigm in the strategic management studies during the 90s. According to this perspective a firm's competitive advantage derives from those resources that match specific conditions such as value, heterogeneity, rareness, durability, imperfect mobility, imperfect imitability, and ex ante limits to competition (Barney, 1991). Several classifications of firms' resources-based have been developed by literature and generally they build on the distinction between tangible and intangible resources.

firms' capabilities, capabilities represent the way firms unfold their resources. Specifically, dynamic capabilities (Teece, Pisano, Shuen, 1997) are those which transform resources into new sources of competitive advantage as they are processes that enable firms to obtain new resource configurations and generate new and innovative forms of competitive advantage.

The distinction between a static and a dynamic approach can be understood by referring to the distinction between the competitive advantage as a firm's position within an industry and the competitive advantage as a firm's actions and abilities to work more effectively and efficiently than its competitors.

As far as the *ex post* approach is concerned, it looks at competitiveness as the outcome of competitive advantages; it includes those research works a firms performance measurement. Superior economic or market performance are generally considered as an indicator of competitive advantages. Profitability is considered the most important measure of competitive success: economic performance in the short term can be measured through profitability ratios. Costs and productivity also are good signals of competitiveness.

A critical element characterizing such an approach is that it is able to give information on past competitiveness performances, but it is not able to fully evaluate whether and to which extent the firm will be competitive in the future. In fact, even if past performance signals the presence of competitive advantage, it does not provide enough information about the sustainability of those advantages.

In addition to the ex-post and ex-ante approaches, it is possible to study competitiveness at different levels of aggregation: firm, industry, and country. Firm level analysis focuses on behaviors and performance of firms. Competitiveness is frequently analyzed also at industry level or "cluster" level. The competitiveness of an industry can be assessed by a comparison with the same industry in another region or country which there is open trade with. Beyond firm-specific and industry-specific factors, in recent years globalization has emphasized the importance of country-related effects as determinants of performance.

Resource endowments, cost of labour and production inputs, financial and technological infrastructures, access to markets, institutional and regulatory frameworks are examples of country-specific factors that affect firm performance.

Studies on competitiveness can moreover be carried out for various levels of product aggregation, across the entire economy, for a specific sector or for a single product.

The different dimensions of competitiveness are strongly related: for example, country's competitiveness factors are determinants of its firms' international competitiveness. On the other hand, the most evident aspect of a country's international competitiveness is represented by its firms' competitiveness in comparison to other countries' firms.

It is possible to distinguish between microeconomic and macroeconomic interpretation of the concept of competitiveness.

At macroeconomic level it is possible to identify at least three ways to see competitiveness: competitiveness as productivity, competitiveness as capacity to create welfare, competitiveness as ability to sell on external markets.

The best known interpretation of competitiveness at macroeconomic level is proposed by Michael Porter and World Economic Forum. They define the national competitiveness as a set of factors, policies and institutions that determine the level of the productivity of a country. Raising productivity, meaning making better use of the resources, is the driving force behind the rates of return on investment which, in turn, determine the aggregate growth rate of an economy. (Global Competitiveness Report 2006-2007).

The prosperity and the nation's standard of living are determined by the productivity of its economy, which is measured by the value of goods and services produced per unit of the nation's human capital and natural resources.

As far as competitiveness as capacity to create welfare is concerned, the definition proposed by European Competitiveness Reports (European Commission) is the key element for this interpretation of such a point of view. Competitiveness is related to high and rising standards of living of a nation or a group of nations with the lowest possible level of involuntary unemployment, on a sustainable basis.

Standard of living can be decomposed into employment and labour productivity performances, but in the long run, improvements in employment performance are bound by the natural rate of employment, leaving this way the burden of ever increasing living standards to the productivity.

The interpretation of competitiveness as ability to create welfare includes an “outcome assessment” and a “process assessment” (Aiginger, 2006).

The definition of outcome competitiveness as the welfare of nation deals with per capita income, employment, distributional, social and ecological goals. The definition of process competitiveness refers to processes and capabilities generating competitiveness. Processes and capabilities which generate competitiveness are considered as drivers of competitiveness and include strategies that foster competitiveness as indicators of the generating process in the competitiveness evaluation.

Depending on specific situation, the analysis of “outcome competitiveness” can focus on income, social and ecological indicators as well as on financial sustainability (budget balances, debt), external balance sustainability (trade balance, current account), political stability.

The main rival to productivity based definition of competitiveness is the market-share based definition. It defines competitiveness as the ability to sell on international markets and is fundamentally concerned with the sustainability of an economy’s overall external balance. From this point of view, competitiveness is measurable through the share of global markets a country hold with its products.

This last definition of competitiveness is quite controversial as it is important to bear in mind that exports can results from subsidies or other incentives provided, for instance, by exchange rate misalignment. Such incentives can explain the growth of the country’s share of the world market but are not based on comparative advantage. Therefore it must be remembered that real competitiveness and nominal competitiveness are two different ways to achieve a better position in the world trade.

At microeconomic level it is possible to individuate two field of analysis: the cluster level and the firm level.

Studies about competitiveness conducted during the last decade stressed out that the geographical location of economic activities has a crucial impact on competitiveness. One of the most conspicuous tendencies in economies shaped by globalization process is the strengthening of localization and regionalization (especially palpable in developed countries with knowledge-based economies).

In the area of applied economics, Michael Porter has analyzed the competitive strategies and advantages of companies and found the role of locality and that one of regions to be exceptionally important. Porter has argued that regional cluster are capable of improving competitiveness and proposed a cluster-based approach to economic development.

Thus, in regional policies, proposal for improving competitiveness have stated to rely on the standard notion of competitiveness.

When trying to understand regional competitiveness is important to take into account that the regional levels forms an intermediate, aggregation level layered between the macro and the micro levels.

Hence it makes sense to define the notion of regional competitiveness either by using macro-level concepts of competitiveness (disaggregation) or, starting from the micro-level, by adding up the competitive advantages of companies active in the given region (aggregation).

From a regional point of view, the classification competitiveness *ex post* and competitiveness *ex ante* is still helpful.

As said before *ex post* competitiveness is about the measurable past output of the economy. Its most important indicators are: growth rate of the GDP, productivity, changes in the trade balance, export market shares, market exchange rates, etc. It results difficult to apply some of the indicators common to this approach on the regional level since it is difficult to individuate regional monetary or currency policies. On the contrary, competitiveness *ex ante* focuses on the sources of the competitive advantages rather than on a given figure or set of indicators of economic performance. As said before, this approach is primarily related to business and environmental conditions and it less interested in economic performance. In short, this approach analyzes the grounds of competitiveness and also provides a number of considerations which can prove useful for the assessment of regional competitiveness: knowledge-base, qualified labour, infrastructure, agglomeration input, etc.

Microeconomic approaches consider a firms as successful if it reaches a high level of productivity and is also capable of maintaining a high level of productivity growth. As far as the identification of the factors responsible for micro-level competitiveness are concerned, it would be interesting to consider and adopt a pyramid-model of competitiveness (Porter, 1990).

This model seeks to provide a systematic framework of the elements characterizing and determining competitiveness development.

Factors influencing micro-level competitiveness can be divided into two groups of direct and indirect factors. Basic factors with a direct influence on economic output are profitability, labour productivity and employment rates; they are able to ensure only a short-term competitive advantage. The elements determining a long-term competitiveness structure depend on social, economic, environmental and organizational processes and parameters, the so-called success determinants, with an indirect impact on competitiveness.

Three levels can be distinguished with regard to elements characterizing firms development processes:

Basic categories of competitiveness: *ex-post* indicators measuring competitiveness from an economic point of view (income, labour productivity, value added and openness).

Development factors of competitiveness: *ex-ante* factors related to firms resources that helps in improving competitiveness and have an immediate impact on basic categories.

Success determinants of competitiveness: social and environmental features explaining development and guarantying a long-term competitiveness. They have an indirect impact on basic categories and development factors, but are fundamental as they represent the ground on which competitiveness growth and develops.

The just described competitive analysis framework sheds light on the multidimensional nature of micro-level competitiveness, and allows to understand which are the element to be taken into account for the full understanding of the phenomenon.

The review of the meanings competitiveness assumed over time and on the different approaches used in order to assess it has been of fundamental importance for the development of the present study. They allowed us to better focus the objectives of the research, as well as to orient our choices.

Specifically, by starting from the awareness that micro-level competitiveness structures are fundamental in determining macro-level growth processes, we decided to adopt a micro-level point of view, by using an *ex-ante* approach, thus conceptualizing the phenomenon as determined by economic, tangible as well intangible elements.

Chapter 2: Measures of multidimensional phenomena.

2.1 INTRODUCTION

As said in the previous chapter competitiveness is a multidimensional phenomenon whose study and measurement seems to raise both theoretical and technical issues.

In the following sections a review of the main approaches to the measurement of multidimensional phenomena will be presented, with the aim to choose the most suitable tools for the measurement of competitiveness, by taking into account the most controversial questions regarding the construction of composite measures.

The measurement of multidimensional, complex phenomena is a hugely critical issue if faced from the statistical information point of view, as it depends on the theoretical reference models, as well as on the development of economic and social background.

Traditionally, the multidimensional phenomena measurement processes start with the accurate definition of the object of the analysis, subsequently the most relevant elementary indicators have to be individuated in order to move toward the final step consisting in the choice of the methodological tools that effectively allow to measure the phenomenon of interest. It is easy to understand that the multidimensional phenomena measurement processes involve, as a first step, theoretical issues such as the definition of the phenomenon under investigation and the understanding of its main features; in a second phase statistical and methodological issues have to be addressed in order to guarantee some quality requirements: objectivity, coherence, accuracy, usability as well as comparability.

There is no doubt that the use of composite indicators for the measurement of complex concepts are appealing as the use of a unique measure, obtained by the combination of several indicators representing different aspects of a multidimensional phenomenon, helps in capturing the complexity of reality and in garnering the attention of those who are interested in understanding the phenomenon itself. However, the debate on the statistical foundation of composite indicators has been characterized, above all in recent years, by increasing attention toward the methods to be implemented in order to overcome some limits characterizing the composite measures construction processes.

The purpose of the present section is to understand how to aggregate multiple indicators into a composite one, by using a critical review of the literature on the measurement approaches to multidimensional phenomena. Our aim is to identify a statistical approach allowing to overcome and solve the controversial issues characterizing the debate on the computation of composite indicators.

2.2 MULTIDIMENSIONAL PHENOMENA MEASUREMENT PHASES.

Composite measures have been defined as the mathematical combination of individual indicators representing different dimensions of a phenomenon whose understanding and description is the objective of the analysis (Saisana and Tarantola, 2002).

It is common knowledge that the construction of composite indicators involves different stages where subjective judgments have to be made: the selection of indicators, the treatment of missing values, the choice of aggregation model, the weights of the indicators, etc. The quality of composite indicators strongly depends on the above mentioned subjective choices. It is, thus, important to identify the sources of subjective or imprecise assessment and use uncertainty and sensitivity analysis to gain useful insights during the process of composite indicators building, including a contribution to the indicators quality.

As said before, the measurement of multidimensional phenomena through the use of composite indicators can be split in different phases. It would be helpful to list and briefly describe them for understanding which are the awkward points to be deepened in order to individuate the most suitable statistical tools guarantying against subjectivity and arbitrariness.

The composite indicators building process is generally structured as follows:

- *Deciding on the phenomenon to be measured* and analyzing it for understanding its main features and whether it would benefit from the use of composite measures.
- *Selection of sub-indicators*. A sound theoretical background is necessary for understanding which are the most relevant elements to be taken into account for the exhaustive analysis of the phenomenon to be measured.
- *Assessing the quality of the data***.** The quality of a composite indicator as well as the soundness of the messages it conveys depend not only on the methodology used in its construction but primarily on the quality of the framework and the data used. A composite based on soft data containing large measurement errors can lead to misleading results. Thus, once the theoretical basis explaining the phenomenon of interest have been studied and the objective of the research have been clearly individuated, it is necessary to assess the quality of the disposable data, unavoidable aspect for the proper development of the subsequent phases. To this end it is necessary to check for the presence of missing values, estimate them and provide reliability measures of each imputed value, for assessing the impact of the imputation process on the composite indicator results[4]; it is also important to analyze the data distribution characteristics and, specifically, to check for skewness, that implies the discussion on the

[4] The uncertainty in the imputed data should be reflected by variance estimates; this makes it possible to take into account the effects of imputation in the course of the analysis. However, single imputation methods (mean, median or mode substitution, regression imputation, hot or cold deck imputation, expectation-maximization imputation) are known to underestimate the variance, because they partially reflect the imputation uncertainty. The multiple imputation (Markow Chain Monte Carlo algorithm), provides, on the contrary, several values for each missing value, thus allowing to more effectively represent the uncertainty due to imputation.

presence of outliers, and therefore adopt appropriate data transformations measures[5].

- *Assessing the data structure.* The underling nature of the disposable data have to be carefully analyzed as a preliminary step for assessing the suitability of the data set as well as for understanding which methodological choices have to be made during the composite indicator building phases. The data structure analysis conducted by means of multivariate analysis techniques such as Principal Component Analysis, Factor Analysis or Cluster Analysis is fundamental for investigating on the relationships among the selected sub-indicators, reduce the dimensionality of data, remove redundant information, measure the internal consistency in the set of sub-indicators (that is how well they describe the construct under analysis), as well as to investigate on the presence of latent structures explaining the relationships among elementary indicators and exploring whether the different dimensions explaining the phenomenon of interest are well-balanced from a statistical point of view.
- *Normalizing the elementary indicators.* The elementary indicators selected in order to measure the multidimensional phenomenon of interest generally convey information of different kinds. Indicators may be expressed in different units of measurement, it is therefore necessary to bring them to the same pure, dimensionless measure. Normalization methods are also helpful for reducing the effects of extreme values and outliers when the original distribution is highly skewed. The objective is therefore to identify the most suitable normalization procedures to apply,

[5] A transformation that is often applied is the truncation of the raw data. The choice of trimming the tails of the elementary indicators' distributions is supported by the need to avoid having extreme values overly dominate the result and, partially, to correct for data quality problems in such extreme cases.
Another possible transformation is the one modifying the functional form of the disposable variable. The functional transformation is applied to the raw data to represent the significance of marginal changes in its level. In most cases, the linear functional form is used on all of the variables. This approach is suitable if changes in the indicator's values are important in the same way, regardless of the distribution level. If changes are more significant at lower levels of the indicator, the functional form should be concave down (e.g. log or the n^{th} root). If changes are more important at higher levels of the indicator, the functional form should be concave up (e.g. exponential or power).

by taking into account the data features and properties. Different normalization methods can be used, supplying different results for the composite indicator. Overall robustness tests should therefore be carried out in order to assess their impact on the final outcomes. Careful attention should be paid to the problem of the scale effect during the choice of the normalization method, as some procedures are not invariant to changes in the measurement unit and should modify the original features of the disposable data set.

- *Assigning weights and aggregating the elementary indicators.* Central to the construction of a composite indicator is the need to combine in a meaningful way the previously selected dimensions, which implies a decision on the weighting model and the aggregation procedure. The choice of the weighting scheme to be assigned to each sub-indicator in the aggregating phase of the composite indicator is probably the most relevant and awkward issue that have to be solved for obtaining a sound and coherent measure of the phenomenon of interest. Indicators should in fact be weighted and aggregated according to the underlying theoretical framework, by the use of the most suitable statistical tools. The challenge of weighting and aggregating composite indicators for describing multidimensional phenomena is a very discussed theme in the reference literature; subjectivity and arbitrariness are identified as the most controversial aspects characterizing the above mentioned phases.

  During the weights assignment phase the contribution of each selected elementary indicator (representing a different aspect of the phenomenon under analysis) to the overall composite measure has to be established. Several methods for weighting the sub-indicators are reported in the literature.

  Most composite indicators rely on the equal weighting scheme in which all variables are given the same weight. This essentially means that the elementary indicators are hypothesized to give the same contribution in determining the final composite measure. However, such a weighting choice could also disguise the absence of a statistical or an empirical basis, the insufficient knowledge of the phenomenon under analysis as well as of the statistical features of the selected sub-indicators.

When an equal weighting scheme is chosen, correlation and compensability issues among indicators should be checked for and corrected. In fact, it could happen that by combining variables with a high degree of correlation, elements of double counting are introduced into the indicator. In such a case, the solution could be to test indicators for statistical correlation and to choose only indicators which exhibit a low degree of correlation or to adjust weights giving less weight to correlated indicators. Furthermore, minimizing the number of variables in the indicator on the basis of multivariate methods may be desirable not only for eliminating double counting problems, but also on other grounds, such as transparency and parsimony.

Moreover, when elementary variables are grouped into dimensions and those are further aggregated into the composite indicator, applying equal weighting may imply an unequal weighting of the dimension (the dimensions grouping the larger number of variables will have higher weight), resulting in an unbalanced structure in the composite indicator.

Using a different weighting scheme could help in overcoming the limits characterizing the choice of assigning equal weights to each variable in the composite indicator. Different weights may be assigned to sub-indicators, based on their theoretical significance, statistical features[6], cyclical conformity, etc. Among the available weighting techniques, it is possible to distinguish between the weighting schemes based on statistical models (e.g. multivariate analysis, Data Envelopment Analysis, regression approach, Unobserved Components Models) whose main advantage is that they do not imply any manipulation of weights through *ad hoc* restrictions, and those based on participatory methods (e.g. budget allocation, analytic

[6] Weights may reflect the statistical quality of the data, thus higher weight could be assigned to statistically reliable data (data with low percentages of missing values, large coverage, sound values). In this case the concern is to reward only sub-indicators easy to measure and readily available, punishing the information that is more problematic to identify and measure.

hierarchy processes) in which indicators are weighted on the basis of experts opinion, who know the phenomenon priorities and its theoretical backgrounds.

It is undoubted that the use of methods based on statistical models gives the chance to solve critical issues related to the arbitrariness and subjectivity of the weights determining the contribution of the variables to the overall composite measure, as they are completely data-driven.

Being data-driven is a objectivity guaranty, but can also be a dangerous element when the statistical model selected in order to determine the indicator weights in not compatible with the statistical features of the disposable dataset. It is therefore necessary to choose the most suitable statistical tools by taking into account not only the theoretical background of the analysis, but also the characteristic of the variables used in order to conduct it.

For example, multivariate methods such as principal component analysis or factor analysis should be used when dealing with correlated variables as they group together sub-indicators that are collinear to form an intermediate composite indicator capable of capturing as much of common information of those sub-indicators as possible.

The basic idea is that it may be possible to describe a set of variables in terms of a smaller number of factors; that is to account for the highest possible variation in the indicators set using the smallest possible number of factors. Each factor (usually estimated using principal components analysis) reveals the set of indicators having the highest association with it. Therefore, the composite indicator obtained by using multivariate techniques do not depends upon the dimensionality of the dataset but it is rather based on the “statistical” dimensions of the data. The weighting process only intervenes to correct for the overlapping information of two or more correlated indicators, and it is not a measure of importance of the associated indicator.

If the aim of the analysis is instead to understand and measure the linkages between a number of indicator and an overall output measure, a multiple regression approach or may be used to retrieve the relative weights (multiple regression coefficients) of the sub-indicators. This approach, although suitable for a large number of variables of different types, implies the assumption of linear behavior and requires the independence of explanatory variables. If these variables are correlated, in fact, estimators will have high variance meaning that parameters estimates will not be precise and hypothesis testing not powerful. However some remedies can be found associating principal component analysis with regression analysis or using a Partial Least Squares regression approach.

The brief example presented above shows that weighting models have to be explicit and transparent, as well as that it is fundamental to choose the weighting scheme by considering both the theoretical background of the research and the statistical features of the disposable data, in order to guarantee against arbitrary solutions and scarcely coherent choices.

Moreover, one should have in mind that, no matter which method is used, weights are essentially value judgments and have the property to make explicit the objectives underlying the construction of a composite indicator (Rowena et al., 2004).

Once the weighting scheme has been chosen, the sub-indicators have to be brought together in order to form a unique, composite measure. The principle lying at the base of the aggregation approaches is to simultaneously combine and synthetize several numerical values into one indicator, at individual level, in order to obtain a measure for each unit of analysis (helpful for units comparisons and rankings), or at aggregate level, putting together a series of indicators that have been previously aggregated across units.

The simplest aggregation method consist in an additive approach that entails the calculation of the ranking of each unit according to each individual indicator and summation of the resulting rankings. It is a simple method based on ordinal information, independent of outliers. Its main disadvantage is that it implies a loss in the information contained in the original data.

Another very simple aggregation method is based on the number of indicators that are above and below a given benchmark. This method uses nominal scores for each indicator in order to calculate the difference between the number of indicators that are above and below an arbitrarily defined threshold around the mean. It is as well a simple method, unaffected by outliers, but implying a loss in the interval level information.

The most widespread aggregation method consists in a linear additive approach, characterized by the summation of the weighted and normalized elementary indicators, with the constraint that the weights sum up to one:

$CI_i = \sum_{q=1}^{Q} w_q I_{qi}$ with $\sum_q w_q = 1$ and $0 \leq w_q \leq 1$; for all $q = 1,...,Q$ and $i = 1,...,M$.

Although the linear additive aggregation techniques are widely used in the empirical studies on the measurement of multidimensional phenomena, it is necessary to underline that the quality of the resulting composite indicator strongly depends on the quality of the underlying elementary variables; moreover such an aggregation scheme open troublesome questions on the interpretation of the weights role.

Specifically, when using a linear additive aggregation technique a necessary and sufficient condition for the existence of a proper composite indicator is preference independence: an additive aggregation function exists if and only if these indicators are mutually preferentially independent[7] (Debreu, 1960; Keeney and Raiffa, 1976; Krantz et al., 1971).

Preferential independence implies that the trade-off ratio between two variables is independent of the values of the other disposable ones (Ting, 1971). From a practical point of view this means that an additive

[7] A subset of indicators Y is preferentially independent of Y^c (the complement of Y) only if any conditional preference among elements of Y, holding all elements of Y^c fixed, remain the same, regardless of the levels at which Y^c are held.
Variables can be said mutually preferentially independent if every subset Y of these variables is preferentially independent of its complementary set of evaluators.

aggregation function permits the assessment of the marginal contribution of each variable separately. These marginal contribution can then be added together to yield an overall value.

If a full compensability condition hold (that is, poor performance in some indicators can be compensated by sufficiently high values in other indicators) and a linear additive method is nevertheless used, the resulting composite indicator will be biased and it will not entirely reflect the information of its sub-indicators.

The problem can be solved by using geometric aggregation approaches, appropriate when non-comparable and strictly positive sub-indicators are expressed in different ratio-scales and when compensability is not constant, that is, when there is the need of lower compensability when the composite contains indicators with low values. In practical terms, if the aggregation of information is geometric, compensability is admitted and a unit with low scores on one indicator will need much higher score on the others to improve its situation.

It appears quite clear that the compensability (substitutability) of the elementary indicators is a fundamental issue to be faced for ensuring the quality of the final indicator as well as of the information it carries out.

The sub-indicators substitutability can be taken into account and summarized by using an aggregation function characterized by a weighted mean of order β such that

$$CI_i = \left(\sum_{q=1}^{Q} w_q \left(x_{qi} \right)^{\beta} \right)^{\frac{1}{\beta}} \quad ;$$

where β represents a parameter which determines the substitution level between attributes. It is easy to understand that the additive linear aggregating method and the geometric one are special cases of the above presented expression.

The β parameter value determines the functional form of the composite indicator, thus implying different interpretations of the weights role inside the overall measure. The choice of the values it can assume is based not only on statistical and methodological considerations, but also on the objectives lying at the base of the use of a composite indicator measurement approach.

The aggregation phase is the conclusive step bringing to the effective computation of composite measures for the analysis of multidimensional phenomena. The subsequent phases concerns the assessment of the quality of the obtained indicator.

- *Sensitivity analysis.* As said before, the composite indicators construction processes follow an ideal sequence of several steps going from the development of a theoretical framework to the presentation of the resulting composite measure. Each step requires different, subjective choices to be made. Choices in one step can have important implications for the other ones, as well as for the features of the final, overall measure. There is the need of theoretical and methodological coherence in the whole process: the most appropriate choices in each step have to be made and it is necessary to identify whether they fit together well.

  The choices made during the composite indicator construction process can introduce uncertainty into the output variables, for this reason there is the need to conduct a robustness analysis for verifying the quality of the indicator. It is important to analyze how much the composite indicator values are influenced by uncertainty characterizing the its various components. Two combined tools can be used: Uncertainty Analysis[8] (UA) and Sensitivity Analysis (SA). Uncertainty Analysis focuses on how uncertainty in the input factors propagates through the structure of the composite indicator and affects the composite indicator values. Sensitivity Analysis studies how much each individual source of uncertainty contributes to the output variance.

[8] Uncertainty Analysis is generally carried out by means of Monte Carlo simulations, by plugging all uncertainty sources simultaneously, as to capture all possible synergistic effects among uncertain input factors. This involve the use of triggers, that is the use of uncertain input factors used to decide which system or scheme to adopt (with reference to the possible uncertainty elements characterizing the composite indicator development line).

The brief analysis of the phases characterizing the composite measures computation process let us understand that the reliability of the studies on multidimensional phenomena strongly depends on the subjective choices made in the composite indicator development line. The soundness of such indicators is based both on theoretical and methodological matters, this is the reason why the debate on the composite measures quality is still opened and is especially focused on the subjectivity lying at the base of the choice of the key variables composing the final indicator, in the arbitrariness of the weighting and aggregation processes, as well as in the difficulty in the interpretation of movements in the composite measure, that is, when an indicator moving toward a certain direction is presented, it is not always possible to identify which components are the driving forces of the movement itself.

The need is, therefore, to identify the most suitable statistical tools allowing to assure and prove the quality of the resulting composite indicators against subjective and misleading solutions.

For better understanding the implications of the choices that it is possible to make during the composite indicators construction process, we decided to adopt a framework that would allow us to take into account some statistical approaches to the measurement of multidimensional phenomena on the basis of the statistical tools they adopt, in particular, during the weighting and aggregation phases of the selected elementary indicators.

2.3 MULTIDIMENSIONAL PHENOMENA MEASUREMENT APPROACHES.

Although the framework used in order to obtain composite measures for the analysis of complex phenomena consists of almost standard phases, the empirical literature on the multidimensional approaches to the creation of composite indicators can be organized on the basis of a different, surely non-conflicting structure.

Two main approaches to the measurement of multidimensional phenomena can be identified (the reference criterion being strictly related to the elementary indicators aggregation procedures): the axiomatic and the non-axiomatic ones.

The former are characterized by an aggregation process that combine different dimensions into a composite indicator in accordance with some, desirable properties (or axioms) governing the dimensions and the relations among them. The latter can be in turn split in two further approaches, according as the aggregation procedure is carried out at individual level, in order to obtain a measure for each unit of analysis (helpful for units comparisons and rankings), or at aggregate level, putting together a series of indicators that have been previously aggregated across units.

It is important to underline that the above mentioned approaches can be considered as complementary ways of analysis of multidimensional phenomena, because complying with some desirable axioms and properties can assure high quality to the resulting measures, even if a non-axiomatic approach is chosen.

In the next sections we will only focus our attention on the non-axiomatic approaches based on individual data, as the purposes of the analysis of micro-level multidimensional competitiveness address us toward the research of a suitable methodology able to soundly measure the phenomenon of interest for each unit of analysis, in order to allow units comparisons and rankings, for an exhaustive understanding of the main features of the phenomenon itself.

In the non-axiomatic approach, the most widely used methods based on individual data are: the distance function approach, the fuzzy sets approach, the Information Theory approach as well as the inertia one. They will be described and discussed in details in the following sections.

2.3.1 Distance function approach

The distance function approach to the computation of composite indicators belongs to the measurement approaches based on individual data. It allows the retained indicator to be aggregated at the unit level first, and then across units.

The concept of distance function has been widely used in the efficiency analysis. A distance function may have either an input orientation or an output orientation.

To define an output-distance function, it is necessary to define the output set, P(X), which represents the set of all output vectors, $Y \in R_+^M$, which can be produced using the input vector, $X \in R_+^K$, that is

$$P(X) = \left\{ Y \in R_+^M : X \text{ can produce } Y \right\}.$$

The output distance function is then defined on the output set, P(X), as

$$D_o(X,Y) = \min\left\{ \theta : \left(Y / \theta \right) \in P(X) \right\};$$

where θ is the scalar distance by which the output vector can be deflated. *D_O(X,Y)* is non-decreasing, positively linearly homogeneous and convex in *Y*, and decreasing in *X*. The distance function, $D_O(X,Y)$, will take a value which is less than or equal to one if the output vector, *Y*, is an element of the feasible production set, *P(X)*. That is,

$D_o(X,Y) \le 1$ if $Y \in P(X)$. Furthermore, the distance function will take a value of unity if Y is located on the outer boundary of the production possibility set.

The input-distance function is defined in a similar manner. However, rather than looking at how the output vector may be proportionally expanded with the input vector held fixed, it considers how much the input vector may be proportionally contracted with the output vector held fixed. The input distance function may be defined on the input set, *L(Y)*, as

$$D_I(X,Y) = \max\left\{ \rho : \left(Y / \rho \right) \in L(X) \right\}$$

where ρ is the scalar distance by which the input vector can be deflated, and the input set *L(Y)* represents the set of all input vectors, $X \in R_+^K$, which can produce the output vector, $Y \in R_+^M$. That is,

$$L(X) = \left\{ X \in R_+^K : X \text{ can produce } Y \right\}.$$

$D_I(X,Y)$ is non-decreasing, positively linearly homogeneous and concave in X, and decreasing in Y. The input distance function, $D_I(X,Y)$, will take a value which is greater than or equal to one if the input vector, X, is an element of the feasible input set, L(Y). That is, $D_I(X,Y) \geq 1$ if $X \in L(X)$. Furthermore, the distance function will take a value of unity if X is located on the inner boundary of the input set.

The distance functions can be estimated by means of both parametric and non-parametric approaches.

In recent years, several studies have sought to estimate parametric distance functions using econometric methods (Lovell, Richardson, Travers and Wood, 1994; Grosskopf, Hayes, Taylor and Weber, 1997; Coelli and Perelman, 1999, 2000). These studies have specified a translog functional form and have used Corrected Ordinary Least Squares, Ordinary Least Squares or Maximum Likelihood to estimate the unknown parameters of the distance functions.

As far as the non-parametric approach to the estimation of the distance functions is concerned, the most appealing one in a composite indicators computation framework is the Data Envelopment Analysis (DEA) approach (Färe et al., 1994). The method involves the use of linear programming to construct a piecewise linear envelopment frontier over the data points such that all observed points lie on or below the frontier. Specifically, Data Envelopment Analysis (DEA) employs linear programming tools (popular in Operative Research) to retrieve an efficiency frontier and uses it as benchmark to measure the performance of a given set of units.

Two main issues are involved in this methodology: the construction of a benchmark (the frontier) and the measurement of the distance between units in a multi-dimensional framework.

The distance of each unit with respect to the benchmark is determined by the location of the units itself and its position relative to the frontier.

In a composite indicator computation framework this methodology[9], originally proposed for evaluating macroeconomic performance (Melyn and

[9] The most notable difference between general DEA problems and the problem faced when constructing a composite indicators, is that composite indicators typically only look at 'achievements' without taking into account the input-side: they are output-oriented measures.

Moesen, 1991) allows to define the multidimensional measure as the ratio of a unit's performance over its benchmark performance:

$$CI_i = \frac{\sum_{i=1}^{M} I_{qi} w_{qi}}{\sum_{i=1}^{M} I_{qi}^{*} w_{qi}}$$

where I_{qi} is the normalized (max-min method) score of q_{th} sub-indicator *(q=1,…,Q)* for unit *i (i=1,…M)* and w_{qi} the corresponding weight.

The benchmark can be obtained as solution of a maximization problem:

$$I^* = I^*(w) = \max_{I_k, k \in \{1,\dots,M\}} \left(\sum_{q=1}^{Q} I_{qk} w_q \right)$$

*I** is the score of the hypothetical unit that maximizes the overall performance, defined as a weighted average, with the set of weights *w*. It is possible to notice that weights are unit specific: different sets of weights may lead to choose different units as far as there is no unit having the highest score in all sub-indicators; the benchmark would in general be unit-dependent, so no unique benchmark would exist; moreover sub-indicators must be comparable, so they must be expressed by the same unit of measurement.

The second step to be accomplished is the specification of the set of weights for each unit. The optimal set of weighs guarantees the best position for the associated unit with respect to all the other units in the sample. Optimal weights are obtained by solving the following problem:

The use of DEA in CI construction can be divided into two groups. One follows the tradition of DEA by first identifying inputs and outputs and then constructing an aggregated index using the common DEA procedure. Examples of such studies include the construction of child quality of life index (Raab et al., 2000), macro-economic performance index (Ramanathan, 2006a) and environmental performance index (Färe et al., 2004; Zaim, 2004; Zhou et al., 2006, 2007). In the other line, all the sub-indicators are firstly transformed into the same type of variables (output variables) and then aggregated into a CI by some DEA-like models. In recent years, much attention has been focused on this line of research, e.g. Lovell et al. (1995), Mahlberg and Obersteiner (2001), Cherchye (2001), Lau and Lam (2002), Cherchye et al. (2004), Despotis (2005).

$$CI_i^* = \max_{w_{qi}, q=\{1,\dots,Q\}} \frac{\sum_{q=1}^{Q} I_{qi} w_{qi}}{\max_{I_k, k\in\{1,\dots,M\}} \sum_{q=1}^{Q} I_{qk} w_{qk}} \text{ for } i=1,\dots,M$$

subject to non-negativity constraints on weights. The resulting composite index ranges between zero (lowest possible performance) and 1 (the benchmark). Operationally, the expression above can be reduced to a linear programming problem by multiplying all weights by a common factor, that does not alter the index value, and solved by using optimizations algorithms

$$CI_i^* = \max_{wqi} \sum_{q=1}^{Q} I_{qi} w_{qi}$$

s.t.

$$\sum_{q=1}^{Q} I_{qk} w_{qk} \le 1$$

$$w_{qk} \ge 0$$

$$\forall k = 1,\dots,M; \forall q = 1,\dots,Q;$$

The above presented model is an output maximizing multiplier DEA model with multiple outputs and constant inputs, which measures how far the evaluated entity is from the best practice entity under the best possible weights.

In substance, the weights are chosen such that the CI value for each unit is maximal. The full model has two additional and important features: the presence of normalization constraint that ensures the chance to assess the relative performance of units and the non-negativity constraint that restricts the composite indicator to be a non-decreasing function of its composing sub-indicators.

The intuition behind the idea to use DEA approach to the construction of composite indicators is that that relative performance on a set of indicators is, at least to some extent, a revealed preference by the organizational unit about the relative importance of the indicators. Thus it is possible to recognizes these revealed preferences by assigning higher weights to indicators on which performance is better and lower weights to indicators on which performance is poorer. With relative strengths being interpreted, each unit is in fact entitled to its own optimal weighting scheme. Each unit is put in the best possible light relative to other units in the sample when its aggregate performance is gauged.

The above described approach seems to be useful in the composite indicator building process as it avoids the subjectivity in determining weights and therefore provides a relatively objective performance score for each unit, without making any distributional assumption on the data structure. It produces a composite indicator by using two sets of weights that are generated from data themselves. However, it presents some disadvantages: without imposing constraints on weights (except the non-negativity) the most likely solution is to have all units with a composite equal to 1. When constraints on weights are imposed it may be the case that, for some units, no solution of the maximization problem exist, likewise it may happen that there exist a multiplicity of solutions making the optimal set of weights undetermined. Moreover the value of the scoreboard depends on the benchmark performance. If this changes, the composite will change, as well as the set of weights and the units ranking.

2.3.2 Fuzzy-set approach

The fuzzy set approach to the measurement of multidimensional phenomena is based on the theory of fuzzy sets introduced by Zadeh (1965) as an extension of the classical notion of set. Differently from the classical set theory based on a bivalent logic (an element either belongs or does not belong to the set), fuzzy set theory allows the gradual assessment of the membership of objects in a set. A fuzzy set is in fact a class of objects with a continuum of grade membership; such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one.

From a composite indicator construction point of view, this approach gives the chance to identify the sample unit features, with respect to each of the dimensions chosen in order to measure the phenomenon under investigation, by using its degree of belonging to the fuzzy sets which is determined by the degree of possession of a given attribute.

In order to aggregate the variables expressing different aspect of the observed phenomenon into a composite index, two operational steps have to be accomplished: the specification of the unit membership function for each of the variables taken into account and the specification of the weighting structure and aggregating form of the membership functions.

Formally, if X is a set of elements $x \in X$; a fuzzy subset A of X is a set of ordered pairs:

$$A = \left[x, \mu_A(x)\right] \quad \forall x \in X$$

where $\mu_A(x)$ is the membership function of x to A in the closed interval [0, 1].

If $\mu_A(x) = 0$ then x does not belong to A, while if $\mu_A(x) = 1$ then x completely belongs to A. If $0 < \mu_A(x) < 1$ then x partially belongs to A and its membership to A increases according to the values of $\mu_A(x)$.

The subset A defines the position of each element with reference to the multidimensional concept to be measured.

If we consider a set of *n* units or elements e_i ($i = 1,2,\dots,n$) and *p* variables X_s ($s = 1,2,\dots,p$) reflecting the multidimensional phenomenon of interest[10], the first step to be accomplished in order to build a composite "fuzzy" indicator is to define the membership function for each variable. To this end it is necessary:

to identify the extreme situation such that $\mu_A(x) = 0$ (non-membership) and $\mu_A(x) = 1$ (full membership);

to define a criterion for assigning membership function values to the intermediate modalities of the variables.

The determination of the individual membership function depends on the variable type.

In the case of quantitative variables, both an inferior (lower) threshold *l* and a superior (upper) threshold *u* have to be defined. The degree of membership

[10] Without loss of generality, it is possible to assume that each variable is positively related with that phenomenon, i.e. it satisfies the property "the larger the better". If a quantitative variable shows negative correlation, it can be substituted with a simple decreasing function transformation, e.g. $f(x_{si}) = \max(x_{si}) - x_{si}$; in case of an ordinal variable it can be considered it in reverse order.

to the fuzzy set A of the e_i^{th} unit ($i = 1,2,\ldots,n$) with respect to the s^{th} attribute ($s = 1,2,\ldots,p$), can be obtained as follows:

$$\mu_A\left(X_{si}\right)=\begin{cases} 0 & X_{si} \le l \\ \dfrac{X_{si}-l}{u-l} & l < X_{si} < u \\ 1 & X_{si} \ge u \end{cases}$$

The above described membership function is a linear increase function between the values of the two thresholds. A critical aspect of the present approach (known as Totally Fuzzy Approach) lies in the subjective and arbitrary definition of the two threshold values.

An alternative solution has been proposed in order to overcome the limits characterizing the just mentioned formulation, it is known as Totally Fuzzy and Relative (TFR) approach (Cheli and Lemmi, 1995). It is totally fuzzy because, it avoids the specification of lower and higher critical thresholds. Completely relative, because the levels of the phenomenon under investigation of each unit on a given attribute depends on its place in the distribution of the attribute as opposed to the Total Fuzzy Approach that determines a linear function of belonging.

The determination of membership functions depends on whether the variables are dichotomous, categorical or ordinal and continuous or quantitative.

In the case of continuous and categorical variables the starting step is to arrange the values x_i in non-decreasing order, subsequently the membership function can be defined as follows:

$$\left(X_A\left(x_{si}\right)\right)=\begin{cases} 0 & X_{si} \le l \\ \mu_A\left(X_{s(i-1)}\right)+\dfrac{F_s\left(x_i\right)-F_s\left(x_{i-1}\right)}{1-F_s\left(x_{i(l)}\right)} & l < X_{si} < u \\ 1 & X_{si} \ge u \end{cases}$$

where $F_s(x_n)$ is the sampling cumulative function of the variable X_s and $x_{i(l)}$ is the highest value $x_i \leq l$. When $l = x_1 = \min(x_i)$ and $u = x_n = \max(x_i)$ the formula above exactly correspond to the Totally Fuzzy and Relative Approach membership function formulation.

Once the units membership function for each variable have been computed, it is necessary to identify some criteria for aggregating the *p* obtained fuzzy variables into a fuzzy composite indicator.

A general aggregation function is the weighted generalized mean:

$$\mu_A(i) = \left(\sum_{s=1}^{p} \left[\mu_A(x_{si}) \right]^{\alpha} \cdot w_s \right)^{\frac{1}{\alpha}}$$

where $w_s > 0$ is the normalized weight[11] that expresses the relative importance of the variables X_s. For fixed arguments and weights, the aggregating function is monotonic non-decreasing with α.

As far as the weighting scheme to be adopted is concerned, different criteria may be used:

equal weights, implying a careful selection of the variables in order to assure a balance of the different aspects of the phenomenon under investigation;

factor loadings, obtained by principal components analysis (PCA) for quantitative variables or by nonlinear PCA for ordinal variables; this method of weighting is valid if the first component accounts for a high percentage of the total variance and the weights (loadings) of the variables are proportional to their correlation with the first component (factor) reflecting the underlying concept;

expert judgements;

Analytic Hierarchy Process (Kwong & Bai, 2002).

It is however possible to individuate a weighting scheme in a fuzzy set approach framework. It is possible to use a criterion for the determination of the

[11] The sum of the weights is fixed to one: $\sum_{s=1}^{p} w_s = 1$.

weights that considers, for each variable X_s, the fuzzy proportion $g(X_s)$ of the achievement of the target:

$$g\left(X_s\right)=\frac{1}{n}\sum_{i=1}^{n}\mu\left(x_{si}\right)$$

The normalized weights are determined as an inverse function of $g(X_s)$, in order to give higher importance to the rare features in the *n* units . To avoid excessive weights to the variables with low value of g(Xs) it is possible to choose a scheme that attach to each variable a weight sensitive to the fuzzy membership of the units to A (Cerioli, Zani, 1990):

$$w_s=\ln\left[\frac{1}{g(X_s)}\right]/\sum_{s=1}^{p}\ln\left[\frac{1}{g(X_s)}\right].$$

The fuzzy set approach to the measurement of multidimensional phenomena is advantageous because, as complexity of systems increases, the ability to make precise and significant information diminishes and increases the vagueness (fuzziness) concerning the description of the semantic meaning of phenomena. In such contests, the fuzzy set approach provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied and uncertainty can be modeled. Moreover, it does not require any distributional assumption on the disposable data, and gives the chance to endogenously individuate the composite indicator weighting scheme, on the basis of the membership of each variable to the computed fuzzy set. A drawback of this approach is that it does not account for the correlation among the selected elementary indicators, giving rise to double accounting issues; a different fuzzy approach taking into account and solving the above mentioned issue have been proposed by Vero and Werquin (1997), in the context of multidimensional measures of poverty.

2.3.3 Information Theory approach

The issue of the aggregation of attributes expressing different aspects of a multidimensional phenomenon using Information Theory techniques has been mainly addressed in the context of the inequality measures (Theil, 1967; Maasoumi, 1986).

Information theory was developed in the 1940s by Claude Shannon as a discipline within the mathematical theory of communication. The goal was to determine how much data can be transmitted through a channel without significant losses or errors (Shannon, 1948). The measure of data (information) transmitted is known as entropy, in reference to the concept used in thermodynamics. Shannon proposes to measure the information using the expected information content or entropy index:

$$H(X) = -\sum_{i=1}^{n} p(x)\log_i p(x) = \sum_{i=1}^{n} p(x)\log\frac{1}{p(x)}$$

where X is a random variable with a probability function $p(x) = Pr\{X = x\}$.

The entropy index is a measure of the average uncertainty of the random variable, in other words, a measure of the amount of information required on average to describe the random variable itself (Cover & Thomas, 2003). Values of H(X) lie between 0 and log N; minimum entropy is achieved when the probability of one event *i* is 1 and $p(x_j) = 0$ and maximum entropy is reached when all events are equally likely. H(X) is a concave function of p(x) and satisfies the properties of continuity, normalization, grouping and decomposability (Shannon, 1948).

When comparing two probability distributions *p(x)* and *q(x)*, it is possible to use a relative entropy measure in order to assess the distance between them. The relative entropy measure, is expressed as

$$D(p\,||\,q) = \sum_{i=1}^{n} p(x)\log\frac{p(x)}{q(x)}$$

the relative entropy measure D(*p*||*q*) gives the minimum additional information that *q(x)* provides over *p(x)*.

In the context of the multidimensional phenomena measurement, the information theory approach can be used both in the aggregation across attributes, in order to obtain an index for each individual, and in the aggregation across individuals to obtain an overall measure. In the present dissertation we will only focus our attention on the former step: the aim is to individuate a function that would summarize the information on all attributes for each individual in an efficient manner.

Every attribute j has a distribution $x^j = (x_1^j, x_2^j, ..., x_n^j)$ containing all the information about the variable that can be accessed and inferred objectively. The aim is to select a functional form for the aggregator function that would have a distribution as close as possible to the distributions of its constituent members. The optimal function $S_i(.)$ can be achieved by solving an information theory inverse problem, based on distributional distances, where the divergences represent the difference between their entropies, that is their relative entropy.

S_i denote the summary or aggregate function for individual i, based on its q attributes $(x_i^1, x_i^2, ..., x_i^q)$. The distance function $D_\beta(\cdot)$ is the weighted average of the relative entropy divergences between $(S_1, S_2, ..., S_n)$ and each $x^j = (x_1^j, x_2^j, ..., x_n^j)$, defined as follows:

$$D_\beta(S \parallel X; w) = \sum_{j=1}^{q} w_j \frac{1}{\beta(1-\beta)} \sum_{i=1}^{n} S_i \left[1 - \left(\frac{S_i}{x_i^j}\right)^\beta\right]$$

where w_j is the weight attached to the generalized entropy distance for each attribute. Minimizing the distance function with respect to S_i subject to produces the following optimal aggregation functions:

$$S_i = \left(\sum_{j=1}^{q} w_j \left(x_i^j\right)^\beta\right)^{\frac{1}{\beta}} \quad \text{for } \beta \neq 0 \text{ and } \beta \neq -1,$$

The index is a generalized weighted mean of order β of the achievements in each dimension. The dimension weights are generally assumed to be equal across units and to sum up to one.

The parameter β is related to the degree of substitutability between attributes α (with $\alpha = 1/(1-\beta)$) and determines the shape of the contours for all pairs of attributes. The smaller is β, the smaller is the substitutability between dimensions, that is the more one has to give up of one attribute to get an extra unit of a second attribute, while keeping the level of the indicator constant. Generally, for $\beta \leq 1$ (non-negative elasticity of substitution) the index is a weakly concave function, which reflects preferences for bundles that are more equally distributed. In the limit, $\beta \to -\infty$ and $\alpha \to 0$, dimensions are treated as perfect complements and the function is of Leontief type, thus favoring units with more balanced achievement among all dimensions.

Significant special cases are obtained for β = 0 and β = 1. When β = 0 the composite indicator is a is a Cobb-Douglas function, with unit substitution elasticity. When β = 1 the indicator is a linear function of the attributes and $\alpha \rightarrow \infty$, that is, attributes are perfect substitutes, so that low levels on one of them can be perfectly be compensated by high levels on another one.

Obviously, different choices of β and for the weighting structure will lead to different composite indices. Sensitivity analysis should be implemented with the aim to reduce uncertainty deriving from subjective choices, thus guarantying the quality of the obtained indicator.

As already said, the information theory approach to the measurement of multidimensional phenomena pioneered by Maasoumi (1986), is a two-step approach having the advantage of making the aggregation procedure explicit, arriving firstly to a single composite measure for each unit and then applying some univariate inequality measures.

The inequality measure proposed by Maasoumi (1986) is obtained by calculating a Generalized Entropy index on the vector of indexes obtained during the first step.

2.3.4 Inertia approach

The inertia approach is based on a series of multivariate analysis tools, used for the assessment of the structure of the disposable data as well as for determining the sub-indicators weights in an objective way.

The mainly used multivariate techniques for the measurement of multidimensional phenomena are Principal Component Analysis and Factor Analysis.

Principal component analysis is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components.

Let **X** be the n x p data matrix, and ***X*** the column vector containing the p variables. The p principal components, obtained as linear combination of the original variables, can be written as follow:

$$
\begin{aligned}
&Y_1 = a_{11}X_1 + \ldots + a_{1k}X_k + \ldots + a_{1p}X_p = \mathbf{a}_1^{'}\mathbf{X} \\
&\ldots \\
&Y_i = a_{i1}X_1 + \ldots + a_{ik}X_k + \ldots + a_{ip}X_p = \mathbf{a}_i^{'}\mathbf{X} \\
&\ldots \\
&Y_p = a_{p1}X_1 + \ldots + a_{pk}X_k + \ldots + a_{pp}X_p = \mathbf{a}_p^{'}\mathbf{X}
\end{aligned}
$$

where $\boldsymbol{a}_i$ is the column vector containing the coefficients of the linear combination individuating the principal component Y_i, for $i=1,\ldots,p$. The coefficients (weights) are mathematically determined to maximize the sum of the squared correlation of the principal component with the original variables or, equivalently, to maximize the variation of the principal component; for each principal component they correspond to the eigenvectors of the data covariance matrix associated to the highest eigenvalue.

In a composite measure computation framework, principal component analysis can be used when dealing with highly correlated variables which implies information redundancy; in such cases it is possible to hypothesize that some variables are measuring the same aspect of the phenomenon of interest and that the number of original variables can be reduced in a smaller set of orthogonal principal components that will account for most of the variance in the observed variables, without losing essential information. In this way an objective selection of the elementary indicators can be carried out and it is possible to obtain uncorrelated variables making the weighting and aggregation phases less difficult and controversial.

Factor analysis has similar aims to principal component analysis. The basic idea is still that it may be possible to describe a set of P variables in terms of a smaller number of m factors, thus elucidating the relationships between these variables. There is, however, an important difference: factor analysis, differently form principal component analysis is based on a statistical model[12] (Spearman, 1904).

In a general form the model is given by:

$$
\begin{aligned}
&x_1 = \alpha_{11}F_1 + \ldots + \alpha_{1k}F_k + \ldots + \alpha_{1m}F_m + e_1 \\
&\ldots \\
&x_i = \alpha_{i1}F_1 + \ldots + \alpha_{ik}F_k + \ldots + \alpha_{im}F_m + e_i \\
&\ldots \\
&x_p = \alpha_{p1}F_1 + \ldots + \alpha_{pk}F_k + \ldots + \alpha_{pm}F_m + e_p
\end{aligned}
$$

where x_i is a variable with zero mean and unit variance; $\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{im}$ are the factor loadings related to the variable X_i; $F_1, F_2, \ldots, F_m$ are m uncorrelated common factors, each with zero mean and unit variance; and e_i are the P specific factors supposed independently and identically distributed with zero mean.

The idea at the base of the factor analysis is that the influence of common factors on the original variables give rise to the correlations among the variables themselves. Given the correlation among a number of elementary indicators, it is possible to determine the number of the common factors and to obtain numerical

[12] The main difference between factor analysis and principal component analysis lies in the way the communalities are used. In principal component analysis it is assumed that the communalities are initially 1. In other words, principal component analysis assumes that the total variance of the variables can be accounted for by means of its components (or factors), and hence that there is no error variance. On the other hand, factor analysis does assume error variance. This is reflected in the fact that in factor analysis the communalities have to be estimated, which makes factor analysis more complicated than principal component analysis, but also more conservative.
In factor analysis the different assumption with regard to the communalities is reflected in a different correlation matrix as compared to the one used in principal component analysis.
Since in principal component analysis all communalities are initially 1, the diagonal of the correlation matrix only contains unities. In factor analysis, the initial communalities are not assumed to be 1; they are estimated by taking the squared multiple correlations of the variables with other variables. These estimated communalities are then represented on the diagonal of the correlation matrix, from which the eigenvalues will be determined and the factors will be extracted.

coefficients representing the degree of effect of each common factor on the disposable variables. Based on this information, it is possible to interpret the nature of the common factors themselves, as well as to obtain estimates of the amount of common and unique variance in each variable.

Different methods can be used in order to extract factors, but in a composite indicators construction framework the most common is the use of principal component analysis to extract the first *m* principal components and consider them as factors and neglect the remaining. Principal components factor analysis is most preferred in the development of composite indicators because it allows the construction of weights representing the information content of sub-indicators.

Obviously different extraction methods supply different values for the factors as well as for the weights, influencing the score of the composite indicator.

Factor analysis is considered an advantageous method because it represent a way of exploring data whose structure is unknown, thus knowing the factorial structure in advance and helping to select the sub-indicators to be used in the subsequent phases of the composite indicator development process.

However, one of the limit of factor analysis is that the identified correlations do not necessarily represent the real influence of the sub-indicators on the phenomenon being measured and that the contribution of sub-indicators which do not move with other sub-indicators is underestimated.

When dealing with the computation of multidimensional measures, factor analysis can as well be used during the weights assessment phase. Weights can be constructed from the matrix of factor loadings, given that the square of factor loadings represents the proportion of the total unit variance of the indicator which is explained by the factor. The approach generally used is to group the sub-indicators with the highest factors loadings in intermediate composite indicators. Then the intermediate composites are aggregated by weighting each composite using the proportion of the explained variance in the dataset. Weights are thus estimated in an objective way, they are able to correct for the overlapping information of two or more correlated indicators, but they are not a measure of importance of the associated indicator. Moreover they are sensitive to the methods chosen for the extraction and rotation of factors.

The brief review of some statistical approaches to the measurement of multidimensional phenomena showed that there exists a series of open questions to be faced when dealing with the construction of composite measure.

Although the validity of the above described approaches is undoubted, the aim of the present study is to propose a model-based approach to the construction of composite indicators, by using the statistical tools offered by the Structural Equation Models methodology (based on a series of multivariate techniques that let us include it among the inertia approach for the measurement of complex phenomena).

The choice of a model-based approach arises from the necessity to develop a multidimensional measure able to take into account the features of the phenomenon under investigation through the analysis of the causal relationships among the different aspects characterizing it, and to objectively estimate and assess the extent to which each aspect contribute in explaining and determining the phenomenon itself.

In the next chapter the Structural Equation Model approach to the measurement of multidimensional phenomena will be described in details, for an exhaustive understanding of the pros and cons of using such a method for the computation of composite measures.

Chapter 3: Structural Equation Models and Partial Least Squares Path Modeling methods for the construction of composite indicators

3.1 INTRODUCTION

As already said, the debate about the measurement of multidimensional phenomena has excited, above all during last years, a renewed interest in the scientific community: it is common awareness that most of socio-economic complex phenomena can no more be measured by using single descriptive indices. There is, therefore, an increasing need to represent them by means of several dimensions.

The challenges of constructing a global measure for describing complex concepts by aggregating different dimension representing different aspects of the phenomenon under investigation is a very discussed theme. In particular, two elements seems to be the main objects of debate: the identification of key indicators to be used and the way in which these indicators can be brought together to make a coherent system of information. This last issue has to be handled by statisticians that have to provide operational tools to aggregate variables in order to build composite indicators.

There is no doubt that composite indicators are appealing as the use of a unique measure obtained by combining different indicators can help in capturing the complexity of reality. However, as said before, composite indicators have some disadvantages. The choice of the key variables composing the final indicator is subjective, moreover, movements in composite indicators are difficult to interpret, that is, when an indicator moving a certain direction is presented, one would wonder which components are driving the movement; another issue is that the weighting and aggregation processes by which the variables are combined is often considered as arbitrary.

According to this, the selection of the weights and the way the indicators are put together do not always seems not to be a methodological but an empirical issue to be faced.

Here a new approach to compute complex composite indicators where the computation of the weights as well as the aggregation process are not subjective will be presented, in particular a Structural Equation Model approach to the construction of a composite indicator will be used.

Structural Equation Models are used in order to investigate complex causal relationships (Bollen, 1989; Kaplan, 2000). They give the chance to study the real world complexity by taking into account a whole network of causal relationships among latent concepts (Latent Variables), each measured by several observed indicators usually defined Manifest Variables.

From a composite indicator construction perspective, when a SEM framework is chosen, it is possible to take into account that the several variables used in the construction of a composite indicator express different aspects of the complex phenomenon under investigation and for this reason they can be conceptually split in several blocks of indicators. Each block represent a latent feature of the analyzed phenomenon, measured by means of a number of observed variables. In substance, each block is resumed by a composite indicator, which is considered causative with respect to a second-order composite indicator, that is, the phenomenon under investigation.

As a matter of facts, SEM models allows us to aggregate indicators by simultaneously taking into account both the variables membership to blocks and the causal relationships among blocks.

It is therefore possible to obtain two kind of weights: the former measuring the impact of each variable on the corresponding component based block and the latter measuring the impact of each block on the second order composite indicator. This two levels of weights can help to understand which are the most important variables defining each dimension and which dimension is the main driver of the overall composite indicator.

Two different approaches exist for the model parameters estimation in Structural Equations Models methods: the parametric (covariance-based) techniques also known as LISREL type modeling, and the non-parametric (component-based) ones, among which the best known is the Partial Least Squares Path Modeling (PLS-PM) approach.

The covariance based methods for Structural Equation Models dates back to the original development due to the works of Jöreskog (1973), Keesling (1972), and Wiley (1973). It was first conceived as confirmatory model for assessing cause-effect relations among two or more set of variables, based on the maximum likelihood (ML) estimation method (SEM-ML). Its widespread popularity is due in large part to the availability of the LISREL (Linear Structural RELations) software implementing the Jöreskog and Sörbom (1996) methodology.

The covariance-based approach to SEM had such a rapid development that several, new parameters estimation methods have been introduced in few years (Generalized Least Squares (GLS), Asymptotically Distribution Free (ADF)).

In general, parametric SEM attempts to minimize the difference between the sample covariances and those predicted by the theoretical model. The fundamental hypothesis underlying these approaches is that the implied covariance matrix of the manifest variables is a function of the model parameters.

The use of the LISLREL-type estimation techniques involves constraints in the form of parametric assumptions, sample size, model complexity and identification. One of the most important assumption to be met is that the observed variables follows a specific multivariate distribution (normality in the case of the ML function) and that observations are independent of one another.

Anyway, there exist other protocols of SEM estimation which impose different assumptions about data, theory, and the tie between unobservable variables and indicators, that avoiding many of the assumption underlying ML techniques, ensure against many kind of problems, such as improper solutions and factor indeterminacy.

An alternative to covariance-based SEM analysis is the “soft modeling” (distribution free) approach to the analysis of the relations among several blocks of variables, observed on the same statistical units.

The method, known as PLS approach to SEM (SEM-PLS) was first introduced by Herman Wold in 1979. The PLS method was developed for handling a huge amount of data characterized by missing values, strongly correlated variables and small sample size with respect to the number of disposable variables.

Its widespread use in several field has continued to show great flexibility in the case of several kind of data structures.

The aim of the non-parametric approach to SEM is to provide an estimate of the latent variables in such a way that they are the most correlated with one another and the most representative of each corresponding block of manifest variables.

The PLS algorithm attempts to obtain the best weight estimates for each block of indicators corresponding to each latent variable. The resulting component score of each latent variable, based on the estimated indicator weights, maximizes the explained variance for dependent variables. Although PLS method can be used for theory confirmation, it can also be used to suggest if relationships might or might not exist and to suggest propositions for later testing, that is, for predictive purposes.

New estimation techniques for Structural Equation Models have been presented recently: in 2003 Al-Nasser proposed to extend Information Theory knowledge to Structural Equation Models context via a new technique called Generalized Maximum Entropy (GME) (Al-Nasser, 2003).

More recently, instead, Hwang and Takane (2004) presented the Generalized Structured Component Analysis (GSCA).

3.2 PLS APPROACH TO STRUCTURAL EQUATION MODELS FOR THE CONSTRUCTION OF A MODEL-BASED COMPOSITE INDICATOR.

As said before, Structural Equation Models seems to be a very useful tool for the construction of model based composite indicators.

In particular, the PLS-PM approach to SEM, that will be described in details in the following sections, offers suitable methods for overcoming the main controversial features of the traditional approaches.

Constructing a model-based indicator in a PLS-PM framework gives the chance to specify the relations between the unobserved constructs and their indicators in different ways (reflective, formative or both), by taking into account the *a priori* knowledge on the field of interest and thus the role of each observed variable in the theorized model (input, output or outcome).

It is possible to take into account several features of a phenomenon object of study and to contextualize them in systemic vision by the use of a path model.

Moreover, one of the most interesting aspects is the one related to the weights estimation process that, differently from most of the traditional weighting schemes in the construction of composite indicators, is not subjective, but based on statistical method: first, the weight relations, which link the indicators to their respective unobservable variables, are estimated. Second, case values for each unobservable variable are calculated, based on a weighted average of its indicators, using the weight relations as an input. Finally, these case values are used in a set of regression equations to determine the parameters for the structural relations, linking the latent constructs in order to best explain the latent variable representing the phenomenon under investigation. This brief explanation makes it obvious that the most crucial part of a PLS-PM analysis is the estimation of the weights that allows us to individuate two kind of optimal weights: one measuring the impact of each indicator on the corresponding latent dimension, the other measuring the impact of each latent construct on the complex indicator, allowing to understand the different impacts of each latent construct on the complex indicator itself.

Another advantage of the choice of such a method is that it is possible to estimate the hypothesized relationships without making assumptions on data distribution and without problems of model identification; moreover there is the possibility to control the local quality fitting of the model, and to validate the composite indicator and the model estimation by means of resampling techniques.

After this quick description of the main features of the PLS-PM approach to the creation of a composite indicator, it would be useful to individuate the phases in which the construction of the indicator could be structured:

- Data selection and data editing;
- Model specification;
- Model estimation and Composite Indicators aggregation;
- Model evaluation and selection.

In the following section only the last three phases will be described and discusses as they directly concern the PLS-PM approach to Structural Equation Models.

The first phase, instead, consist in the theoretical choice of the variable to be put in the model and in the subsequent series of data transformation and analysis tools for the improvement of the quality of the disposable data.

Let’s see in detail the above mentioned phases.

3.2.1 Model Specification

As already said Structural Equation Models are used in order to investigate complex cause-effect relationships inside a certain phenomenon object of scientific research.

In a Structural Equation Model framework the researcher must specify a model in order to conduct the analysis. The model’s specification must have some basis, whether it be theory, results of previous studies, or an educated guess that reflects the researcher’s knowledge and experience. Hence the first step to be made before moving toward a multivariate SEM analysis is the specification of the model that will allow to conduct the study.

As well known, a SEM model is composed by two sub-models formally defined by two sets of linear equations: the inner model and the outer model. The inner (structural) model specifies the relationships between unobserved or latent variables, whereas the outer (measurement) model specifies the relationships between a latent variable and its observed or manifest variables.

Manifest variables or indicators are observable variables who are supposed to convey information about the behavior of latent variables, theoretical concepts that are not directly observable but who are fundamental for the understanding of the features of a phenomenon object of research.

As far as the relations linking the manifest variables to the corresponding latent variables are concerned, it is helpful to underline that in a PLS-PM framework three different directions of causation between the observed indicators variables and the latent ones exist, respectively called reflective scheme, formative scheme and MIMIC (multiple effect indicators for multiple causes) mode.

Specifically, each unobservable construct in a structural equation model can be seen as an underlying factor or as an index produced by the observed variables composing it.

The reflective measurement model has its roots in classical test theory and psychometrics (Nunnally & Bernstein, 1994). Each indicator represents an error-afflicted measurement of the latent variable. The direction of causality is from the construct to the indicators; thus, observed measures are assumed to reflect variation in the corresponding latent variable. In other words, changes in the construct are expected to imply changes in all of its indicators.

When a reflective way is chosen the block of manifest variables related to a latent one is assumed to measure a unique underlying concept, for this reason some measures can be removed in order to improve construct validity without affecting content validity.

Reassuming, the reflective mode assumes causal relationships going from the latent variable to the manifest variables in its block. Thus, each manifest variable plays a role of endogenous variable and is assumed to be generated as a linear function of its latent dimension and the residual term

$$X_{hj} = \pi_{h0} + \pi_{hj}\xi_j + \varepsilon_{hj};$$

where π_{hj} is the loading associated to the h-th manifest variable in the j-th block and the error term represent the imprecision in the measurement process; ξ_j has mean m and standard deviation 1.

There is only one hypothesis made on the model and is called by H. Wold the predictor specification condition

$$E\left(x_h/\xi\right)=\pi_{h0}+\pi_{hj}\xi_j;$$

this hypothesis implies that the residual ε_h has a zero mean and is uncorrelated with the latent variable.

In general, reflective models account for observed variances or covariances, they minimize "the trace of the residual variances in the measurement equations" (Fornell and Bookstein, 1982).

When a reflective scheme for the specification of the outer model is chosen, internal consistency of each measurement block has to be checked. Three tools are available to check the unidimensionality of a block: use of principal component analysis in each latent dimension, Cronbach's alpha and Dillon–Goldstein's indices.

In the formative way it is supposed that the latent variable is generated by its own manifest variables. Each manifest variable represents a different dimension and captures different aspects of the underlying concept, an increase in the value of one indicator translates into a higher score for the composite variable, regardless of the value of the other indicators. The formative measurement model is supposed to exhausts the entire domain of the index, meaning that the indicators collectively represent all the relevant dimensions or independent underpinnings of the latent variable. One implication of this direction of causality is that omitting one indicator could mean to omit a unique part of the formative measurement model, thus changing the meaning of the variable (Diamantopoulos & Winklhofer, 2001).

The formative measurement model features presented above let us simply understand that it is not necessary to assume the homogeneity or unidimensionality inside each component-based block, these properties are perhaps even undesirable for the estimation errors that can arise due to multicollinearity among formative indicators.

Formative indicators are not used in order to account for the observed variances in the outer model, but rather to minimize residuals in the structural relationships; they "minimize the trace of the residual variances in the structural equations" (Fornell and Bookstein, 1982) and error should thus be assessed at a construct level rather than at the item level.

In substance, the latent variable is a linear combination of their manifest variables and each manifest variable is an exogenous variable in the measurement model.

The latent variable is a linear function of its manifest variables plus a residual term

$$\xi_j = \sum_h \omega_{hj} x_{hj} + \delta_j$$

where ω_{hj} is the coefficient linking each manifest variable to the corresponding latent variable and the error term δ_j represent the fraction of the corresponding latent variable not accounted for by the block of the manifest variables.

The predictor specification condition is supposed to hold for

$$E(\xi_J / x_{hj}) = \sum_h \omega_h x_h$$

this hypothesis implies that the residual vector δ has a zero mean and is uncorrelated with the MVs.

The MIMIC way is a mixture of the reflective and formative ways. The measurement model for a block is the following:

$$x_{hj} = \pi_{h0} + \pi_{hj}\xi_j + \varepsilon_h \qquad \text{for h=1 to } p_1,$$

where the LV is defined by

$$\xi_j = \sum_{h=p_1+1} \omega_{hj} x_{hj} + \delta_j$$

The p_1 first MVs follow a reflective way and the $(p-p_1)$ last ones follow a formative way.

The predictor specification hypotheses hold and lead to the same consequences as before on the residuals.

Misspecification of measurement models can bias inner model parameters estimates and lead to incorrect assessments of relationships (Jarvis et al., 2003). The decision to use either formative or reflective indicators for a construct should be based on the nature of the causal relationship between the indicators and the latent variables in the measurement model (Bollen, 1989). The most suitable approach to avoid misspecification of measurement models in SEM is to consider the conceptual discussion of the differences between formative and reflective measurement models by, e.g., Howell, Breivik, and Wilcox (2000a, 2007b); Bagozzi (2007); Bollen (2007); Bollen and Lennox (1991); Diamantopoulos and Winklhofer (2001); Edwards and Bagozzi (2000) and the rules for determining the specific type of measurement model put forward by Jarvis et al. (2003).

Summarizing, the choice of the way in which unobservable variables and data should be related, which substantially influences estimation procedures, involves three major considerations: the objectives of the study, the theoretical basis of the study and the empirical contingencies.

From a strictly statistic point of view if the study is intended to account for observed variance, reflective models are most suitable. If the object is instead the explanation of abstract or unobserved variance, formative indicators would give greater explanatory power.

Indicator mode is also shaped by the way in which the latent variable is conceptualizes, that is, by the theoretical basis used in order to specify the model: there are some constructs that are typically viewed as underlying factors giving rise to some observed and strictly linked phenomena: their indicators tend to be specified as reflective. In contrast, when constructs are conceived as explanatory combination of indicators determined by a set of variables, measurement relation must be formative.

From an empirical point of view the choice of the measurement mode has to be accomplished by taking into account that in the formative scheme sample size and variables multicollinearity affect the stability of the indicator coefficients (based on multiple regression); in the reflective scheme the problem does not exist as indicator coefficients, calculated by means of simple regressions, are not affected by multicollinearity, but in this case the unidimensionality of each construct as to be checked.

Another important difference is that whereas reflective indicators should have a high correlation (as they are all dependent on the same unobservable variable), formative indicators of the same construct can have positive, negative, or zero correlation with one another (Hulland, 1999), which means that a change in one indicator does not necessarily imply a similar directional change in others (Chin,1998).

Independently of the measurement model chosen, the specification of the causality model leads to linear equations relating the latent variables among them (structural or inner model)

$$\xi_j = \beta_{0j} + \sum_i \beta_{ji}\xi_i + \upsilon_j$$

where ξ_j is the generic endogenous latent variable, β_{ji} is the generic path coefficient interrelating the q-th exogenous latent variable to the j-th endogenous one, and υ_j is the error term in the inner relation, that is, the disturbance term in the prediction of the j-th endogenous latent variable from its explanatory latent variables.

Thus, the structural (inner) model constitutes a causal chain system (i.e. with uncorrelated residuals and without correlations between the residual term of a certain endogenous latent variable and its explanatory latent variables).

3.2.2 Model Estimation

Once the model has been specified by taking into account the methodological features described in the previous section, the second step is to estimate the theorized net of causal relationships.

The basic approach in PLS is to construct proxies for the latent variables, in the form of linear compound, by means of a sequence of alternating least square algorithm, each time solving a local, linear problem, with the aim to extract the predictive information in the sample. Once the compounds are constructed, the parameters of the structural form are estimated with the proxies replacing the latent variables.

The PLS-PM estimation method consists in an iterative procedure that allows us to estimate the model parameters: the outer weights and the latent variables scores. The estimates of the latent variables scores are obtained through the alternation of two estimation processes: the outer and the inner estimation, iterated until convergence. The procedure starts with the arbitrary choice of ω_{jh}

weights linking each manifest variable to the corresponding latent variable; this weights are then standardized in order to obtain latent variables with unitary variance.

Then, in the outer estimation the standardized latent variables are estimated as linear combinations of their centered manifest variables

$$y_j \propto \pm\left[\sum \omega_{jh}\left(\mathbf{x}_{jh} - \bar{x}_{jh}\right)\right]$$

where the symbol $\propto$ means that the left side of the equation corresponds to the standardized right side and the $\pm$ sign shows the sign ambiguity, solved by choosing the sign making y_j positively correlated to a majority of x_{jh}.

The standardized LV is finally written as

$$y_j = \sum \tilde{\omega}_{jh}\left(\mathbf{x}_{jh} - \bar{x}_{jh}\right)$$

The mean m_j is estimated by

$$\hat{m}_j = \sum \tilde{\omega}_{jh}\bar{x}_{jh}$$

and the latent variable by

$$\hat{\xi}_j = \sum \tilde{\omega}_{jh}\bar{x}_{jh} = y_j + \hat{m}_j \text{.}$$

The coefficients ω_{jh} and $\tilde{\omega}_{jh}$ are both called the outer weights.

There are two ways to estimate the weights ω_{jh}, usually related to the choice between the different kinds of measurement model specification described in the previous section (i.e. the reflective or the formative scheme): modes A and B.

In mode A, the weight ω_{jh} is the regression coefficient of z_j in the simple regression of x_{jh} on the inner estimate z_j :

$\omega_{jh} = \operatorname{cov}\left(x_{jh}, z_j\right)$ as z_j is standardized.

In mode B, the vector $\mathbf{w}_j$ of weights w_{jh} is the regression coefficient vector in the multiple regression of z_j on the centered manifest variables $\left(x_{jh} - \bar{x}_{jh}\right)$ related to the same LV:

$$w_j = \left(X_j^{'}X_j\right)^{-1} X_j^{'}z_j$$

where X_j is the matrix with columns defined by the centered manifest variables $\left(x_{jh} - \overline{x}_{jh}\right)$ related to the j-th latent variable.

Mode A is appropriate for a block with a reflective measurement model and mode B for a formative one. Mode A is often used for endogenous LV and mode B for exogenous ones. Modes A and B can be used simultaneously when the measurement model is the MIMIC one. Mode A is used for the reflective part of the model and mode B for the formative part.

As said before, mode B is not so easy to use because it often can present strong multicollinearity inside each component block. In cases like the above mentioned one it is better to use a PLS regression instead of a traditional OLS one.

Once the standardized latent variable scores have been estimated by means of the outer estimation procedure, the internal estimate procedure of the algorithm starts and each latent variable is estimated by considering its links with the other adjacent latent variables.

The inner estimate z_j of the standardized LV $\left(\xi_j - m_j\right)$ is defined by

$$z_j \propto \sum e_{jj'} y_{j'}$$

where $y_{j'}$ is the outer estimate of the latent variable and $e_{jj'}$ are the inner weights equal to the sign of the correlation between y_j and the y_j 's connected with y_j.

This kind of internal estimation procedure in known as Centroid scheme.

However, two other schemes can be used in order to obtain the inner estimates of the latent variables: the factorial scheme and the path weighting (or structural) scheme.

In a factorial scheme the inner weights are equal to the correlations between the y_j latent variable and the y_j 's connected with y_j.

When a path weighting scheme is chosen the latent variables connected to ξ_j are divided into two groups: the predecessor of ξ_j, which are latent variables explaining ξ_j, and the followers, which are latent variables explained by ξ_j.

For a predecessor $\xi_{j'}$ of the latent variable ξ_j, the inner weight is equal to the regression coefficient of $y_{j'}$ in the multiple regression of y_j on all the $y_{j'}$'s related to the predecessor of ξ_j. If $\xi_{j'}$ is a successor of ξ_j then the inner weights is equal to the correlation between $y_{j'}$ and y_j. It is important to notice that the path weighting scheme is the only one that gives the chance to take into account the difference between endogenous and exogenous variables.

The alternation of the internal and the external estimates is iterated until convergence.

After convergence the structural coefficients are estimated through an OLS multiple regression among the estimated latent variable scores. As usual, the use of OLS multiple regression could be inadequate in presence of multicollinearity between the estimated latent variables. In such a case, PLS regression may be applied instead.

As far as the statistical properties of the PLS-PM estimation method are concerned, several studies (using Monte Carlo simulation), (Cassel et al., 1999) showed that PLS is quite robust with regard to several inadequacies (e.g. skewness or multicollinearity of the indicators, misspecification of the structural model) and that the latent variable scores always conform to the true values.

However, there is another side of the coin, namely, the problem of "consistency at large".

In general, a consistent estimator can be described as "one that converges in probability to the value of the parameter being estimated as the sample size increases" (McDonald, 1996, p. 248).

However, as the case values for the latent variables in PLS are aggregates of manifest variables that involve measurement error, they must be considered as inconsistent (Fornell & Cha, 1994). Therefore, "the path coefficients estimated through PLS converge on the parameters of the latent-variable model (only) as both the sample size and the number of indicators of each latent variable become infinite" (McDonald, 1996, p. 248): a problem known under the term "consistency at large". Hence in all real-life situations, in which both the number of cases in the sample and the number of indicators per latent variable will be finite, PLS tends to underestimate the correlations between the latent variables and overestimate the loadings (i.e., the parameters of the measurement model; Dijkstra, 1983). Only when the number of cases in the sample and the number of indicators per latent variable increase to infinity the latent variable case values approach the true values and this problem disappears (Lohmöller, 1989).

3.2.3 Model evaluation

As pointed out at the beginning of this section, one of the weak points of the PLS-PM approach to Structural Equation Models is the lack of a well identified global optimization criterion that has as a direct consequence the absence of a global fitting function to be evaluated to determine the goodness of the model.

In the PLS-PM framework the model evaluation focuses instead on the model prediction capability, being a variance-based approach strongly oriented to the latent variables prediction.

A model can be validated at three levels: the quality of the measurement model, the quality of the structural model and of each structural regression equation.

The Communality index measures the quality of the measurement model for each block. It is defined, for the j-th block, as

$$com_j = \frac{1}{p_j}\sum_{h=1}^{p_j} cor^2\left(x_{jh,}\hat{\xi}_j\right), \ \forall j : p_j > 1$$

This index measures how much of the manifest variable variability in the j-th dimension is explained by its own latent variable, that is, how well the manifest variable describe its underlying latent construct. It is nothing but the average of the squared correlation between each manifest variable in the j-th block and the j-th latent variable.

It is also possible to measure the quality of the whole measurement model by means of the average communality index calculated as the weighted average of the J block specific communality indexes with weights equal to the number of manifest variables in each block:

$$\overline{com} = \frac{1}{\sum_{j:p_j>1} p_j} \sum_{h=1}^{p_j} \sum_{j:p_j>1} p_j com_j$$

Moreover, since the *communality* index for the q-th block is nothing but the average of the squared correlation in the block, then the *average communality* is the average of all the squared correlations between each manifest variable and the corresponding latent variable scores in the model, i.e.:

$$\overline{com} = \frac{1}{\sum_{j:p_j>1} p_j} \sum_{j:p_j>1} \sum_{h=1}^{p_j} cor^2\left(x_{jh,} \hat{\xi}_j\right)$$

Let's now shift the attention to the structural model evaluation tools offered by the PLS-PM approach. The quality of each structural equation could be measured by a simple analysis of the R^2 fit index, but this seems not to be sufficient for the evaluation of the whole structural model since the structural equations are estimated once the convergence is achieved and the latent variable scores are estimated, then the R^2 values only take into account the fit of each regression equation in the structural model[13].

It is anyway possible to link the prediction performance of the measurement model to the structural one by means of the *redundancy* index computed for the j-th endogenous block. The redundancy index measures the portion of variability of the manifest variables connected to the j-th endogenous latent variable explained by the latent variables directly connected to the block, i.e.:

$$red_j = com_j \times R^2\left(\hat{\xi}_j, \hat{\xi}_{j:\xi_j \to \xi j'}\right)$$

[13] Some authors suggest that it would be a good choice to replace the current practice by a path analysis on the latent variable scores considering all structural equations simultaneously rather than as independent regressions. This method could be profitable as path coefficients would be estimated by optimizing a single discrepancy function based on the difference between the observed covariance matrix of the latent variable scores and the same covariance matrix implied by the model; the structural model could be assessed as a whole in terms of a chi-square test related to the optimized discrepancy function. The results of such a procedure does not actually change the prediction performance of the model in terms of explained variances for the endogenous latent variables and up to now, no available software has implemented the path analysis option in a PLS-PM framework.

The *average redundancy* index for all endogenous blocks can also be computed and it represent a global quality measure of the structural model.

The index is computed as:

$$\overline{red} = \frac{1}{j}\sum_{j=1}^{J} red_j$$

where J is the total number of endogenous latent variables in the model.

As said before, there is no overall fit index in PLS Path Modeling because it does not optimize any global scalar function so that it naturally lacks of an index that can provide user with a global validation of the model (as it is instead the case with χ^2 and related measures in SEM-ML).

Nevertheless, a global criterion of goodness of fit has been proposed by Tenenhaus, Amato et al. (2004): the GoF index. It represents an operational solution to the above mentioned problem as it may be meant as an index for validating the PLS model globally.

It has therefore been developed in order to take into account the model performance in both the measurement and the structural model and thus provide a single measure for the overall prediction performance of the model.

The GoF index is calculated as the geometric mean of the *average communality* index and the average R^2 value:

$$GoF = \sqrt{\overline{com} \times \overline{R^2}}$$

where the average R^2 value is obtained as:

$$R^2 = \frac{1}{J} R^2\left(\hat{\xi}_j, \hat{\xi}_{j:\xi_j \to \xi j'}\right)$$

being based on average communality, the GoF index is conceptually appropriate when the measurement models are specified as reflective. However, communalities may be also computed and interpreted in case of formative models knowing that, in such a case, the results will be lower communalities and higher R^2 as compared to reflective models. Therefore, for practical purposes, the GoF index can be interpreted also with formative models as it still provides a measure of overall fit.

The GoF index can be written as:

$$GoF = \sqrt{\frac{\sum_{j:p_j>1}\sum_{h=1}^{p_j} cor^2\left(x_{jh}, \hat{\xi}_j\right)}{\sum_{j:p_j>1} p_j} \times \frac{\sum_{j=1}^{J} R^2\left(\hat{\xi}_j, \hat{\xi}_{j:\xi_j \to \xi j'}\right)}{J}}$$

A normalized version is obtained by relating each term in the formula to the corresponding maximum value[14].

Both the version of the GoF index are descriptive, i.e. there is no inference-based threshold to judge the statistical significance of their values. As a rule of thumb, a value of the relative GoF equal to or higher than 0,90 clearly speaks in favour of the model.

Bootstrap confidence intervals for both the absolute and the relative Goodness of Fit indexes can also be computed. In both cases the inverse

[14] In particular, it is well known that in principal component analysis the best rank one approximation of a set of variables $\mathbf{X}$ is given by the eigenvector associated to the largest eigenvalue of the $\mathbf{X}'\mathbf{X}$ matrix. Furthermore, the sum of the squared correlations between each variable and the first principal component of $\mathbf{X}$ is a maximum.
Therefore, if data are mean centered and with unit variance, the left term under the square root is such that

$$\sum_{h=1}^{H_j} cor^2\left(x_{jh}, \hat{\xi}_j\right) \le \lambda_{(j)}^1,$$

where $\lambda_{(j)}^1$ is the first eigenvalue obtained by performing a Principal Component Analysis on the j-th block of manifest variables. Thus, the normalized version of the first term of the GoF is obtained as:

$$T_1 = \frac{1}{\sum_{j:p_j>1} H_j} \sum_{j:p_j>1} \frac{\sum_{h=1}^{p_j} corr^2\left(x_{jh,} \hat{\xi}_j\right)}{\lambda_{(j)}^1}$$

In other words, here the sum of the communalities in each block is divided by the first eigenvalue of the block itself.
As concerning the right term under the square root in, the normalized version is obtained as:

$$T_2 = \frac{1}{J}\sum_{j=1}^{J} \frac{R^2\left(\hat{\xi}_j, \hat{\xi}_{j:\xi_j \to \xi j'}\right)}{\rho_j^2}$$

where $\rho_{j'}$ is the first canonical correlation of the canonical analysis between $\mathbf{X}_j$ containing the manifest variables associated to the j -th endogenous latent variable, and a matrix containing the manifest variables associated to all the latent variables explaining $\boldsymbol{\xi}_j$.
Thus, the relative GoF index is:

$$GoF_{rel} = \sqrt{\frac{1}{\sum_{j:H_j>1} H_j} \sum_{j:H_j>1} \frac{\sum_{h:1}^{H_j} cor^2\left(x_{jh}, \hat{\xi}_j\right)}{\lambda_{(j)}^1} \times \frac{1}{J}\sum_{j'=1}^{J} \frac{R^2\left(\hat{\xi}_{j'}, \hat{\xi}_{j:\xi_j \to \xi j'}\right)}{\rho_{j'}^2}}$$

this index is bounded between 0 and 1.

cumulative distribution function (*cdf*) of the GoF (ϕ_{GoF}) is approximated using a bootstrap-based procedure. B (usually more than 100) re-samples are drawn from the initial dataset of N units defining the bootstrap population. For each of the B re-samples, the GoF^b index is computed, with b=1,…,B. The values of GoF^b are then used for computing the Monte Carlo approximation of the inverse *cdf*, ϕ_{GoF}^{B} . Thus, it is possible to compute the bounds of the empirical confidence interval from the bootstrap distribution at the $(1-\alpha)$ confidence level by using the percentiles as:

$$\left[\phi_{GoF}^{B}\left(\frac{\alpha}{2}\right), \phi_{GoF}^{B}\left(1-\frac{\alpha}{2}\right)\right]$$

Several applications have shown that the variability of the GoF values is mainly due to the inner model while the outer model contribution to GoF is very stable across the different bootstrap re-samples.

As PLS Path Modeling is a *soft modeling* approach with no distributional assumptions and it is also possible to estimate the significance of the parameters trough cross-validation methods like jack-knife and bootstrap (Efron and Tibshirani, 1993). Moreover, it is possible to build a cross-validated version of all the quality indexes (i.e. of the *communality* index, of the *redundancy* index, and of the GoF index) by means of a *blindfolding* procedure (Chin, 1998; Lohmöller, 1989).

3.3 MULTI-GROUP STRUCTURAL EQUATION MODELS ANALYSIS

Similarly to classical covariance-based methods, PLS Path Modeling assumes homogeneity over the observed set of units: all units are supposed to be well represented by an unique model estimated on all the units.

Nevertheless, in many cases it is reasonable to expect that different classes showing heterogeneous behaviors may exist in the observed set of units. In these cases, treating all units as a single class may lead to biased results both in terms of model parameters and of validation indexes (Jedidi et al., 1997).

As with any other statistical method, PLS path modeling applications are usually based on the assumption that the analyzed data stems from a single population, that is, a unique global model represents all the observations well. However, in many real-world applications this assumption of homogeneity is unrealistic (e.g., Jedidi, Jagpal, & DeSarbo, 1997; Sarstedt & Ringle, 2010).

Although several studies explicitly deal with the issue of group-specific effects in their research questions, ignoring population heterogeneity when performing PLS path modeling on an aggregate data level can seriously bias the results and, hereby, yield inaccurate conclusions (Sarstedt, Schwaiger, & Ringle, 2009).

It is important to underline that heterogeneity can also be unobserved, that is, it cannot be attributed to one or more pre-specified variables. Similar to ignoring observed heterogeneity, “unobserved heterogeneity” is a serious problem in respect of interpreting PLS-PM results if it is not considered in the analysis.

Various response-based segmentation approaches have recently been developed to deal with unobserved heterogeneity. These segmentation approaches generalize, for example, genetic algorithm (Ringle, Sarstedt, & Schlittgen, 2010), and typological regression approaches (Esposito Vinzi, Ringle, Squillacciotti, & Trinchera, 2007; Esposito Vinzi, Trinchera, Squillacciotti, & Tenenhaus, 2008) to PLS path modeling. Finite mixture PLS (FIMIX-PLS; Sarstedt & Ringle, 2010; Hahn, Johnson, Herrmann, & Huber, 2002; Sarstedt, Becker, Ringle, & Schwaiger, 2011) is currently regarded as the primary approach of all these segmentation techniques, and has become mandatory for evaluating PLS path modeling results (Sarstedt, 2008; Hair et al., 2012). Hair et al. (2011, p. 147), for example, point out that "using this technique, researchers can either confirm that their results are not distorted by unobserved heterogeneity or they can identify thus far neglected variables that describe the uncovered data segments". Although these response-based segmentation approaches rely on different statistical concepts, they all share the same final analysis step: a comparison of the PLS parameter estimates across the identified latent segments.

Therefore, no matter whether heterogeneity is observed or unobserved, there is a need for PLS-based approaches to multi-group analysis.

As with other statistical methods multi group comparison in SEM can be quite useful, whether the groups are fixed, chosen at random or assigned non-randomly. However, because of the complexity of SEM in terms of total number of variables and relationships between the observed and latent variables there are many ways in which to compare the groups.

Four approaches to multi-group analysis have been proposed within a PLS-PM framework.

The first approach, introduced by Keil et al. (2000), involves estimating model parameters for each group separately, and using the standard errors obtained from bootstrapping as the input for a parametric test. This method is generally labeled as the parametric approach (Henseler, 2007). The parametric approach was initially applied by Keil et al. (2000) (see also Chin, 2000) and depicts a modified version of a two independent samples t-test.

It is based on standard bootstrapping techniques. For each group, the parameter to be investigated is estimated by performing standard PLS analysis. Then the standard deviation for each estimated group specific parameter is calculated by means of bootstrapping. The following test statistic is then computed:

$$t = \frac{\left|\beta_{ij}^{G_1} - \beta_{ij}^{G_2}\right|}{\sqrt{\frac{(n_1-1)^2}{n_1+n_2-2}s_{G_1}^2 + \frac{(n_2-1)^2}{n_1+n_2-2}s_{G_2}^2} \times \sqrt{\frac{1}{n_1}+\frac{1}{n_2}}}$$

where n_1 and n_2 are the sizes of the two groups under comparison, and β_{ij} is the generic estimated parameter.

Under several distribution assumption (which runs contrary to PLS path modeling's distribution-free character), such as the normality of the residuals, the test statistic defined is asymptotically distributed as a t-Student with (n_1+n_2-2) degrees of freedom. In this way a parametric test can be performed and the null hypothesis on the equality of coefficients can be tested.

This procedure is quite easy to be applied, nevertheless, as said before, it requires a distributional assumption, at least on the residuals. This assumption does not always hold[15] and therefore the use of this procedure to assess differences among model parameters has to be carefully evaluated.

Since the parametric approach's distributional assumptions do not fit PLS path modeling's distribution-free character, Chin (2003) proposed and further described a distribution-free data permutation test (Chin & Dibbern, 2010; Dibbern & Chin, 2005). This test seeks to scale the observed differences between groups by comparing these differences to those between groups randomly assembled from the data.

The procedure is as follows:

1. The PLS path modeling algorithm is run separately for each group.
2. The data are randomly permuted; that is, the observations are randomly exchanged between the two groups. More precisely, $n_{(1)}$ observations are drawn without replacement and assigned to the first group; all remaining observations are assigned to the second group. Thus, in each permutation run, the group-specific sample size remains constant. In accordance with commonly suggested rules of thumb for bootstrapping sample sizes (Hair et al., 2012), the minimum number of permutation runs should be 5.000.
3. The PLS path modeling algorithm for each group obtained after the permutation is run in order to obtain the group-specific parameter estimates.
4. The differences in the permutation run-specific parameter estimates are computed.
5. The null hypothesis $H_0 : \beta_{ij}^{G_1} = \beta_{ij}^{G_2}$ that the population parameters are equal across the two groups is finally tested[16].

[15] A Kolmogorov–Smirnov test with Lilliefors correction (or, in the case of small sample sizes below 50, the Shapiro–Wilk test) in order to assess whether the data follow a normal distribution should be run. In addition to carrying out these tests the theoretical and empirical probability distributions by means of q–q plots should be visually inspected.

[16] Permutation tests (Edgington, 1987) are based on the permutation of units among classes. In particular, let g_1 and g_2 be two groups of units and S a statistic that allows to test the null hypothesis of parameters equality H_0. This test need to compute the statistic S several times on different samples obtained by unit permutation in order to obtain an empirical distribution of the statistic S under the null hypothesis. H_0 is rejected if the p-value obtained by the empirical

By not relying on distributional assumptions, the permutation-based approach overcomes a key disadvantage of the parametric approach and, thus, fits the PLS path modeling method's characteristics. However, the permutation-based approach requires group-specific sample sizes to be fairly similar (Chin & Dibbern, 2010), which is its central limitation.

The third method developed in order to overcome the shortcomings of the above described approach is the non-parametric approach to the multi-group analysis (Henseler, 2007). It can be considered as a bridge between the parametric and the permutation approaches.

The basic idea is to obtain, by means of bootstrapping, the empirical cumulative distribution of the parameters of interest. The procedure requires four steps, that are:

1. For each group, the parameter of interest are estimated, and the null hypothesis is fixed.
2. For each group, G bootstrap samples are built and the G estimates for the parameter of interest are computed.
3. All the possible combinations (G^K) of the bootstrap parameters across groups are built, in the case of two groups we will have G^2 possible combinations.
4. In the G^K combinations, how often the null hypothesis is rejected is counted. That is, in the case of two groups, how often the path coefficients of group one is smaller than or equal to the one estimated for group two is

distribution is lower than a certain threshold α. In other words, H_0 is rejected if the value of the statistic S computed on the original groups is an extreme value of the empirical distribution of the statistics S computed on the permuted data. The probability of $S_{original} < S_{permuted}$ is:

$$p_{S_{original} < S_{permuted}} = \frac{1}{G+1}\left(\sum_{g=1}^{G} I\left(S_{original} < S_{permuted}\right) + 1\right)$$

where I is the Boolean function with

$$I\left(S_{original} < S_{permuted}\right) = \begin{matrix} 0 & if\ S_{original} < S_{permuted} \\ 1 & \text{if not} \end{matrix}$$

And G is the number of random permutations.

counted. The relative frequency of these counts reflects the error probability, i.e. the probability that in the population the path coefficient computed for group one is smaller than or equal to the one computed for group two:

$$P\left(\beta_{ij_1} > \beta_{ij_2}\right) = 1 - \frac{1}{G^2}\sum_{g=1}^{G}\sum_{s=1}^{G} I\left(\beta_{ij_1}^{g} > \beta_{ij_2}^{s}\right)$$

where $\beta_{ij_1}^{g}$ is the parameter estimated for group one in the g-th bootstrap sample, and I is a Boolean function with:

$$I\left(\beta_{ij_1}^{g} \le \beta_{ij_2}^{s}\right) = \begin{matrix} 1 & \text{if } \beta_{ij_1}^{g} \le \beta_{ij_2}^{s} \\ 0 & \text{otherwise} \end{matrix}$$

The idea behind the non-parametric approach is simple. Each centered bootstrap estimate of the second group is compared with each centered bootstrap of the first group across all the bootstrap samples. The number of positive differences divided by the total number of comparisons indicates the probability that the second group's population parameter will be greater than that of the first group.

From a procedural perspective, the approach proposed by Henseler closely resembles the parametric approach. In fact, initially, the subsamples are exposed to separate bootstrap analyses, and the bootstrap outcomes serve as a basis for testing the potential group differences. However, Henseler's approach differs in the way the bootstrap estimates are used to assess the robustness of the group-specific parameter estimates. Instead of relying on distributional assumptions, the new approach evaluates the bootstrap outcomes' observed distribution. However, such an approach only allows testing the one-sided hypotheses. As the bootstrap-based distribution is not necessarily symmetric, it cannot be used to test two-sided hypotheses.

The fourth method used in PLS-PM framework in order to assess differences among parameters is the use of moderating variables.

Conceptually, the comparison of group-specific effects entails the consideration of a categorical moderator variable which "affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable"[17]. Following this concept, group effects are nothing more than a variable's moderating effect whereby the categorical moderator variable expresses each observation's group membership. As a consequence, multi-group analysis is generally regarded as a special case of modeling continuous moderating effects.

A first attempt to take into account moderating variables in PLS-PM by including interaction effects was made by Chin, Marcolin & Newsted (2003). Since then, other proposals exist for modeling moderating effects in PLS-PM framework, as the one by Tenenhaus et al. (2008) and the one by Hensler & Fassott (2008), Henseler & Chin (2010); Henseler & Fassott (2010).

Chin et al. (2003) suggest to assessing moderating by comparing the R^2 value, i.e. the proportion of the variance explained by the model, computed for the model without moderating effects with the R^2 value obtaining for the model taking into account interaction effects[18]. The effect size f^2 is computed as:

$$f^2 = \frac{R^2_{\text{model with moderating}} - R^2_{\text{model without moderating}}}{1 - R^2_{\text{model without moderating}}}$$

Moderating effects with an effect size f^2 of 0,02 are regarded as weak, an effect size between 0,15 and 0,35 as moderated and an effect size higher than 0,35 as strong (Chin et al. 2003). The significance of the coefficient linked to the interaction effect can be tested also by means of bootstrap-based techniques (Hensler & Fassott, 2008).

[17] Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182.

[18] As Hensler & Fassott (2008) suggest, in the case that the exogenous variable or the moderating variable is formative, the pairwise multi- plication of the manifest variables is not feasible. In this case they propose to use a two-step procedure to include product terms. In the first step they suggest performing PLS-PM by considering both the exogenous variable and the moderating variable as independent latent variables in the model. Once latent variable scores are estimated, the product term is computed as the elementwise product of the exogenous latent variable scores and the moderating latent variable scores. A multiple linear regression between the endogenous latent variable scores and the exogenous, the moderating, and the product term latent variable scores is then performed. The interaction effect is estimated.

Chapter 4: Model-Based Micro-Level competitiveness composite indicator: theoretical basis

4.1 INTRODUCTION

As said in the previous sections the aim of this study is to construct a model-based composite indicator in order to measure competitiveness at micro-level. The methodology chosen for reaching the objective is the Partial Least Squares approach to Structural Equation Models.

The use of such an approach gives the chance to take into account the multidimensional structure of competitiveness by reducing the phenomenon complexity through a set of causal relationships among its determinants, explaining different features of micro-level competitiveness.

Structural Equation Model gives the chance to specify a causal model in order to conduct the analysis on the field of interest. The model's specification may have some theoretical or empirical basis, or may reflect the guess of the researcher's domain knowledge and experience.

Hence, before moving toward a the multivariate SEM analysis, the first step made has been the specification of a competitiveness model.

One of the most important problems in science in general and in economic analysis in particular is the formulation of the most appropriate approach to the identification of a cause-effect relationship. Due to this fundamental methodological difficulty, it is hardly possible to establish a clear distinction between causes and effects above all in the field of competitiveness, where the development of the level of a certain performance variable is the result of the influence of other factors or a determinant of other elements. This fundamental issue has to be taken into account during the choice phase of both the variable and the causal relationships determining the level of firm competitiveness in order to obtain an information set that is as comprehensive as possible.

In order to do it, a previous work of analysis and systematization of the literature about competitiveness and its determinants has been realized.

As already said, competitiveness is a complex, multidimensional and relative concept, linked to a number of interdependent variables; its complex structure makes difficult to study and define it.

In the first section of the present work it has been widely explained how the definition of the concept of competitiveness is itself a research problem, and the attempt to found an exhaustive definition, including the most important features and elements of competitiveness was made.

Among the several, different definition analyzed the one formulated by the Research Centre for Competitiveness seems to be the most complete found in literature: micro-level competitiveness is defined as "the company's ability to permanently offer consumers products and services, which are in compliance with the standards of social responsibility, and for which they are willing to pay more than for the competitors' products, ensuring profitable conditions for the company. Condition of this competitiveness is that the company should be able to detect changes in the environment and within the company, by performing permanent better market competition criteria compared to the competitors".

The above eclectic definition takes into account some competitiveness features whose consideration seems to be unavoidable for a complete understanding of the conceptual, theoretical and practical underpinnings of competitiveness.

In particular, it is possible to individuate three different aspects that, at the enterprise level, are fundamental for assessing the competitive performance: it is immediately clear that at the base of the definition lies the concept of competitiveness as the ability for assuring the efficiency in the utilization of resources and the results of competitive performance in terms of growth of output, productivity, and profitability, that is, to attain the basic economic and financial objectives.

A firm is thus competitive if it can produce products or services of superior quality or lower costs than its domestic and international competitors. It is, therefore, synonymous with a firm's long-run profit performance and its ability to compensate its employees and provide superior returns to its owners. In the narrow sense, such measures of competitiveness at the firm level comprise indicators of financial performance, such as the development of sales, profits, and costs, as well as stock performance.

The importance of the economic and financial side of competitiveness represent the substratum of most of the economic theories on competitive advantages, that, above all in the past, was mainly grounded in outstanding products, creative marketing and aggressive pricing.

However, by reading the definition under analysis, it is easy to understand that competitiveness is not only a question of economic or financial performance, but it is to a large extent strictly related to the enterprise culture, the management ability and the human resources of the company to adapt to changing conditions, by the ability to influence the enterprise environment, innovate, develop or explore new technologies and markets. This is mainly due to the fact that in recent years companies have to cope with a radical change in their approach to competitiveness: no more economic and financial elements but also the rules of the rising information society have to be taken into account.

In this contest the importance of intangible assets and the resource-based view of firms has to be underline as they determine the firm capacity to renew competence and processes in order to match up with changing environment.

The third element emerging from the definition is the one related to the concept of Corporate Social Responsibility that can play a key role in contributing to sustainable development while enhancing firms innovative potential and competitiveness. To take into consideration the principles of social responsibility while attempting to individuate a comprehensive competitiveness structure, means to focus on how enterprises do their work: how they treat their employees, how they produce goods, how they market them, and so on; that is, to emphasize not so much about what enterprises do with their profit, but how they make that profit.

In the next section, some of the key element individuated through the basic analysis of the competitiveness definition will be discussed in details.

In particular, literature on intangible assets, innovation, gender policies and environmental policies in a micro-level framework and their relationship with competitiveness will be presented.

4.2 COMPETITIVENESS AND CORPORATE SOCIAL RESPONSIBILITY PRINCIPLES.

As said before, assessing micro-level competitiveness means not only to take into account a firm's economic and financial performance, but also to consider its compliance to the Corporate Social Responsibility (CSR) rules.

In recent years, one of the most widespread debates among UE researchers is on the competitive advantages companies may obtain by paying attention to CSR initiatives. The importance of acting beyond corporate philanthropy and incorporating social and environmental issues into business operations is becoming more and more evident (Loew, 2005).

Most of CSR researchers and practitioners assert that the prevailing companies approaches to CSR are so fragmented and so disconnected from business and strategy as to obscure many of the greatest opportunities to benefit society.

They maintain that if corporations were to analyze their prospects for social responsibility using the same frameworks that guide their core business choices, they would discover that CSR can be much more than a cost, a constraint, or a charitable; it can indeed be a source of opportunity, innovation, and competitive advantage (Porter and Kramer, 2006).

One of the most widely known definition of CSR is the definition of European Commission (2001) that describe CRS as "a concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with their stakeholders on a voluntary basis".

By reading the EC definition it is possible to understand that the to maintain CSR is the integration of social and environmental concerns within business operations, means that CSR is not just philanthropy. The emphasis is on how enterprises do their work: how they treat their employees, how they produce goods, how they market them, and so on. Moreover by describing CSR as voluntary, implies that CSR relates to what enterprises can do in the social and environmental fields over and above what they are required to do by law[19].

CSR is a very wide-ranging concept, which is one of the reasons why its measurement and analysis presents complex methodological problems. CSR is often divided into four main areas: workplace, market-place, environment and community related issues.

Workplace CSR refers to how a company treats its employees. It includes issues such as recruitment, work-force diversity, pay and working conditions, health and safety, and recognition of trade unions.

Marketplace CSR refers to the ways in which a company operates in relation to its suppliers, customers and competitors. It covers issues such as responsible advertising and marketing, dealing with customer complaints, anti-corruption measures and ethical practice, and imposing social and environmental requirements on suppliers.

Environment-related CSR describes the measures a company can take to mitigate its negative impact on the environment, for example energy efficiency measures or less use of pollutants. It can also refer to goods and services that actively help to improve the environment.

Community-related CSR refers to the relations between the company and the citizens and communities that may be affected by its operations. It includes issues such as human rights, dialogue and partnership with potentially affected communities, and active contribution to community wellbeing, for instance through employee volunteering schemes.

The four-area division presented above does not pretend to be exhaustive, but is useful for showing the high complexity characterizing the topic of CRS. Such a complexity becomes particularly evident when looking at the numerous instruments (e.g. international documents, standards and indices) and attempting

[19] This aspect of the definition works well within the European Union and in other contexts where the rule of law generally applies.

to conceptualize it. However, most of these instruments focus on different key subjects of CSR consequently covering a wide range of sub-issues.

Together with the attempts made in order to conceptualize and define CRS, in recent years increasing attention has been paid to the relation between CRS and firm competitiveness. That is, how do firms benefit tangibly from engaging in CSR policies, activities and practices.

A quick literature review has shown that various publications examine the competitive advantage of CSR on a corporate level (e.g. Pivato, 2008; Lankoski, 2008; Smith, 2007; Wade, 2005; Bhattacharya and Sen, 2004). The so-called "business case for CSR" analyses CSR on the corporate level and maintains that companies added value might gain trough responsible behavior (Garriga et al., 2004).

According to this concept, companies view the possibility of furthering their economic success (Branco, 2006) for example through added shareholder value, enhanced market share, reputation and image gains, increased customer loyalty and trust, staff motivation and retention, increased share prices (Beckmann et al., 2006; Hansen et al., 2005).

Additionally, the business case perceives CSR engagement as a source of opportunity, innovation and competitive advantage (Porter et al., 2006) because the focus on societal issues and interaction with external stakeholders leads to the development of new products, services and business models.

Companies need to align CSR with their operations in a way that allows them to operate in a cost-efficient and competitive manner in order to secure their position in the face of augmented global competition.

Several studies examine the effect of CRS on different determinants of micro-level competitiveness such as cost structure (Welford, 2003; Woodward et al., 2001), human resource performance (Brown and Grayson, 2008; Cochran, 2007; Kramer et al., 2007 , Longo et al., 2005; Montgomery and Ramus, 2003;), customer perspectives (Mandl and Dorr, 2007; Longo, 2005; Tuppen, 2004), innovation (Beurden and Gossling, 2008; Chand and Fraser, 2006; Brammer, 2004; McWilliams, 2001; Siegel, 2001), risk and reputation management (Kurucz, 2008; Chen, 2008; Smith, 2007). Positive impact of CSR seems to be particularly evident with regards to human resources, risk and reputation management and innovation.

In the present study the focus will be on two CRS element and their relationship with micro-level competitive advantages: special attention will be paid to firms environmental and labour management system.

4.2.1 Environmental policies and competitiveness

The relationship between being proactive in environmental issues and firm performance represent a perplexing issue in the existing literature: some studies have documented a positive relationship (Galdeano-Gomez et al., 2008; Nakao et al., 2007; Wahba, 2008; Aragón-Correa and Rubio-López, 2007), some others do not identify any impact of environmental proactivity on economic performance (Link and Naveh, 2006; Wagner, 2005; Watson et al., 2004).

It is possible to maintain that the main reason of these contrasting results is the lack of a solid and shared theoretical background. One important issue at the base of the above mentioned lack of knowledge convergence concerns the choice of the type of environmental variables and competitiveness indicators used in order to conduct studies.

Specifically, some studies are conducted by the use of environmental management variables, others only use environmental performance variables.

Environmental management and environmental performance are two different concepts, not automatically linked: environmental management variables regard technical and organizational activities undertaken by the firm with the aim to reduce environmental impacts and minimize their effect on natural environment. Environmental performance is instead generally considered in terms of harmful environmental impacts[20].

[20] Implementing a certain environmental performance level may carry competitiveness implications for a firm. For example, reducing energy use may require investment in energy efficient equipment, produce savings in input costs, and result in a favorable image among stakeholders. Environmental policy may force environmental performance improvements on a firm, and thus in effect impose on it the competitiveness impacts associated with those improvements. Moreover, environmental policy may have competitiveness impacts that arise directly from the policy itself rather than from environmental performance improvements by the

The issue of the choice of the measures to be used in environmental studies seems to be far from being solved. It is possible to try to organize them by using different categories: a possible categorization is in terms of environment performance indicators, environment management accounting, environment management strategies.

Environmental performance indicators, which are the most used in empirical environmental studies represent numerical financial or non-financial measures, providing key information about environmental impact, regulatory compliance, stakeholder relations, and organizational system; they represent the quantification of the effectiveness and efficiency of environmental action with a set of metrics, for this reason they can be considered as a component of environmental management accounting.

Environmental management accounting represent the management of environmental and economic performance through the development and implementation of appropriate environmental-related accounting systems and practices. It typically involves lifecycle costing, full-cost accounting, benefits assessment, and strategic planning for environmental management.

The environmental management accounting is considered in its turn as one component of environmental management strategies. The latter refers to the formal systems that integrate procedures and processes for the training of personnel, monitoring, summarizing, and reporting of specialized environmental performance information to internal and external stakeholders of the firm.

A second possible way of grouping of environmental performance indicators is the classification according to ISO 14031[21] guidelines. This standard

firm. This is the case when complying with an environmental policy does not change the physical environmental performance level of a firm; for example, when an emissions trading system is established, a firm purchases a sufficient amount of emission allowances and continues to emit at the same level than previously. Or, such impacts are also present in those cases where the environmental performance of the firm is improved, but the competitiveness impacts are different from what they would have been if the firm had made a corresponding environmental performance improvement without the regulation. For example, it is possible that a firm can implement a given environmental performance level more cost-efficiently if the ways and means for this are left for the firm to decide rather than prescribed through a technology standard.

[21] ISO 14031 is a subcategory of ISO 14001 and concerns the evaluation of environmental performance.

proposes guidelines for the development of monitoring and measurement tools that evaluate the efficiency of an environmental system.

Three categories are proposed (Bennett and James, 1998; Marshall and Brown, 2003):

- Environmental condition indicators, providing information about the local, regional, national, or global condition of the environment. Those measures include receptor indicators (e.g. eco-toxicity, biological oxygen demand), sustainability indicators (e.g. emissions of a substance per volume of production or per unit of value added), and proxy indicators that express emissions and waste data in terms of their capacity to cause environmental damage.
- Operational performance indicators provide information about the environmental performance of an organization's operations. They include input of materials, energy, and services, operation of facilities and equipment and logistics, and output of products, services, waste, and emissions.
- Management performance indicators provide information about management's efforts to influence an organization's environmental performance. Four sub-categories are identified: implementation of policies and programs, conformity of actions with requirements or expectations, community relations, and environment-related financial performance.

As before said, environmental performance indicators do not, by themselves, provide information about specific management efforts being made by a firm to modify performance, but to some extent, they may be considered as being the outcome of management efforts; this is probably the reason why they are the most used and debated in the environmental literature. In particular, they seems to be influences and determined by internal firm-specific drivers (such as organizational and technological factors, as well as by the implementation of environmental management systems) and by external elements (such as regulatory and stakeholder pressures, compliance with environmental regulations and pressure groups).

The brief analysis on the environmental variables and indicators that may be used when implementing researches of environmental interest show that not only quantitative data, but also information coming from qualitative studies should be used in order to take into account the multidimensional nature of the field under investigation.

As far as the relationship between environmental policies (or performances) and competitiveness is concerned, several studies have been realized, resulting in different, sometimes contradictory conclusions, thus leading researchers to maintain that competitiveness impacts of environmental performance are not universal but contingent. Moreover most of these studies takes into account different competitiveness element, by obtaining, in this way, different results.

There is, for example a relatively large body of literature that seeks to establish a connection between environmental policy and productivity. This is not surprising considering the fact that for many authors, productivity is the key element in defining competitiveness (e.g. Porter et al., 2007).

The analysis of the literature about the above mentioned relationship shows that while the earlier studies have shown a negative impact of environmental regulation on productivity, more recent papers have found positive results[22] (Lanoie et al., 2008).

The fact that most researchers found declines in productivity due to the cost of complying with environmental regulation, seems to be true by definition, because if standard measures of productivity are taken into account, it happens that an increase in inputs is recorded, but the "output" generated by this input (reduced emissions) is not counted in traditional output measures. In fact, when

[22] A number of empirical studies on environmental policy and productivity have been published, with mixed findings: some researchers have discovered a positive relationship (for example, Berman & Bui, 2001; Alpay et al., 2002, for the Mexican case), some others found negative relationship (for example, Gray & Shadbegian, 2003; Dufour et al. 1998), or even no relationship (for example, Alpay et al., 2002, for the US case).

avoided environmental damage costs are counted in the equation, a more positive view emerges of the effect of environmental regulation on productivity.

Thus, one factor in assessing the impacts of environmental policy on productivity is whether a traditional productivity measure is used or one that takes account of the environmental benefits obtained (Repetto et al., 1997).

There exists another empirical research approach that investigate on the relationships between competitiveness and environmental policy through a resource-based point of view which takes into account the role of some mediating variables representing the firm innovative level.

The motive for these studies is that environmental policy may foster innovation in firms that, besides efficiency improvements, may result in product differentiation, access to new markets or the creation of new business, new production procedures, and that particular benefits may be available to the “first-movers” in these areas (e.g. Porter & van der Linde, 1995).

In particular some researchers have shown that cost-saving innovations arise when a firm has to comply with a new environmental measure. Thus it is possible to maintain that quality improvements or production cost reductions can result from closer attention to resource efficiency and sustainable production technology.

Most of the above mentioned studies focus on input measures such as R&D expenditures or output measures such as successful patent applications. According to Lanoie et al. (2008), studies have found a positive relationship between environmental policy and R&D expenditures (e.g. Jaffe & Palmer, 1997; Arimura et al., 2007) and between environmental policy and successful patent applications (e.g. Brunnermeier & Cohen, 2003; Popp, 2006).

An important body of empirical research on environmental policy and competitiveness consists of studies that link environmental policies to trade flows. The thinking behind these

studies is that the overall net competitiveness impacts created on individual firms by environmental policy are reflected in sectorial trade flows.

The earliest studies on this topic showed that differences in the stringency of environmental policy have little or no effect on trade and investment flows was premature, however a second wave of empirical studies has produced reversal findings.

In particular Levinson and Taylor (2008) argue that studies on the relationship between environmental policy and trade flows suffer from inadequate accounting for unobserved heterogeneity in country and sector characteristics, and from the endogeneity of pollution abatement cost measures, and that ”these issues are responsible for the mixed results produced so far”. Accounting for these econometric and data issues (with panel data and instruments to control for endogeneity of regulatory stringency), Levinson and Taylor found that environmental policy did have an impact on trade flows that was consistent with the pollution haven hypothesis, and that this impact was not only statistically but also economically significant.

4.2.2 Gender equality and competitiveness

In the previous sections describing the main features of Corporate Social Responsibility (CSR) the importance of the workplace CSR has been pointed out.

In particular, it has been explained that workplace CSR refers to how a company treats its employees: it includes issues such as recruitment, work-force diversity, pay and working conditions.

In the following section one of this element will be emphasized: the importance of the work-force diversity management with kind attention toward gender policies. Moreover the studies on the relation between gender policies (work-force gender equality strategies) and micro-level competitiveness will be investigated.

Gender equality is a multidimensional term embracing economic, cultural and social dimensions alike.

In the present study only the employment-related factors will be taken into account. The analysis will be restricted to two important aspects that serve the purposes of the research: the former concerns the equal right (and opportunity) to work, the latter is about the nature of women’s work and pay.

Despite the strategy for the working condition equality between women and men represents one of the most important objectives both for European and national level work programs since many years, there are still several differences in the levels of labour force participation.

Female employment rates are generally increasing, and gender gaps in labour force participation is narrowing, but occupational segregation has not improved, gender pay gaps persist and women are still under-represented at more job levels, especially among managers and in company boards.

Women are still constrained to choose part-time works as they facilitate combining work and family responsibilities, and this frequently represent an obstacle to their long-term career and earnings prospects. Moreover, women are less keen than men on starting their own business and women entrepreneurs continue to be a minority in many countries. Enterprises owned by women are significantly smaller and less represented in capital-intensive sectors, and these and other factors tend to penalize them in terms of sales, profits and labour productivity.

Furthermore, it is generally known that women have lower pay levels than man, which directly reflects the differing conditions and circumstances under which women and men work.

In a global business context characterized by rapidly changing industrial strategies, companies have to face issues such as market maturity, increasing competition and fragmentation of markets. Given the demand for high skills in a shrinking labour pool, it is important to reckon on the strengths of non-traditional labour and work to meet employees' changing needs and aspirations. In this context, among corporate strategies, particularly important seems to be the promotion of gender equality in the workplace.

There are several reasons why firms should be interested in enhancing the role of women in their companies. These include: to attract and retain the best talent, to enhance diversity and improve overall performance in the workplace, and to better serve consumer markets, including those in which women are the main clients.

The main reasons presented above are related to improving the workplace environment and human relationships, improving production processes, and promoting innovation in the workplace.

Other motivations are linked to business positioning in the marketplace; gender equality bring to increases in firms prestige and market share: modern marketing is built on the image of a comprehensive business, where respect and care for clients and workers is a fundamental part of good sales tactics and profits earning.

Moreover proper treatments, the recognition of good work, the adoption of a merit-based promotion system, the adoption of gender equality strategies, the existence of affirmative measures for promoting women to decision-making positions, and considerations for family and personal needs better employees commitment to their work, thus helping them to improve their productivity. Such a kind of workplace management is positively valued by qualified and dynamic personnel interested in succeeding in challenging careers (as it perceives real opportunities for professional growth), thus giving to firms the chance to attract and retain high-skilled employees. This helps firms to improve its positive image in front of both employees and responsible consumers.

Another reasons is that there exists a good market for women with purchasing power who would be inclined to buy products and services that have implemented equality strategies.

The above mentioned features of the gender equality management strategies can be included in the so called Business Case of equality (Hutching and Thomas, 2005; Kirton and Greene, 2005; World Bank, 2002; Maddock, 1995). It focuses on persuading employers or even managers to adopt equality practices to reap benefits where they are in line with organizational objectives. In particular, the Business Case literature emphasizes the need for equal treatment to reflect the diversity among potential employees and an organization’s customers. Equality is seen, on the one hand, as an incentive or a pre-condition to attract a larger and therefore more diversified supply of labour and, on the other hand, as a way to ensure that differences become comparative productive advantages within organizations favoring equality, hence sources of productivity.

Briefly, addressing gender equality in the labour force and in the boardroom of a company enables it to attract and retain the best employees, increase productivity, improve morale, reduce absenteeism, increase return on investment in staff training and career development, and enhance corporate image and reputation.

For the whole understanding of the importance of gender equality for firms competitiveness a step beyond the Business Case has to be done. In particular, for this purpose, it would be useful to take into account the Economic Case (Pollert, 2005) for equality, that considers gender equality to be central to economic thinking with a potential positive impact on economic growth. In this way equality can be seen as a means to promote future economic performance and not necessarily a cost or an issue that can be postponed.

Greater gender equality in economic opportunities contributes to stronger and more sustainable economic growth[23].

Two principal types of economic benefits that companies seek from investments in workforce diversity policies can be individuated. Specifically, such investments create economic benefits for companies by: strengthening long-term value-drivers by means of tangible and intangible assets that allow companies to be competitive, to generate stable cash flows, and to satisfy their shareholders. Investments in gender policies contribute to a strategy of long-term value creation by generating and strengthening human and organizational capital. Along with knowledge capital, these are the principal intangible assets used by companies to establish competitive advantage and to create value (Bassi, Lev et al., 2001) .

The second type of economic benefit is the chance to generate short and medium-term opportunities to improve cash flows, by reducing costs, resolving labour shortages, opening up new markets, and improving performance in existing markets. These are also known as return-on-investment (ROI) benefits. Because

[23] Empirical studies of gender equality and growth have been conducted at macro level. These studies, on the whole, concluded that the role of women is crucial to economic growth (Bassanini and Scarpetta, 2002; Arnold, Bassanini and Scarpetta, 2011; Dollar, Fishman and Gatti, 2001; Forsythe et al., 2000). Moreover at EU level several indexes (Gender Equity Index - GEI, Social Institutions and Gender Index - SIGI, Gender Equality Index – EU-GEI, Global Gender Gap Index – GGG) for the benchmark of gender equality have been constructed, using different indicators such as education, activity rate in the labour market, paid work, pay and income, political and social power, pay and professional practice, economic activity, literacy level. Most of these indexes have been used for studying the correlation between gender policies and GDP (Asa Löfström, 2009), showing positive correlation, and thus confirming the importance of gender equity policies for the economic growth.

of their nature, many of these benefits are more straightforward to measure, and a link to investments in diversity can, in certain circumstances, be identified. However, most of these benefits are context-specific; they are particular to the strategy and market position of specific companies. Another important issue is the difficulty of linking together business benefits and investments in diversity. Even for short and medium-term improvements in cash flows, it is likely that diversity policies are only one of a number of factors that contribute to improvements in performance.

However, a number of studies (Catalyst, 2007; McKinsey and Company, 2007; Campbell and Minguez-Vera, 2007) have highlighted, for example, positive correlation between gender diversity management and financial performance. In particular, such studies have proved that companies with the highest percentage of women board directors on average outperform[24] companies with lowest percentages of women board directors. Another argument for gender equality is that it enhances creativity and innovation, which are increasingly critical to competitive success. Recruiting women in the workplaces allows companies to gain competitive advantages though deeper cultural adaptation to the marketplace (Chatered Institute of Personnel and Development Survey, 2005).

The brief discussion on the Business and Economic case of gender equity showed some important aspects to be taken into account in the present research: the linkages between gender policies and economic growth are investigated and analyzed by means of empirical researches above all through a macro-level approach; as far as the micro-level empirical studies are concerned, they mainly focus on some, narrow element, such as the economic results of firms giving executive assignment to women; while the whole characteristic of firms gender equity policies are often taken into account only under a strictly theoretical point of view. One of the aims of the present study is to study micro-level competitiveness by taking into account, among other aspects, elements describing

[24] The firm's financial measures generally used are return on equity, return on sales, return on investments, operating result, and stock price growth.

firms gender policies, with a variable selection process driven by both previous empirical researches and theoretical background.

Our hypothesis is that investing in gender equality policies increases labour productivity and the available talent pool, which provides businesses with greater opportunities to expand, innovate and compete. Investment in human capital improves the economic and social opportunities thereby helping to foster technical progress.

4.3 INTANGIBLE ASSETS, INNOVATION AND COMPETITIVENESS

Competitiveness is not only a question of economic or financial performance, it is to a large extent strictly related to the enterprise culture, the management skill and the human resources of the company that result in its ability to adapt to changing conditions and to influence the enterprise environment, innovate, develop and explore new technologies and markets.

In this context the importance of intangible assets and the resource-based view of firms has to be underline as they determine the firm capacity to renew competence and processes in order to match up with changing environment.

The Resource-Based View (RBV) of the firm suggests that firm resources are responsible for generating firm sustainable competitive advantage and superior performance.

Firms resources can be divided into tangibles and intangible ones. Intangibles assets are identifiable non-monetary assets that cannot be seen, touched or physically measured; they are created through time and effort, and are fundamental in determining a firm’s value.

Firm intangible resources are said to confer enduring competitive advantages to a firm to the extent that they are rare or hard to imitate, have no direct substitutes, and enable companies to pursue opportunities or avoid threats (Barney, 1991).

Thus, such resources should be difficult to create, buy, substitute, or imitate. This last point is central to the arguments of the resource-based view (Barney, 1991; Lippman & Rumelt, 1982; Peteraf, 1993).

Because intangibles are valuable, rare, mostly inimitable and non-substitutable, they are able to generate sustainable competitive advantages and superior performances. Those assets can be seen as the basis of firms competitiveness outcomes. A firms capacity to attain and keep profitable market positions depends on its ability to gain and defend advantageous positions in those resources relevant for production and distribution improvements[25]. The duration of the competitive advantages obtained through the firm resources and the persistence of the obtained rents are strictly related to the strength of isolating mechanisms, including property rights, high learning processes and development costs (Dierickx and Cool, 1989).

Thus, the theory also focuses on the competitive advantages that can be obtained if "the firm effectively deploys its resources in its product-markets" (Fahy and Smithee, 1999). In substance the resource-based view provides an explanation of competitive heterogeneity based on the premise that close competitors differ in their resources and capabilities in important and durable ways.

The RBV theory provides a static notion of competitive advantage, it does not takes into account that competitive advantages comes about over a period of time and also may shift over time. Therefore, in order to explain competitive advantage, the resource-based view must incorporate the evolution over time of the resources and capabilities that form the basis of competitive advantage. Taking into account the resources lifecycle helps to make resource-based theory dynamic by providing a framework for understanding the evolution of resources and capabilities over time. Starting from this belief the resource-based view has naturally evolved toward dynamic terms into theories known as Dynamic Resource-Based View and Dynamic Capabilities Approach (Helfat, 2000, Helfat

[25] By specifying the distinctive advantages of different types of resources, it may be possible to avoid vague inferences that impute value to a firm's resources simply because it has performed well (Black & Boal, 1994; Fiol, 1991).

and Peteraf, 2003, Teece, Pisano and Shuen, 1997). Those views have their theoretical foundations in works of Schumpeter (1934) and Nelson and Winter (1982) and focus on a firm's ability to achieve new and innovative forms of competitive advantage through new resource combinations that, in the end, lead to innovation and value creation (Kor and Mahoney, 2004).

Teece et al. (1997) define dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments". More recently, Helfat et al. (2007) has defined a dynamic capability as "the capacity of an organization to purposefully create, extend or modify its resource base".

Proponents of this view assume dynamic process: the strategy of accumulating valuable technology assets is often not enough to support a significant competitive advantage; companies need dynamic perspectives, so as to understand how firms evolve over time (through the deployment and acquisition of resources), and the reason why firms must continuously renew and reconfigure themselves if they are to survive (Zahra et al., 2006).

Dynamic capabilities are organizational processes in the most general sense (Helfat et al., 2007) or routines (Zollo and Winter, 2002) which may have become embedded in the firm over time, and are employed to reconfigure the firm's resource base by deleting decaying resources or recombining old resources in new ways. The firm's dynamic capabilities can thus be considered as the evolutionary outcomes of its past experience gained during the history of its existence. This means that dynamic capabilities are viewed to be essentially path dependent (Dierickx and Cool, 1989), as they are shaped by the decisions that the firm has made throughout its history, and the stock of assets that it holds (Eisenhardt and Martin, 2000; Zollo and Winter, 2002). Path dependency could be grounded in knowledge, resources familiar to the firm (Monteverde and Teece, 1982), or influenced by the social and collective nature of learning (Teece et al., 1997).

This suggests that the processes of knowledge creation and accumulation and the concept of learning by doing (Arrow, 1959) plays a key role in the creation and development of dynamic capabilities.

The difference between the original resources-based theories and their extension and evolution can be summarized with the help of two simple concept: a resource refers to an asset or input to production (tangible or intangible) that an organization owns, controls, or has access to, on a semi-permanent basis. An organizational capability refers, instead, to the ability of an organization to perform a coordinated set of tasks, utilizing organizational resources, for the purpose of achieving a particular end result.

The theoretical developments of the resources-based management theories reveal the importance of intangible assets in determining non only a firm’s value, but also its chances to survive in an ever-changing global market.

Strategic literature has recently paid special attention to the relevance of intangible resources as factors determining a firm’s competitiveness, but the youth and the lack of maturity of this investigation line is mainly demonstrated by the fact that there is not yet consensus on the definition of those resources and that they are not univocally measured and identified.

In the literature neither a unified definition, nor a general classification can be found. Some authors maintain that intangible resources consist of elements such as knowledge, information, as well as intellectual property that can be used to create wealth (Steward, 1997); for some other intangibles resources can be classified in employee competence, internal structure, external structure (Sveiby, 1997). Mortensen, Eustace and Lannoo (1997), from a financial perspective, distinguished between innovation capital, structural capital, executory contracts, market capital and goodwill.

Corrado, Hulten and Sichel (2005) have grouped the various items that constitute the intangible resources of the firm into three basic categories: computerized information, innovative property and economic competencies. Whereas computerized information is embedded in computer programs and computerized databases, innovative property reflects the scientific knowledge embedded in patents, licenses and general know-how, and economic competencies category of intangibles are the value of brand names and other knowledge embedded in firm-specific human and structural resources. It comprises expenditures on advertising, market research, firm-specific human capital and organizational change.

In the present study the Hall's approach will be taken into account, as his classification provides insights into the nature of the firm and suggests a consistent and coherent explanation of many empirical observations about firms. According to Hall's theory intangibles resources can be instead grouped into two categories, according to whether they are people dependent or independent. The former are represented by human capital related resources, the latter include those resources that remain at firms disposition independently of the firms workforce composition. The people independent intangible assets can, in their turn, be split into three groups: organizational capital, relational capital, and technological capital.

Human capitals refer to processes that relate to training, education and other professional initiatives put in order to increase the levels of knowledge, skills, abilities, values, and social assets of an employee which will lead to the employee's satisfaction and performance, and eventually on a firm performance. Thus, the definition of human capital is referred to "the knowledge, skills, competencies, and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being" (Organization for Economic Co-Operation and Development or OECD, 2001: 18). As said before, the constantly changing business environment requires firms to strive for superior competitive advantages via dynamic business plans which incorporate creativity and innovativeness processes: this is essentially important for their long term sustainability. To this extent human resource input undoubtedly plays a key role (Barney, 1995).

It is however clear that firms success not only depends on the capacity to innovate and the ability to have the necessary know-how and knowledge level for doing it; it also depends a lot on the capability a company has to generate dynamic communication with clients, suppliers and strategic partners in an effective matter (Teece, 2000). It is undoubted that innovation is a fundamental determinant to value creation in firms and therefore a factor of economic growth, but the ability of a firm to innovate can be surely enhanced by an extended knowledge base offered through linkages in a network of external agencies, suppliers, customer, competitors, universities and public agencies. Success can be achieved through an interactivity of systems with exchanges of ideas, problems and solutions. These are the reason why relational capital is considered as an unavoidable element in determining firms economic growth. Nevertheless, relation capital not only represent the relationships network a firm has to construct in order to better its production processes through knowledge and innovation transfers activities, it also concerns intangibles resources such as reputation, brand recognition, customer loyalty, long-term customer relationships, commercial power, environmental activities, distribution channel and so on, that is, all the elements that reveal the trust level that external agents place on firms processes and products (Meritum, 2002).

It is easy to understand that relational capital is strictly related to the concept of trust: building a relationship based on trust and confidence are important conditions for knowledge transfer and creation of value (von Krogh et al., 2000). Moreover, trust and reputation are correlated. Trust is an essential factor in a relationship, and promotes greater information sharing and definitely eases the transfer of tacit knowledge, and trust is a basic factor in the business: it can open doors, build loyalty and increase sales. In short, relational capital covers everything that might be connected externally to the company, and it is the connected value with the external world.

As far as the organizational capital is concerned it is defined as an agglomeration of technologies, business practices, processes and design, incentives and compensation systems, that together enable some firms to consistently and efficiently extract from a given level of physical and human resources a higher value of product than other firms find possible to attain (Lev and Radhskrishnan, 2005).

Organizational capital includes firms norms, guidelines, databases, organizational routines and corporate culture that contributes to them order, stability and quality. The norms and guidelines constitute the firm’s administrative procedures forming part of its organizational knowledge. Another important element is determined by organizational routines which define regular, predictable pattern of activity, consisting of a sequence of coordinated actions and processes put in practice by mobilizing and animating human and technological resources, competencies and knowledge, in order to follow a certain strategy or to face a specific problem or stimulus (Nelson and Winter, 1982). Routines represent therefore firm-specific knowledge and results of its collective learning processes. Companies modify their routines in order to improve and adapt them to the environment's changing circumstances, following patterns marked by their own dynamic routines of learning and change. Organizational capital also includes corporate culture determinate by the initiatives or personality of the firm founders as well as in the top executives who manage the and formed by the evolution of firm's experiences, rules and work norms. It is in particular formed by means of the interaction and collective learning which is produced in team-work. By considering their features, the organizational resources of firm seems to be strictly related to the concept of dynamic capabilities developed by the second generation of RBV theories, as they are fundamental in guarantying the adaptation of firms to external and continuous business environment changes.

The last intangible typology individuated in the Hall's intangible resources classification is technological capital. It is strictly related to the concept of knowledge because it represent the set knowledge related to the access, use and innovation of production techniques and product technology.

The most important resources determining and widening technological capital are R&D activities (both internal or performed in cooperation) and the adoption and assimilation of the technologies developed by other companies and obtained through head-hunting, reverse engineering, licenses and purchase of machinery or production equipment. The technological capital of firms can take the form of tool and devices embodied in the machinery, product components, materials with advanced characteristic, scientific formulae and so on. All these element show how much relevant is the process of knowledge creation and accumulation in determining the level of technological capital inside a firm; investments in research and development allow firms to increase their knowledge level[26] (by bettering human resources skills and performances), thus fostering innovative production processes and high technologic product.

The analysis of one of the intangible resources classifications present in literature showed that, despite there exists the necessity to group them into categories for better understanding their features, intangible resources are strictly interconnected and that each of them contribute to the development of the others, thus determining improvements in the firms value. Another element emerging from the analysis of the resource-based literature is the importance of intangible assets in influencing and determining firms competitive advantages and heterogeneity. It would be useful to explore the results obtained by empirical researches for understanding if they corroborate theoretical hypotheses.

The first research on the relationship between intangible resources and firms competitive advantages was carried out in 1998, by Bontis. In his pilot study he showed a reliable, significant and positive link between intangibles and firm performance. From that moment on, several studies on the same topic have been conducted, confirming the hypothesis that intangible resources positively contribute in determining firms performances (Wang, 2011; Guo, Shiah-Hou and Pan, 2010; Hsu et al., 2007; Gleason and Klock, 2006; Chen, Cheng and Hwang, 2005; Wergauwen and Schnieders, 2005; Wang and Chang, 2005; Villalonga, 2004; Carmeli and Tishler, 2005; Lòpez, 2003; Roberts and Downling, 2002; Carmeli, 2001; Bontis, Keow and Richardson, 2000). The above mentioned studies lack of uniform criteria in determining which intangible measures and performance outcomes are to be used in researches. As far as the intangible measures are concerned, no agreement exist on which are the most suitable indicators to be used. Anyway, most of information is derived from subjective

[26] Companies often try to protect their knowledge and innovation level by various legal forms such as patents and contractual mechanism, or through the trade secret use. In particular patent are one of most relevant intangible resources utilized in many empirical studies as a firm innovation level measure. The patent is a right of ownership granted by the State which concedes its bearer legal protection for excluding unauthorized people, for a limited period of time, from the commercial use of a new, useful and clearly identified technological invention. The power of the temporary monopoly arising from patents allows the inventor to benefit from his invention recovering the investments made and compensating the risks taken. Once the protection time is over, the knowledge contained in the patent can be freely be exploited, thus facilitating knowledge exchange and accelerating the technological process of industry as a whole.

indicators measured on the Likert's scale, other measurement means are the Value Added Intellectual Coefficient, R&D expenditures, advertising expenditure, and number of patents.

As far as the performance indicator are concerned, two kind of measures are generally used: objective and subjective measures. Objective measures consist of financial, economic and market information[27] and are expresses as ratio measures; subjective measures are self-reported indicators measured on the Likert's scale with different number of item (perceived performance approach).

Despite measurement and methodological differences, these studies confirm the positive relationship between intangible assets and firm economic performance. In particular it emerges that the intangible assets most strongly contributing to performance are company reputation, human capital, and organizational culture.

Briefly resuming the content of the previous sections, the starting point has been the choice and the analysis of the definition of competitiveness that allowed us both to underline the multidimensional nature of the phenomenon of interest and to identify the main features of competitiveness. Two fundamental areas belonging to the wide topic of Corporate Social Responsibility have been analyzed: environmental policies and gender policies management. Their definition, meaning, disputed aspects, and their linkages with competitiveness have been deepened. Furthermore, another critical factor determining competitiveness advantages in a micro-level framework have been studied, the role of intangible assets and innovation has been examined, by taking into account not only the economic and management theories explaining their features and relevance in determining competitiveness, but also empirical studies corroborating the theoretical hypotheses.

[27] Performance and profitability are generally used are: Return on Assets (ROA), Net Value Added, Net Income, Return on Equity (ROE), Tobin's Q, Gross Operating Profit, Sale's Growth, Profit Growth, Return on Investments (ROI), Employee Productivity.
These kind of measures suffer of some disadvantages: they do not take into account the multidimensional nature of firms performance and in addition they are not always reliable as firms earnings tend to be artificially modified by managers.

Such an analysis pattern allowed us to better understand and identify which are the most interesting competitiveness elements to be taken into account during the model specification phase, to individuate which measures and variables should be used in order conduct the empirical study, to have some information both on the direction and sign of the relationships between each of the analyzed element and competitiveness and to know which are the controversial and unsolved question that may represent a threat to the proper development of the research.

Chapter 5: Model-based micro-level competitiveness composite indicator: empirical application

5.1 INTRODUCTION

The analysis framework used in order to go in depth with the knowledge of the multidimensional phenomenon of competitiveness allowed us to trace the theoretical substratum to be taken into account during the micro-level competitiveness composite measure computation and therefore to individuate the measures and the variables that should be used in order conduct the empirical study, to have some information both on the direction and the sign of the relationships between each of the analyzed element and competitiveness, as well as to know which are the controversial and unsolved questions that may represent a threat to the proper development of the research.

In the first sections of the following chapter the phases characterizing the measurement process of micro-level competitiveness by means of a model-based composite indicator will be described in details, with accurate references to the theoretical and methodological considerations lying at the base of the choices made in the course of the empirical analysis.

The last sections of the chapter will instead dedicated to the empirical application of the multi-group Structural Equation Models techniques, with the aim to analyze the differences (if existing) among firms belonging to groups identified by taking into account different firm-specific features and to wonder if the competitiveness model used in order to measure micro-level competitiveness on the whole disposable sample is able to well explain and reproduce the competitiveness structure of different groups of firms having in common certain comparable characteristics (branch of activity, number of employees, geographical area, and so on).

In the next section the sources of the data, the type of information derived from and the modification undertaken in order to better the quality of the disposable variables will be presented.

5.2 DATA SOURCES AND COMPETITIVENESS MEASURES

5.2.1 Data sources

The database used in order to conduct the present research is the result of the link of two data sources: the Istat survey on Italian Small and Medium Enterprises and the Istat statistical archive of Italian active enterprises (known as ASIA register).

The Istat survey on Italian Small and Medium Enterprises furnishes information on Italian active firms with less than 100 employee. It contains variables providing information on the firms balance sheet (economic and financial data), on the workforce composition (including detailed information on personnel costs and expenditure), on fixed and intangible investments as well as on firms environmental practices. The data of the answering enterprises have revised, submitted both to consistency and compatibility checks and to partial missing data and outliers treatment[28].

The Istat statistical archive of Italian active enterprises (known as ASIA register) contains information on the economic units practicing arts and professions in industrial, business as well as services activities. It provides structural and identification information of the statistical units (active enterprises) such as economic activity sector, employed and self-employed number, legal condition, turnover and so on. It represent not only the informative background for the analysis on the structure and demography of Italian enterprises, but also the reference population for the Istat researches on Italian firms.

[28] Missing data have been imputed by means of the Hot-Deck imputation approach; the issue of the indicator sensitivity to extreme values has been faced by adopting a winsorizing procedure for the lowest and highest 0,02% variables observations, replacing those extreme values with the values of trimming thresholds.

The final database to be used for the empirical research development has been obtained by linking the two data sources described above. It contains 22 quantitative variables (some of them constructed by modifying the variables belonging to the original databases) measured on 81.706 Italian small and medium enterprises in 2008.

Some descriptive statistics could help understanding which are the main features of the firms sample. It is characterized by firms belonging both to the manufacturing and services sectors[29]. A more detailed analysis of the economic activity sector which firms belong to, shows that the 65% of firms belong to the services sector, the remaining 35% belong to the manufacturing one; in particular among the services sector firms, the 51% belongs to Knowledge Intensive Services (KIS) and the 49% to Less Knowledge Intensive Sector (LKIS). As far as the firms belonging to the manufacturing sector are concerned, the 75% of them belongs to the medium-low technology level, only the 25% belongs to the medium-high technology level[30].

Looking at the geographical distribution of the sample, the 50% of firms is placed on the north, the 20% on the center and the 30% on the south of Italy. The average employee number for the northern firms is 13,71 and their average turnover (per employee) is 1133,81 euro, the average employee number for the central firms is 13,49 and their average turnover is 1213,78 euro, as far as the southern enterprises are concerned their average employees number is 10,13 and their average turnover is 641,32 euro.

[29] The 2008 Ateco two digit economic activity classification has been utilized in order to understand which sector firms belong to.

[30] The classification used is an aggregation of the manufacturing industries according to technological intensity based on the Statistical Classification of Economic Activities in the European Community (NACE) at 3-digit level. In particular the R&D intensity is used as a criterion of classification of economic sectors into high-technology, medium high-technology, medium low-technology and low-technology industries.

Following a similar approach as for manufacturing, the services sector firms is split in knowledge intensive services (KIS) or as less knowledge-intensive services (LKIS). Knowledge-intensive services industries are intensive users of high technology also having a highly skilled labour force necessary to use and exploit technological innovations.

5.2.2 Competitiveness measures

As said in the course of the present dissertation, one of the most important and tricky aspects of the construction of a model-based indicator is the choice of the variables required for the analysis. To deal with a multi-dimensional concepts, means to specify which are the single aspects (dimensions) to be taken into account for the comprehensive description of the concepts themselves and which are the most suitable indicators to be used in order to measure each of these aspects. All these steps have to be consistent with the theoretical framework lying at the base of the study, as the process of variable selection is fundamental for the coherence and validity of the whole empirical research.

By the analysis of the literature on competitiveness it has been possible to clarify that it is to a large extent determined by the enterprise culture, the ability of management and human resources to adapt to changing conditions, influence the firms environment, innovate, develop or explore new technologies and markets: the multifaceted nature of competitiveness has thus been confirmed.

In the present study a competitiveness framework consisting of five dimensions will be used, as presented in table 5.1.

Table 5.1 *Competitiveness Dimension*

DIMENSION	MAIN FEATURES
ECONOMIC	Provides information on the economic status of firms. It should include measures of firms economic performance, profitability, investment policy, openness, and so on. In most of the analyzed literature it generally coincide with competitiveness itself.
LABOUR	Provides information on the workforce composition, on the contractual typologies and on the firms skills level.
GENDER	Provides information on the gender equality measures implemented by firms.
ENVIRONMENT	Provides information on the environmental management strategies implemented by firms, taking into account both end of pipe and integrated policies.
INNOVATION	Provides information on the innovative ability of firms, by including measures of intangible assets considered fundamental in determining the firms ability to innovate

The above presented dimensions have been hypothesized on the basis of the competitiveness literature previously analyzed, trying to satisfy the need to define a competitiveness structure that is as comprehensive as possible.

Turning now the attention to the variables required for the analysis, they have been assigned to the respective competitiveness dimensions on the basis of the most important aspect emerged from the economic literature analysis. Our aim was to try to individuate a wide and heterogeneous set of variables taking into account different aspect and features of competitiveness, for better exploring and explaining its multidimensional nature.

In particular, the Corporate Social Responsibility theory represent the theoretical substratum at the base of the choice of variables measuring the firms proactivity in implementing environmental policies.

Our hypothesis is that higher levels of environmental proactivity allow firms to gain competitive advantages due to differentiation process rising from the customer perception that green products are more valuable, and to the cost reduction deriving from the adoption of practices that improve the production process[31], by finally increasing firms efficiency and by reducing input and waste disposal costs.

Three environmental variables[32] have been chosen. Specifically, we decided to distinguish between two different types of environmental innovations and investments that mitigate the environmental burden of production: integrated and end-of-pipe investments. Integrated investments reduce resources use and/or pollution at the source by using fair technologies and production methods, whereas end-of-pipe technologies curb pollution emissions by implementing add-on measures. This is the reason why integrated investments are frequently seen as

[31] In this contest the environmental Corporate Social Responsibility theory join together with the Resources Based View one as proactive environmental activities require changes in routines and operation, coordination of human and technical skill in order to be able to reduce environmental impacts by simultaneously maintain or increase the competitiveness of firms. Environmental policies encourage the development of new tangible and intangible firm resources.

[32] Data on end-of-pipe, integrate and current investments were disposable for four categories: water, air, waste and other. For the porpoises of the present study they were aggregated by investment typology by obtaining, in this way, three environmental variables.

being superior to end-of-pipe technologies for both environmental and economic reasons[33].

The Corporate Social Responsibility theory also furnished us the theoretical basis for the choice of variables measuring the gender equality firms engagement.

Our hypothesis is that the implementation of gender equality policies should foster firms competitive advantages from a twofold point of view: gender equality enhance the likelihood to select workforce from a broader talent pool, by improving human resources features and therefore promoting overall performance in the workplace; moreover it helps firms to improve its positive image in front of responsible consumers and other external market agents, thus enforcing the relational capital of firm. It is easy to understand that the topic of gender equality is strictly related to the theories on firm resources and human capital because favoring gender equality helps to contribute to a of long-term value creation firm strategy, by generating and strengthening human, relational and organizational capital.

Three gender equality variables have been chosen: the number of employed women, calculated as a percentage with respect to the number of employed men, the difference (in percentage) between women and men wages, representing the gender pay gap measure, generally considerate one of the most important gender discrimination variable, and the number of women holding executive and managerial position for testing the hypothesis that firms led or managed by women are more competitive than male managed firms.

Although the introduction of the environment and gender dimensions in the micro-level competitiveness model has been justified and explicated by referring to the Corporate Social Responsibility principles, we made the decision to separately treat them because, even if belonging to a common theoretical background, they are generally treated, in most of the empirical studies taken into account, as distinct elements, belonging to different empirical field of research.

[33] Some studies (González-Benito, 2005; Wagner, 2005; Klassen and Whybark, 1999) demonstrated that integrated investment have a stronger impact on firm competitiveness than end-of-pipe activities. In the present work we will also check this hypothesis.

Moreover we were mostly interested in understanding the contribution each of them is able to give in determining micro-level competitiveness levels.

The selection of variables measuring the human resources and organizational side of firms has been accomplished by taking into account the Dynamic Resources Based View theory.

Our hypothesis is that firms investments in human resources are one of the most important element in determining firms competitive advantages. Firms that seek to optimize their workforce through comprehensive human capital development programs not only achieve business goals but also a long term survival and sustainability. To accomplish this undertaking, firms need to invest resources to ensure that employees have the knowledge, skills, and competencies they need to work effectively in a rapidly changing and complex environment. It is fundamental to actuate firm processes that relate to training, education and other professional initiatives in order to increase the levels of knowledge, skills, and abilities of employees, which lead to the employee's satisfaction and performance, and therefore to a better firm performance. The implementation of strategies for improving workforce productivity to drive higher value for the firms is an important focus also from the organizational point of view: the fair workforce management is fundamental in determining employees job satisfaction and therefore better working performances.

Six variables have been chosen with the aim to measure firms human and organizational intangible resources management: the average annual wages per employee, the workforce training investments, and four variables on the employment contractual typology (project workers, temporary workers, part time employees and fixed term employees) for measuring the workers mobility and therefore the organizational side of firms and their ability to cope with the ever-changing external environment.

An unavoidable aspect for the analysis of competitiveness is the importance of intangible assets strictly related to the knowledge and innovation creation and accumulation processes. For the detection of the variable to be used in order to measure the above mentioned micro-level competitiveness aspect the

Resources Based View theory has been taken into consideration, with special attention to the role of intangible assets determining innovation.

Our hypothesis is that the capacity to improve skills, innovate, develop and explore new technologies determine to a large extent the competitive advantages of firms. The deployment of intellectual capital and intangible assets is a key strategic weapon for realizing new and better product and processes innovations: the process of knowledge accumulation mainly realized through the investments in the field of research and development and in information and communication technology brings to a more skilled working environment, resulting in a greater number of innovative processes, thus determining micro-level competitive advantages.

The variables chosen in order to measure the innovative potential of firms are: investments in research and development; advertising expenditure; investments in intellectual property rights (patenting), and software acquisition.

In spite of the huge amount of studies on the intangible side of competitiveness and in spite of the undoubted relevance that continue to be attributed to it, the tangible elements of competitiveness are still recognized to be substantially determinant.

This is the reason why we have introduced some variables measuring the economic and financial performance of firms.

An originality element of the present research lies in the decision to use economic performance variables as input factors. In broad terms, most of the competitiveness studies encountered during the literature systematization process have in common an important feature: the use of firms economic performance measures in the form of output variables. Economic performance measures are interpreted as result variables explaining the firm competitiveness level: competitiveness coincides with economic performance indicators that, therefore, play the role of dependent variables in most of the competitiveness models.

We will instead use them as an input factor, by hypothesizing that economic performance indicators concur, together with the previous listed variables, to the determination of the firms competitiveness level.

The economic and financial performance variable chosen in the present study are: Value Added per employee, EBITDA[34] on value added, return on sales, export on turnover, and depreciation rate.

All the variables present in the database constructed for carrying out the present study have been listed in table 5.2, together with their theoretical sources and the competitiveness dimension they have been assigned to.

[34] EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) is an approximate measure of a company’s operating cash flow based on data from the company's income statement. It allows to compare profitability of companies by eliminating effects of different assets bases (by ignoring depreciation), different takeover histories (by ignoring amortization often stemming from goodwill), effects due to different tax structures as well as the effects of different capital structures (by ignoring interest payments).

Table 5.2 *Competitiveness Measures*

Variable Name	Source	Assigned Dimension
Value added	Economic Theory	Economic Dimension
Ebitda/turnover	Economic Theory	
Return on Sales	Economic Theory	
Export/turnover	Economic Theory	
Depreciation Rate	Economic Theory	
Women employed	Corporate Social Responsibility Theory	Gender Dimension
Leading Women	Corporate Social Responsibility Theory	
Women wages	Corporate Social Responsibility Theory	
Advertising	Resources Based View (Relational intangible resource)	Innovation Dimension
R&D expenditure	Resources Based View (Structural Resources)	
Software	Resources Based View (Structural resources)	
Licenses and Patents	Resources Based View (Structural resources)	
End of pipe investments	Corporate Social Responsibility Theory	Environment Dimension
Current environmental investments	Corporate Social Responsibility Theory	
Integrated environmental investments	Corporate Social Responsibility Theory	
Part time employee	Resources Based View (Organizational Resource)	Labour Dimension
Fixed term employee	Resources Based View (Organizational Resource)	
Employee wages	Resources Based View (Organizational Resource)	
Temporary workers	Resources Based View (Organizational Resource)	
Project workers	Resources Based View (Organizational Resource)	
Workforce training Investments	Resources Based View (Human Capital)	

5.3 COMPETITIVENESS MODEL SPECIFICATION

With the aim of building a micro-level competitiveness indicator by means of Structural Equation Model-based approach we proceeded by specifying the theoretical model explaining the causal relationships characterizing the micro-level competitiveness structure. To this end, within the Structural Equation Modeling framework it is necessary to identify both latent and manifest variables (latent variables are hypothetical construct that cannot be directly observed and therefore measured and that are inferred from other observed and measurable variables, known as manifest variables) and to subsequently assess causal relationships among the identified latent constructs representing different features of the phenomenon under investigation.

Structural Equation Model techniques may thus be helpful in defining and analyzing the micro-level competitiveness framework, for a twofold order of reasons: competitiveness is an heterogeneous phenomenon, whose study and understanding involves several aspects to be taken into account. Such aspects could, in their turn, be characterized by an inner complexity and multidimensionality that have to be taken into account; in addition for a comprehensive analysis, the relationships among the elements defining competitiveness have to be assessed in order to understand which of them influence competitiveness in a more powerful way.

In the previous sections the theoretical substratum of the present study has been presented together with some hypotheses on the micro-level competitiveness composition.

In particular five competitiveness determinants have been identified, as well as the variables to be used in order to measure them.

Our hypothesis is therefore that, before assessing competitiveness, there are five (latent) competitiveness elements that have to be measured. Each of them is inferred from a series of observable variables, describing their multifaceted nature. Once these latent determinants of competitiveness have been measured, they will be used as observed elements determining micro-level overall competitiveness: multidimensional (latent) competitiveness will be influenced by dimensions, representing themselves heterogeneous latent constructs.

The multidimensional competitiveness measure will therefore be obtained by the adoption of a hierarchical second order model; the first order level being composed of the five competitiveness dimensions and the second one by the overall competitiveness latent variable.

Figure 5.1 shows the path diagram[35] specified in order to describe the causal relationships among the facets determining micro-level competitiveness.

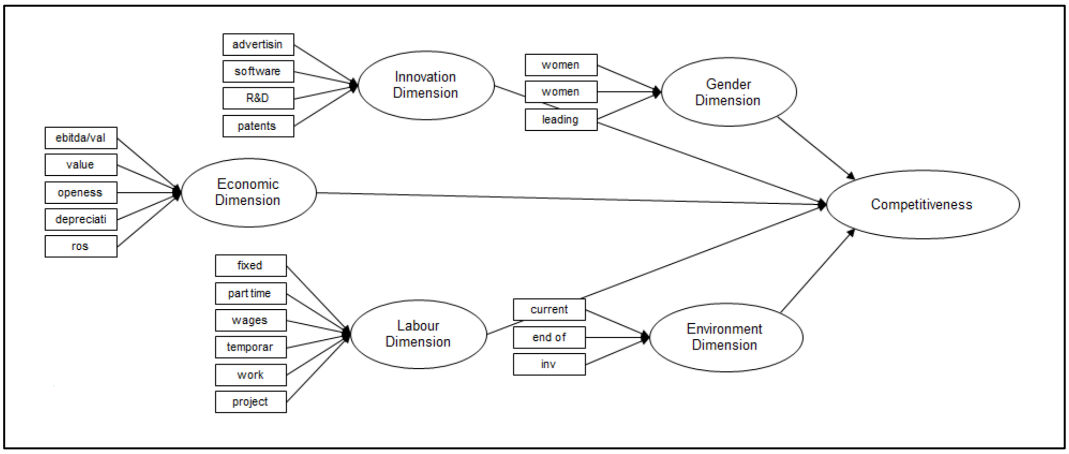


Figure 5.1: *Hypothesized Competitiveness Model*

Focusing on the first order level of the model (composed of the five dimensions representing different, clearly defined aspects of the content domain of the overarching competitiveness), it is useful to underline that formative relationships have been hypothesized to exist between the observed variables and the competitiveness dimension they are linked to. It means that our hypothesis is that each of the observed variable composing the competitiveness dimensions is expression of a different feature of the corresponding pillar; each competitiveness pillar is a linear combination of its own measured variables.

[35] Observed variables are enclosed by rectangles, while latent variables are enclosed by ellipses. Arrows show causation among variables, either latent or manifest, and the direction of the array defines the direction of the hypothesized relation.

It is necessary to remember that the PLS-PM methodology offers the chance to specify the relations linking each competitiveness pillar (latent variable) to its corresponding observed variable by the use of two different ways. It is possible to hypothesize causal relationships going from the competitiveness dimension (latent variable) to its corresponding observed variables; that is, the observed measures are assumed to reflect variations in the dimension they are linked to. Thus, each manifest variable in a certain measurement model plays a role of endogenous variable and is assumed to be generated as a linear function of its latent variable. This specification form is known as reflective mode. In order to specify such a measurement relation the observed variables linked to the competitiveness dimension have to be highly correlated for confirming they belong to (and thus explain) the same underlying pillar.

In the latter specification form, known as formative mode, each observed variable represenst a different dimension and captures different aspects of the underlying competitiveness dimension that, in this case, is a linear combination of its own manifest variables. Thus, observed variables play the role of exogenous variables in the measurement model and should not be correlated as they are hypothesized to explain different aspect and features of the pillar they are linked to. If they are correlated multicollinearity problems may arise.

The first order analysis will provide the weight relation inside each competitiveness pillar, in this way it will be possible to understand whether and to what extent each observed variable contribute in determining the competitiveness dimension it is linked to.

The second order level of the model, represented by the overall competitiveness variable has been hypothesized to be directly influenced by each dimension present in the lower order level. The above mentioned dimensions play the role of observed variables, determining, in a formative framework, the micro-level competitiveness measure. On the basis of the reference literature, we want to test the hypothesis that all the specified dimensions have a positive impact on the latent construct representing multidimensional competitiveness indicator, moreover we are interested in assessing the weight relation between each competitiveness aspect and competitiveness itself, for understanding which are the most relevant elements determining micro-competitiveness levels.

In the next section the results of data analyses made in order to investigate on the quality of the disposable data and to test the pre-specified hypothesis about the competitiveness structure will be presented.

5.4 DATA ANALYSIS

Once the theoretical selection of variable has been concluded and the competitiveness model specified, another phase have to be opened: to check on the statistical features of the disposable data and, if necessary, to transform them for improving their quality.

To this end, the first step accomplished has been the normalization of data, in order to render them comparable, by eliminating the effect of different units of measure. Min-Max normalization has been used, making indicators to have an identical range [0, 1]. Min-Max normalization is obtained by subtracting to each observation the minimum value of the indicator, and dividing by the range of the indicator values. Even if extreme values or outliers could distort the transformed indicator, Min-Max normalization has the advantage of exactly preserving all relationships in the data and of widening the range of indicators lying within small intervals, increasing the final effect on the composite indicator.

The data have then be checked for normality, by means of the Shapiro-Wilk test and of the Q-Q plot graphical method. The results revealed that the variables under analysis are non-normal and that they are characterized by high skewness levels, due to the large amount of zero values characterizing most of the disposable variables. For this reason the decision has be made to transform them in order to eliminate skewness and to try to turn them to nearly symmetric normal-like distribution. To this end the Box-Cox transformation[36] has been chosen, with the optimization for normality of λ parameter in each variable. The results showed that the transformation did not contribute to the "normalization" of variables, that continued to be characterized by high skewness. This is the reason why the transformation results have been omitted and the original variable have been utilized for the rest of the study.

An exploratory analysis has then been conducted in order to investigate the overall structure of the indicators and assess the suitability of the data.

The data correlation matrix has first been calculated, for the whole dataset, in order to have information on the existence of a clear correlation structure in the data and to be able to understand which methodological choice had to be accomplished in the course of the study.

Table 5.3 shows that, where significant, the correlations among variables are very low. The obtained results, thus, revealed that it is not possible to recognize a well-defined data structure; this implied that it made little sense to go further with other multivariate analyses (such as Factor Analysis) wondering on the presence of latent structures to be taken into account during the definition process of the competitiveness dimensions and that it was instead possible to carry on the analysis by using the hypothesized competitiveness dimensions framework without making any modification.

[36] The Box-Cox transformation method consist of a family of power transformation such that the transformed values are a monotonic function of the original observations over some admissible ranges and indexes, such that

$$y_i^{\lambda} = \begin{cases} \left(y_i^{\lambda} - 1\right)/\lambda; & \lambda \neq 0 \\ \log y_i; & \lambda = 0 \end{cases}$$

and that for unknown λ

$$y^{(\lambda)} = \left(y_1^{(\lambda)}, y_2^{(\lambda)}, \ldots, y_n^{(\lambda)}\right)' = \mathbf{X\theta} + \boldsymbol{\varepsilon}$$

where **X** is a matrix of known constants, **θ** is a vector of unknown parameters associated with the transformed values and $\boldsymbol{\varepsilon} \sim MVN\left(0, \sigma^2 I_n\right)$ is a vector of random errors. The transformation is valid only for $y_i > 0$ and, therefore, modifications have had to be made for negative observation.

Table 5.3 *Data Correlation Matrix*

Variables	ebitda	value added	openess	depreciation rate	ros	advertising	software	R&D	patents	current expenditure	end of pipe	inv integrated	fixed	part time	wages	temporary	work training	project	women	women wages	leading women
ebitda	**1**																				
value added	0,000	**1**																			
openess	-0,001	**0,008**	**1**																		
depreciation rate	**0,019**	**0,408**	0,000	**1**																	
ros	0,000	0,006	0,002	0,002	**1**																
advertising	0,000	**0,018**	**0,022**	0,001	0,000	**1**															
software	0,000	**0,039**	**0,029**	-0,001	0,000	**0,023**	**1**														
R&D	0,000	0,007	**0,036**	0,000	0,000	**0,028**	**0,025**	**1**													
patents	0,000	**0,068**	**0,020**	**0,036**	0,000	**0,082**	**0,026**	**0,018**	**1**												
current expenditure	0,000	**0,009**	**0,014**	0,000	0,000	0,001	0,002	0,002	0,001	**1**											
end of pipe	0,000	**0,013**	**0,021**	0,000	0,000	0,001	**0,022**	0,002	**0,007**	**0,259**	**1**										
inv integrated	0,000	0,003	0,000	0,000	0,000	0,002	**0,011**	0,002	0,001	**0,254**	**0,016**	**1**									
fixed	0,000	0,000	-0,002	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	**1**								
part time	0,000	-0,001	-0,004	0,000	0,000	-0,001	-0,001	-0,001	-0,001	-0,001	0,000	0,000	**0,027**	**1**							
wages	**0,009**	**0,088**	**0,151**	**0,016**	**-0,014**	**0,081**	**0,068**	**0,043**	**0,054**	**0,025**	**0,021**	**0,014**	**0,010**	0,006	**1**						
temporary	0,000	0,005	**0,039**	0,000	0,000	**0,017**	**0,007**	0,004	0,006	0,006	0,001	0,000	-0,001	-0,001	**0,057**	**1**					
work training	-0,001	**0,007**	**0,025**	-0,001	0,000	**0,024**	**0,023**	**0,019**	**0,013**	0,006	0,001	**0,015**	0,000	-0,001	**0,065**	0,007	**1**				
project	0,000	0,001	-0,002	0,000	0,000	0,000	0,003	0,003	0,001	0,000	0,000	0,000	0,000	**0,008**	**0,012**	0,000	0,000	**1**			
women	**0,008**	**-0,010**	**-0,038**	0,004	0,001	**-0,008**	**-0,012**	-0,001	-0,001	**-0,018**	**-0,012**	**-0,009**	**-0,008**	0,000	**-0,174**	-0,007	**-0,017**	-0,001	**1**		
women wages	0,001	**0,014**	**0,136**	0,006	0,000	**0,030**	**0,031**	**0,022**	**0,019**	**0,020**	**0,011**	**0,010**	-0,003	0,004	**0,336**	**0,043**	**0,039**	**0,007**	**0,166**	**1**	
leading women	0,006	0,001	**0,060**	**0,010**	0,003	**0,019**	**0,013**	**0,016**	**0,015**	**0,012**	0,005	0,006	0,001	0,004	**0,121**	**0,026**	**0,015**	0,002	**0,306**	**0,308**	**1**

Significant values are in bold line (significance level 5%)

Each selected competitiveness dimension has then been analyzed by means of the correlations matrix analysis. In particular, this step has been accomplished both for investigating on each dimension structure, and for avoiding multicollinearity problems in the model estimation phase that may arise as formative measurement relationships inside each competitiveness dimension have been hypothesized. Table 5.4 shows the correlation matrix for each competitiveness dimension. Correlations among variables belonging to the different pillars, if significant, are very low. These results confirm that it is possible to specify formative measurement models, without caring about multicollinearity questions and that, as previously hypothesized, the variables composing each competitiveness dimension selected for the analysis are expression of different aspects and features of the pillar they measure and explain.

Table 5.4 *Competitiveness Dimensions Correlation Analysis*

Correlation Matrix (Gender Dimension)

Variables	women	women wages	leading women
women	**1**		
women wages	**0,166**	**1**	
leading women	**0,306**	**0,308**	**1**

Correlation Matrix (Labour Dimension)

Variables	fixed	part time	wages	temporary	work training	project
fixed	**1**					
part time	**0,027**	**1**				
wages	**0,010**	0,006	**1**			
temporary	-0,001	-0,001	**0,057**	**1**		
work training	0,000	-0,001	**0,065**	0,007	**1**	
project	0,000	**0,008**	**0,012**	0,000	0,000	**1**

Correlation Matrix (Environment Dimension)

Variables	current expenditure	end of pipe	inv integrated
current expenditure	**1**		
end of pipe	**0,259**	**1**	
inv integrated	**0,254**	**0,016**	**1**

Correlation Matrix (Innovation Dimension)

Variables	advertising	software	R&D	patents
advertising	**1**			
software	**0,023**	**1**		
R&D	**0,028**	**0,025**	**1**	
patents	**0,082**	**0,026**	**0,018**	**1**

Correlation Matrix (Economic Dimension)

Variables	ebitda	value added	openess	depreciation rate	ros
ebitda	**1**				
value added	0,000	**1**			
openess	-0,001	**0,008**	**1**		
depreciation rate	**0,019**	**0,408**	0,000	**1**	
ros	0,000	0,006	0,002	0,002	**1**

Significant values are in bold line (significance level 5%)

In the next section the results of the model estimation by means of Partial Least Square (PLS) non parametric approach to Structural Equation Models will be shown.

5.5 COMPETITIVENESS MODEL ESTIMATION

The Partial Least Square (PLS) non-parametric approach has been used in order to estimate the model parameters since it is a distribution free method, thus enabling to implement the analysis on our non-normal and highly skewed data, and does not require any assumption both on the sample size and the measurement scale.

Moreover through the use of the PLS approach we had the chance to specify a second order hierarchical model, including formative relation among each competitiveness dimension and the observed data used to measure them, without any identification issue. In fact, in PLS path modeling the residual covariance structure for the measurement error terms and the disturbance terms are not restricted, thus guarantying against identification problems.

A first, explorative analysis has been run, by adopting an external weights estimation scheme taking into account the formative nature of the measurement model, for the assessment of the relationship linking competitiveness dimensions to their own indicators; and a factorial scheme for the estimation of the causal relationships between the five dimensions and the overall competitiveness latent construct. The aim has been not only to test the validity of the theoretical bases of the model by analyzing the statistical features of the structural model, but also to take into exam the contribution of each manifest variable in forming each latent competitiveness dimension. The first PLS analysis made possible a process of selection of the observed variables: those indicators which were unable (in terms of weights and bootstrap-derived t-score) to form their own latent construct were removed, and a second, final analysis has be re-run. In table 5.5 the PLS estimates of the external weights, representing the contribute of the observed variable in determining the competitiveness dimension they are linked to, are presented.

Table 5.5 *Explorative Competitiveness Measurement Model Estimates*

Latent variable	Manifest variables	Outer weight	Outer weight (Bootstrap)	Standard error	Critical ratio	Lower bound (95%)	Upper bound (95%)
ENVIRONMENT	Current Expenditure	0,357	0,328	0,147	4,428	0,050	0,584
	End of Pipe	0,797	0,799	0,104	7,699	0,569	1,005
	Integrated Investments	0,214	0,209	0,057	3,741	0,062	0,348
INNOVATION	Advertising	**0,101**	0,089	0,063	1,618	-0,025	0,220
	Software	0,457	0,434	0,085	5,392	0,185	0,612
	R&D	0,288	0,271	0,057	5,011	0,084	0,394
	Patents	0,314	0,286	0,074	4,268	0,086	0,439
GENDER	Women	**-0,592**	-0,594	0,010	-61,139	-0,613	-0,573
	Women Wages	0,853	0,851	0,008	100,826	0,834	0,872
	Leading Women	0,227	0,230	0,014	15,776	0,193	0,260
ECONOMIC	EBITDA	**0,020**	-0,004	0,041	0,472	-0,121	0,047
	Value Added	0,427	0,470	0,065	6,529	0,346	0,629
	Openess	0,913	0,894	0,036	25,724	0,813	0,947
	Depreciation Rate	**-0,100**	-0,080	0,130	-0,774	-0,332	0,114
	ROS	**-0,042**	-0,045	0,040	-1,059	-0,176	0,029

The analysis of the t-scores obtained via non-parametric bootstrap techniques revealed the existence of some non-significant weights (highlighted in bold line). Thus the decision to delete from the model those variables unable to significantly determine the competitiveness dimension they have been hypothesized to be linked to has been made and the new model deprived of the non-significant variables has been run.

As far as the path coefficients linking each competitiveness dimension to the overall competitiveness construct are concerned, they all resulted to be significant and to have different (in terms of relation strength) impacts on competitiveness. We will not discuss the outputs of this first, explorative analysis in details. It is sufficient to remind that it has been implemented in order to select non-significant manifest variables and to confirm that the competitiveness model and the hypothesized hierarchical competitiveness structure have been specified in a correct way.

Let's now turn the attention to the final competitiveness model obtained by the removal of the non-significant variables identified through the PLS analysis shown above. The number of competitiveness dimensions remained unchanged, there are only few difference in the composition of two of them. Three variables representing the contractual typologies trough which workers are employed were deleted from the labour dimension, and two profitability variables were eliminated from the economic dimension. This choice has been made on the basis of the results obtained by the explorative analysis presented in the first part of this section. The above mentioned results were not surprising as the variables revealing non significance relationships with the competitiveness dimensions they were linked to were "experimental" measures, never used (apart from the EBITDA indicator) in previous empirical researches that we decided to put on our model in order to test their validity.

The results of the PLS analysis on the final competitiveness model will be presented by using the following framework: the output of the measurement model estimation process will first be shown, followed by the output of the structural model estimates, finally goodness of fit measures will be presented, in order to evaluate the overall competitiveness model.

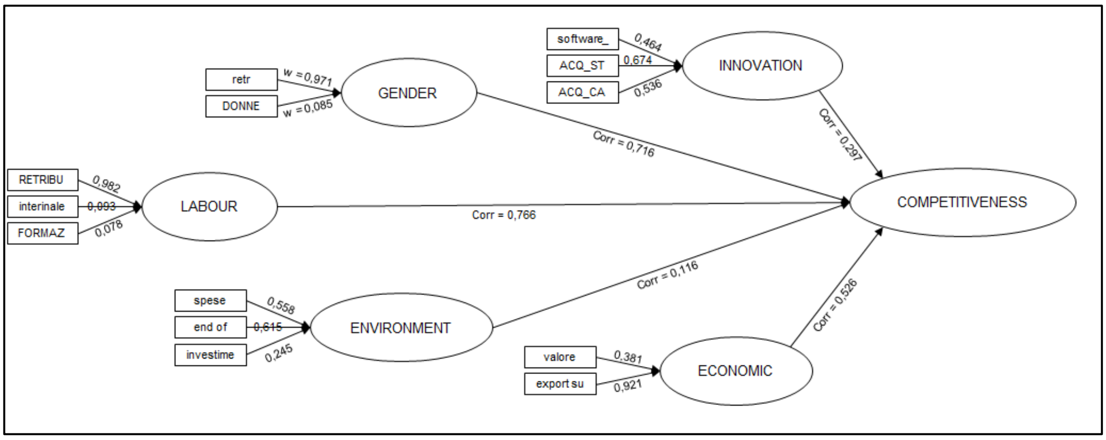


Figure 5.2 *Competitiveness Model Parameters Estimates*

Measurement Model Estimates.

The PLS estimates of the measurement model allowed us to understand to what extent observed variables contribute in determining the corresponding competitiveness dimensions; that is, we obtained the estimates of the weights characterizing the first order level of the competitiveness hierarchical model. First of all, it is possible to notice, by analyzing Table 5.6, that all the relationships linking manifest variables to the related competitiveness dimension are statistically significant. In particular, it would be interesting to analyze each latent competitiveness dimension for understanding which observed variable have the most relevant role in determining it.

Table 5.6 *Measurement Model Estimates*

Latent variable	Manifest variables	Outer weight	Outer weight (Bootstrap)	Standard error	Critical ratio	Lower bound (95%)	Upper bound (95%)
LABOUR	Wages	0,982	0,981	0,004	280,080	0,973	0,987
	Temporary Work	0,093	0,096	0,012	7,703	0,068	0,122
	Workers Training	0,078	0,082	0,019	4,152	0,044	0,119
GENDER	Women's Wages	0,971	0,970	0,006	172,355	0,958	0,981
	Leading Women	0,085	0,086	0,015	5,643	0,055	0,118
INNOVATION	Software	0,674	0,669	0,056	11,990	0,551	0,793
	R&D	0,464	0,465	0,055	8,493	0,371	0,589
	Patents	0,536	0,528	0,066	8,156	0,393	0,694
ENVIRONMENT	Current Expenditure	0,558	0,541	0,081	6,853	0,348	0,687
	End of Pipe	0,615	0,627	0,084	7,356	0,461	0,828
	Integrated investments	0,245	0,243	0,069	3,553	0,078	0,374
ECONOMIC	Value Added	0,381	0,408	0,062	6,130	0,294	0,546
	Openess	0,921	0,907	0,031	29,330	0,832	0,954

The results of the weights estimation process showed that the labour dimension of competitiveness is mostly influenced by the variable representing the annual average wages per employee. The other variable respectively measuring the firm investments in workers training and the number of temporary workers have a significant, positive, but certainly lower impact. These results allows us to understand that the labour dimension of competitiveness is determined not only by the firms organizational ability in improving their employees competences and skills or in answering to the external ever-changing environment, by using more flexible systems of workforce recruitment, but also, and above all, by the way in which firms treat their employees. In particular, the employees' wages amount is the elements reveling the level of workers job satisfaction and, therefore, their occupational performance (they can also be considered as a proxy of the employee level of skills).

The gender equality dimension is mostly determined by the gender pay gap variable, measuring the differences in the wages earned by men and women; it is also determined, even if to a smaller extent, by the number of women holding managerial positions. This result confirms that the gender equality policies of firm are influenced by the implementation of actions aiming at the wages equality achievement, independently of the employees gender, as well as by giving to women the chance to compete for reaching leading positions inside firms.

The innovation dimension of competitiveness is determined, nearly to the same extent, by firms investments in software, patents and licenses as well as in research and development activities. These estimates confirm the importance and relevance of such investments in determining the innovativeness level of firms, by helping us to understand which of them plays a most important role.

As far as the environmental dimension is concerned, an element of novelty with respect to the previous empirical researches on micro-level environmental performance has to be underline: the variable representing the end-of-pipe investments is the most relevant measure determining the level of firms environmental performance, the variable measuring integrated investments has instead the lowest impact. On the contrary, the above mentioned studies proved that environmental proactivity (measured through the amount of integrated investments in fair environmental activities) is the most important determinant of a firm environmental performance, while end-of-pipe investments seem to have lower relevance.

The economic dimension of competitiveness is significantly determined by the two variables composing it. In particular the variable measuring firms export revenues on the overall turnover has a greater (positive) impact with respect to the variable measuring the firm value added per employee. This confirms the importance of the value added measure in determining the economic dimension of competitiveness and proves that ability of a firm to generate export earnings is a key indicator of its economic performance and its ability to create wealth.

Structural model estimates.

The second order parameters of the micro-level competitiveness hierarchical model, representing the causal relationships between the hypothesized dimensions and the overall competitiveness latent construct, are the most important element to be analyzed in order to understand the main features of the model-based competitiveness indicator. As already said, the PLS approach to the measurement of competitiveness gave us the chance to identify two kind of optimum weights, thus solving one of the most debated aspect of the construction of composite indicators that is the subjectivity characterizing the weights determination phase. It is possible to estimate the weights of the relationships linking the observed variables to the corresponding competitiveness dimension (measurement model), allowing to identify the most important features determining each competitiveness sub-indicator as well as the weights of the relations between each competitiveness sub-indicator and the overall competitiveness indicator (structural model). In this way it is possible to take into account both the multidimensional nature of the phenomenon under analysis, and the heterogeneity inside its constitutive determinants.

In the present section the structural model parameter estimates will be presented.

Table 5.7 *Structural Weights Estimates*

Latent variable	Value	Value (Bootstrap)	Standard error (Bootstrap)	Critical ratio	Lower bound (95%)	Upper bound (95%)
LABOUR	0,518	0,516	0,003	158,963	0,508	0,522
GENDER	0,485	0,479	0,007	67,024	0,459	0,492
INNOVATION	0,201	0,208	0,012	16,938	0,185	0,237
ENVIRONMENT	0,079	0,081	0,007	10,911	0,069	0,098
ECONOMIC	0,356	0,357	0,008	43,025	0,342	0,377

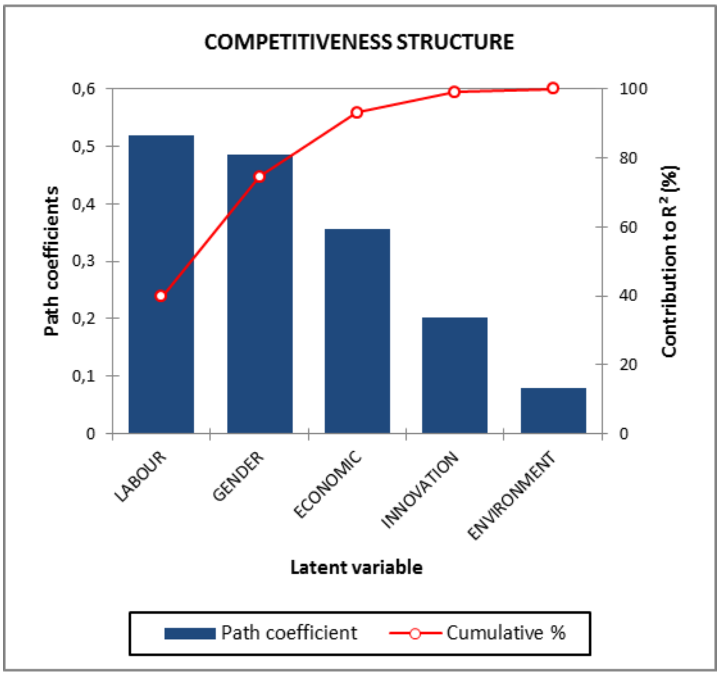
As already said, one of the most important advantages deriving from the use of a Structural Equation Modeling approach to the construction of model-based competitiveness indicators is that it brings to the estimation of the final composite measure by also estimating the intermediate scores of the pillars (latent variables) capturing different features of the multidimensional competitiveness construct. Moreover, the aggregation of such measures into a single competitiveness indicator involves a system of weights based on the estimates of the causal relationships determining the phenomenon structure, thus allowing to understand which are the main drivers of the phenomenon itself. That is, once the latent variables in the model have been estimated, the relationships among them can be assessed by means of OLS regression approach. The results of this estimate process are the weights that have to be used in the aggregation phase of the composite competitiveness indicator. In table 5.8 the PLS estimates of the above mentioned weights are reported. Each weight represents the contribution of the different pillars on the competitiveness indicator; that is, the regression coefficients in the structural model estimated on the standardized latent variables scores.

Going more in depth with the analysis of the results, an important element to be underlined is the significance of each of the structural relations that confirm the theoretical hypotheses made on the structure of micro-level competitiveness: the hierarchical second order model is able to explain the complexity characterizing the multidimensional nature of competitiveness.

Before proceeding with the analysis of the impact of each competitiveness dimension on the overall composite indicator, a short digression on the features of the present study has to be opened. The novelty elements of this research lie in two fundamental aspects: the former is strictly related to the phenomenon under investigation; it concerns the decision to study micro-level competitiveness by considering its multidimensional characterization, this means that we decided not to identify competitiveness with micro-level economic performance and to study it by assessing the relations with its, separately taken into account determinants, as most of the empirical studies on firms competitiveness do; we instead proposed to give competitiveness a huge connotation that would be able to include several aspect of the phenomenon. To this end we conceptualized competitiveness as a latent, huge construct to be estimated by taking into account its several determinant. The latter novelty element is the methodological choice that allowed us to simultaneously consider the elements influencing micro-level competitiveness and to test not only their significance, but also to what extent they determine it.

Going back to the results analysis, Table 5.8. shows the contribution of each pillar to the overall competitiveness indicator, both in terms of regression coefficients and dependent variable R^2 determination.

Table 5.8 *Impact and Contribution of Competitiveness Dimension on the Overall Competitiveness Indicator*



We found that the main drivers of competitiveness are the labour and gender dimensions, followed by the economic, the innovation, and the environment pillars. Better explaining, despite all the dimensions specified in the model significantly contribute in affecting firms competitiveness levels, some of them have a greater influence. In particular, the results of the structural parameters estimation process let us understand that firms investing both in human and organizational capital, by means of on-the-job employees training, fair wages polices as well as by the ability to adapt to the ever-changing external environment conditions through flexible form of workforce recruitment, and in gender equality policies, giving women the chance to advance their career and remunerating them to the same extent of men, are more likely to be competitive.

Another important function in determining competitiveness is carried out by the economic and innovation dimensions. It is possible to state that the economic wellness of firms is a core element for their development, it is the *sine qua non* condition for competitiveness as it enables firms to successfully implement a series of advanced policies, allowing them to gain greater competitive advantages. Innovation, realized through investment in research and development, licenses and patents, and informatics is another important aspect fostering competitiveness, even if to a lower extent with respect to the economic, labour and gender dimensions. This is probably due to the fact that the contribution to competitiveness given by innovation-driven policies and, therefore, by intangible measures linked to the development of innovative products and processes is collateral with respect to the main features concerning the human resources management; that is, despite the recognized importance of innovation in fostering competitiveness, the key element for increasing micro-level competitive advantages is an intensive and fair use of human resources that are the driving forces of firms successes.

As far as the environmental pillar is concerned, the results show that it has a significant, but weak relationship with competitiveness. It is not a crucial element, it only marginally helps in contributing to competitiveness, without playing a determinant role.

From a composite indicator point of view, once the latent variables scores representing each competitiveness dimension level have been estimated, and the weights measuring their impact on the overall micro-level competitiveness measure have been obtained, it is possible to bring together all the disposable information by aggregating them in order to form the final competitiveness composite indicator, by adopting the following scheme:

COMPETITIVENESS =
0,518*LABOUR + 0,485*GENDER + 0,201*INNOVATION + 0,08*ENVIRONMENT + 0,356*ECONOMIC

Resuming, the analysis of the structural relationships linking micro-level competitiveness to its hypothesized determinants showed that improving firms competitiveness means to assign different levels of priority to firms policies implementation; in particular investments in human resources, and a fair and dynamic management of human capital seems to be the unavoidable element for companies to be competitive[37].

Once the competitiveness model parameters have been estimated, the last step to be computed in order to close the composite indicator construction phase is the competitiveness model evaluation. It has been realized in a PLS framework. In the next section the obtained results will be presented and discussed.

5.6 COMPETITIVENESS MODEL EVALUATION

As fully explained in the previous chapter of the present dissertation, the model validation phase reveals one of the weak points of the PLS-PM methodology: the lack of a well identified global optimization criterion has as a direct consequence the absence of a global fitting function to be evaluated for determining the goodness of the model. In the PLS-PM framework the model evaluation focuses instead on the model prediction capability, being a variance-based approach strongly oriented to the latent variables prediction.

A model can be validated at three levels: the quality of the measurement model, the quality of the structural model and each structural regression equation.

As far the measurement model is concerned, a first, preliminary study on the relationships between each manifest variable and the competitiveness dimension it has been linked to has already been conducted by means of the correlation analysis carried out for each competitiveness dimension. As already said, it showed low correlations among the manifest variables forming each pillar, letting us conclude that each observed variable is a measure of a different feature

[37] The results of the present study confirm the hypothesis, supported by a series of empirical studies, that among the categories composing the concept of intellectual capital, the most relevant in determining firms competitiveness is the one concerning the human capital management.
The strong contribution of the labour and gender dimensions (strictly related to the concept of human capital) in determining firms competitiveness level confirms the results of previous empirical studies on intangible assets reveling that, among the several intangible resources of firms, those connected to the notion of human capital have greater impacts on competitiveness.

charactering the competitiveness pillar it is linked to. Moreover, during the parameter estimation phase we had the chance to test the significance of the relation linking the competitiveness pillars to their own observed variables by means of bootstrap procedures that allowed us to individuate and to eliminate the non-significant variables, thus estimating again the competitiveness model.

Assessing the quality of the measurement model has a fundamental relevance for the identification of multicollinearity problems that may arise from the formative specification of the relationships between the competitiveness dimensions and the observed variables chosen in order to measure them. Specifically, the PLS tool for measuring the measurement model quality is the communality index, that can be computed both for each specified dimension and for the overall measurement model. Both the results are reported in Table 5.9.

Table 5.9 *Mean Communalities Values for each competitiveness latent variable*

LATENT VARIABLE	TYPE	MEAN COMMUNALITIES
LABOUR DIMENSION	Exogenous	0,343
GENDER DIMENSION	Exogenous	0,570
INNOVATION DIMENSION	Exogenous	0,349
ENVIRONMENT DIMENSION	Exogenous	0,448
ECONOMIC DIMENSION	Exogenous	0,503
COMPETITIVENESS DIMENSION	Endogenous	0,121
Mean		0,275

It would be useful to remember that the communality index measures how much of the manifest variable variability in each block is explained by its own latent variable, that is, how well the manifest variables describe their underlying latent construct. This means that it is conceptually appropriate whenever measurement models are reflective. However, communalities can be also computed and interpreted in case of formative models knowing that, in such a case, the expected result are lower communalities values, revealing that each observed variable represents a different feature of the dimension it is linked to, and that multicollinearity is not a problem to be faced. Table 5.9 shows the communality index for each latent variable composing the competitiveness model. Communality indexes are very low for most of the dimensions, in particular it should be underline that the competitiveness indicator dimension has the lower communality index value, that confirms that the dimension selected in order to measure it effectively measure different, non-overlapping aspect of the phenomenon under analysis.

As far as the structural model is concerned, apart from the R^2 measure for endogenous variables, it is possible to assess its quality by means of the redundancy index measuring the portion of variability of the manifest variables connected to the endogenous latent variable explained by the latent variables directly connected to the block. In our hypothesized model the R^2 value for the competitiveness indicator construct (the only endogenous latent variable in the model) resulted to be equal to 0.933, while the redundancy index was 0.113, which means that the hypothesized model explaining the relationships among competitiveness dimensions and the overall competitiveness indicator are able to explain most of the variability of the phenomenon object of the present study.

Moreover, the PLS competitiveness model evaluation provided us with an overall goodness of fit measure: the GoF index. It has thus been possible to evaluate the overall specified competitiveness model, and to test the GoF index reliability by using bootstrap techniques.

Table 5.10 shows the obtained results. It displays two goodness of it measure: the absolute GoF index, calculated as the geometric mean of the average communality index and the average R^2, and the relative GoF index, obtained by dividing the absolute value by its maximum value achievable for the analyzed dataset.

Table 5.10 *Microlevel Competitiveness Model Goodness of Fit Measures*

	GoF	GoF (Bootstrap)	Standard error	Critical ratio	Lower bound (95%)	Upper bound (95%)
Absolute	0,524	0,517	0,017	31,092	0,488	0,571
Relative	0,979	0,964	0,031	31,250	0,901	1,000

The indexes displayed in table 5.10 confirm that the second order hierarchical model specified in order to study micro-level competitiveness is able to explain the features of the phenomenon under analysis in a suitable way.

5.7 MICRO-LEVEL COMPETITIVENESS COMPOSITE INDICATOR SCORES

The validation phase of the causal model we specified in order to explain in a comprehensive way the features characterizing micro-level competitiveness, represented the last stage of the model-based composite indicator construction. It brought to the overall model assessment and, most important, gave us the chance to check on the soundness of the obtained competitiveness composite indicator.

At this juncture it would be useful to briefly resume the most important steps accomplished until this moment for better understanding the main advantages resulted from the non-parametric Structural Equation Model approach to the construction of the model-based competitiveness composite indicator.

In the first part of the present study the most controversial and debated aspects characterizing the use of composite indicators for the measurement of multidimensional phenomena have deeply been discussed. Specifically, they have been identified in the subjectivity lying at the base of the choice of the key variables composing the final indicator, in the arbitrariness of the weighting and aggregation processes, as well as in the difficulty in the interpretation of movements in the composite measure, that is, when an indicator moving toward a certain direction is presented, it is not always possible to identify which components are the driving forces of the movement itself.

The choice of the PLS-PM methodology for the micro-level competitiveness measurement allowed us to overcome some of the above mentioned shortcomings. As far as the choice of the key indicators to be used for measuring the different competitiveness features is concerned, even if initially grounded on subjective elements, it has been submitted to a reliability analysis. Better explaining, in a PLS-PM framework, the significance of the hypothesized relationships between the chosen observed variables and the latent dimensions they are linked to can or not be confirmed once the parameter estimation phase is concluded; that is, the parameter estimation can reveal, though the use of bootstrap techniques, the non-significance of some indicator in determining the latent construct they are linked to. In the section describing the competitiveness model estimation phase it has been showed that a first explorative analysis has been performed in order to check the significance of the measurement relationships, showing that some of the variable initially selected to form the different competitiveness dimensions had non-significant relationships with the pillar they were linked to. In this way it has been possible to reformulate the starting hypotheses by removing the non-significant indicators and re-testing their validity. Moreover, although the significance as well as the coherence of the observed variables inside the corresponding latent dimension can be checked by means of internal consistency measures, in the case of reflective indicators, and by the use of the correlation analysis in case of formative measurement relationships, showing the existence of multicollinearity problems, the PLS-PM furnish a goodness of fit measure (communality index) for the measurement model, that indirectly gives information on the elementary indicators suitability.

As far as the weighting system subjectivity issues are concerned, the PLS-PM approach, in detail described in the course of the present study, allowed us to individuate a double system of optimum weights not arbitrarily chosen, but the resulting from an estimation and validation process guarantying against subjective solutions, and giving the chance to identify the driven element of the competitiveness indicator.

Once the suitability as well as the coherence of the procedures implemented in order to measure micro-level competitiveness have been investigated, the focus has been directed toward the evaluation phase of the overall composite indicator scores.

The large size of the Italian firms sample (81.706 units) used for the measurement of micro-level competitiveness, made the presentation of the obtained results very difficult. This is the reason why we decided not to display the final competitiveness rankings for the analyzed firms, as such an approach could not give significant and clear information on the features of the obtained competitiveness composite indicator. We instead decided to adopt an approach allowing us to identify and display, in an as clear as possible way, the main features (profile) characterizing competitive/non-competitive firms.

Specifically, we divided the disposable sample in different groups, on the basis of some fixed criteria (economic activity sector, number of employee, geographic area) with the aim to compare their performance with respect to the five competitiveness (latent) dimensions estimated by means of Structural Equation Model and with respect to the overall competitiveness composite indicator.

By using such an approach it has been possible to identify the profile of the most/less competitive firms as well as to test the ability of the obtained composite indicator to discriminate among different groups or cases.

Figure 5.3 shows the performance (in average) of five firms groups identified on the basis of the number of workers employed (1, 2-9, 10-19, 20-49, more than 50) with respect to the competitiveness dimensions as well as to the overall competitiveness indicator.

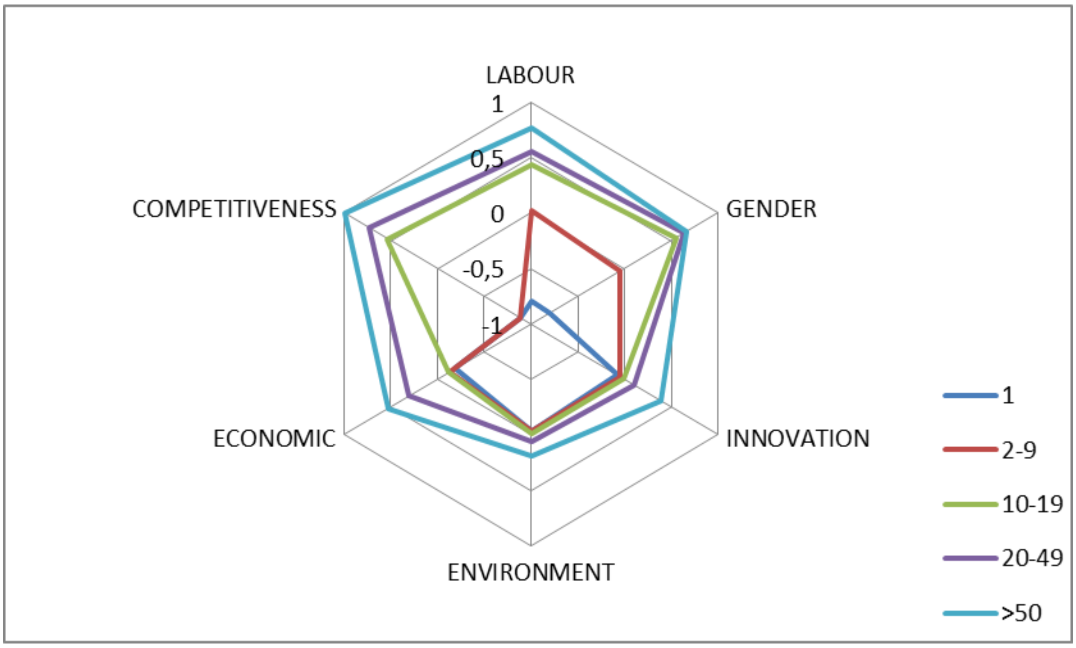


Figure 5.3 Micro-level Competitiveness Mean Scores by Employee Classification

As far as the groups performances with respect to the competitiveness dimensions are concerned, figure 5.3 shows that firms have similar scores with respect to the environment and innovation dimensions, independently of their size; when considering the economic dimension, firms with more than 20 employees shows different scores, greater than those obtained by firms with less than 19 workers, that, in turn, show very similar economic scores. An analogous situation can be observed when taking into account the gender and labour dimensions: in both the competitiveness pillars firms employing more than 10 workers obtained very similar, high scores, firms with less than 9 employees perform to a different extent, with low scores.

As far as the scores obtained by the different groups of firms with respect to the competitiveness composite indicator are concerned, it is possible to notice that the most competitive firms are those employing more than 50 workers (and that obtained the highest scores in each competitiveness pillar), the less competitive ones are instead those with a small number of employees (less than 10).

Moreover, the competitiveness scores confirm that the composite indicator is able to discriminate among groups, above all in correspondence of the higher section of the distribution.

The above described analysis has as well be used for investigating on the competitiveness indicator performance of groups of firms identified on the basis of the economic activity sector they belong to.

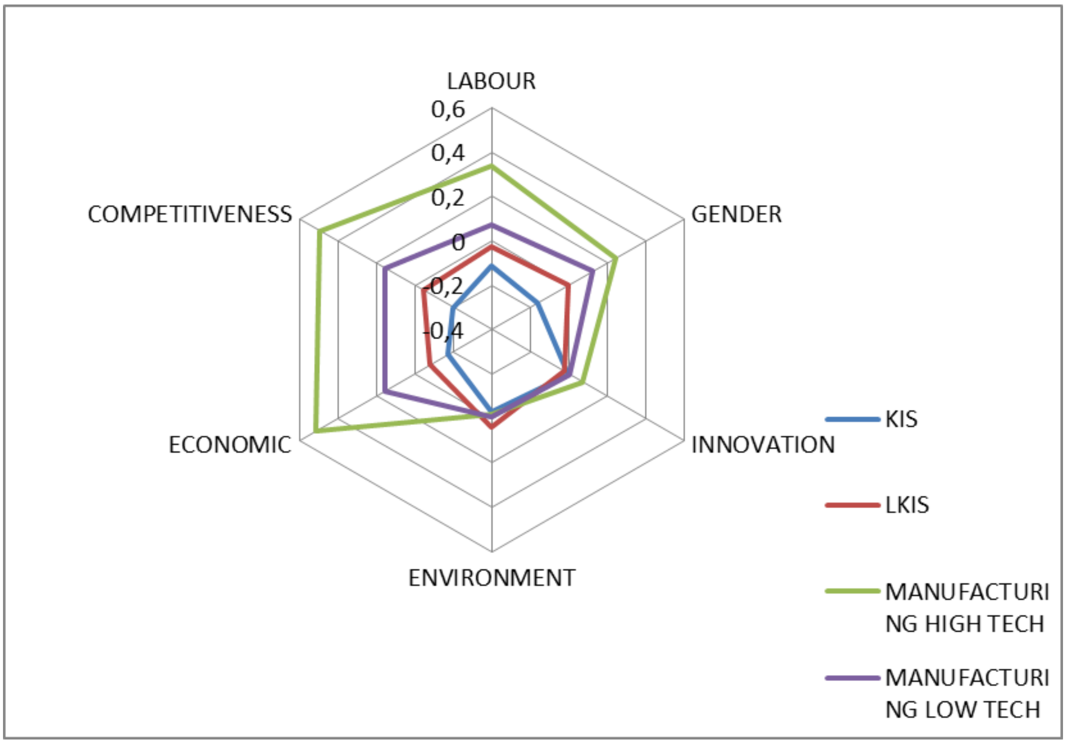


Figure 5.4 *Micro-level Competitiveness Mean Scores by Economic Sector*

Four groups have been extracted, by distinguishing between firms belonging to the manufacturing sectors and those belonging to knowledge intensive sector. Both the categories have been in their turn split depending on their technology level (high tech, low tech). Figure 5.4 shows that firms perform in a very similar way with respect to the innovation and environment dimensions, regardless the economic sector they belong to; well defined differences emerges instead when considering the groups scores with respect to the labour, economic, and gender dimensions.

The manufacturing high-tech firms perform better than the other groups in most of the dimension taken into account (lower scores are obtained only in the environment dimension, that is however the pillar contributing to a lower extent in determining competitiveness levels), the knowledge intensive firms have instead the lowest score in each dimension. These elements obviously affect the results obtained in the composite indicator, manufacturing firms are, in fact, the most competitive; the KIS group shows instead the lowest competitiveness scores. The differences among the competitiveness scores obtained by the firms groups taken into account, confirm the discriminant validity of the composite indicator.

Another firms characteristic taken into account in order to try to draft the profile of the Italian competitive/non-competitive enterprises, is their geographical location. The firms sample has been divided in five groups, on the basis of the ISTAT geographical repartition of the Italian territory.

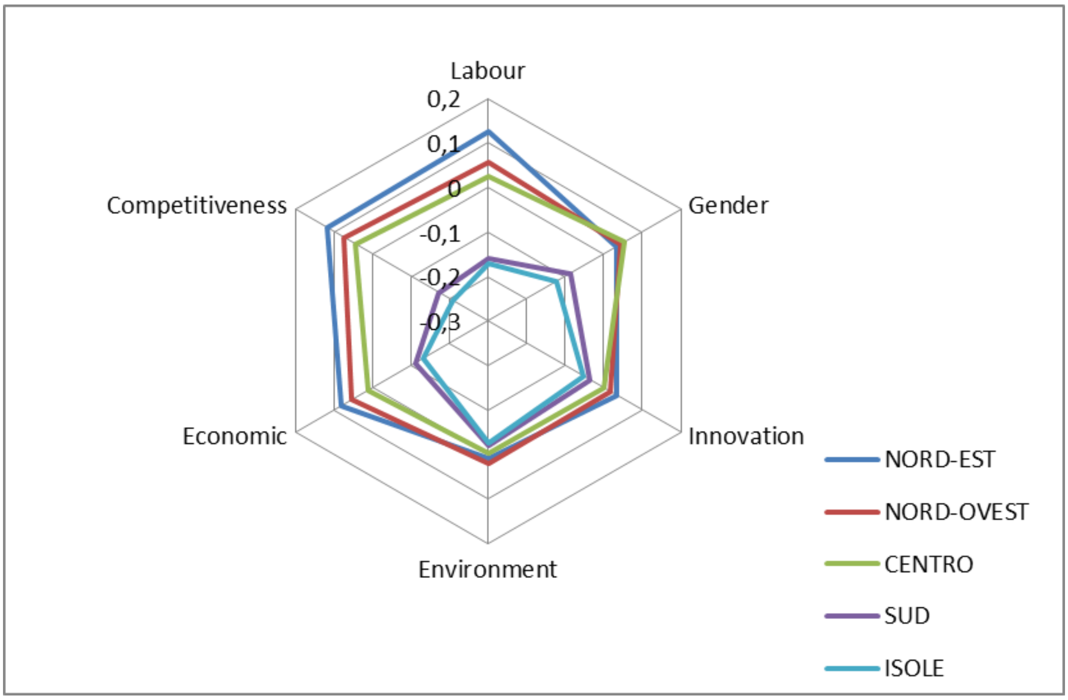


Figure 5.5 *Micro-level Competitiveness Mean Scores by Geographic Area*

Figure 5.5 shows that the firms performances on the environment and innovation dimensions are quite similar, there are no well-defined differences in the obtained scores. It would be helpful to remember that similar results have been obtained during the previously described analysis; it is thus possible to conclude that Italian firms have similar profiles with respect to innovative and environmental performances, regardless their specific peculiarities.

Differences instead emerge when analyzing the economic, labour as well as the gender dimensions. Specifically, it results from the analysis that firms located in the center and in the north have similar scores and perform better than the firms developing their activities in the south of Italy.

As well as the performance of the five groups with respect to the competitiveness indicators are concerned, a non-surprising result emerges: there exist a significant difference in the competitiveness levels depending on the geographic location of firms. As expected, firms located in the north and in the center of Italy are the most competitive, southern firms are on the contrary the less competitive ones.

The analyses described in the present section confirmed the ability of the micro-level competitiveness indicator in discriminating among units groups identified on the basis of different features, moreover it allowed us to investigate on the profile of the Italian competitive firms.

The competitive Italian firm-type emerging from our study is located on the north-east of Italy, develops its activities in the high-tech manufacturing sector by employing a number of workers greater than 50, is a firm with a wealthy economic situation, investing on human capital, careful to gender policies and able to adapt its productive processes to ever changing environmental condition.

5.8 MULTI-GROUP ANALYSIS

The analysis of the model-based competitiveness composite indicator measured by means of the PLS non-parametric approach to Structural Equation Models revealed a significant specification of the competitiveness model, as well as a good discriminant power of the indicator itself, although it has been observed on a huge number of units that, as already emphasized in the section containing the sample description, are characterized by a strong heterogeneity.

It is common knowledge that heterogeneity among units is an important issue in statistical analysis because treating the sample as homogeneous, when it is not, may seriously affect the results. This is the reason why the decision to identify some homogeneous groups of firms and to assess the differences or similarities among the detected classes of units has been made.

In our specific framework, this essentially entails comparing the obtained local models (estimated on the identified groups of units) to one another and to the global model (estimated on the whole sample). Hence, in Structural Equation Models, group comparison can be considered as a model comparison issue.

From a micro-level competitiveness framework point of view, it would be interesting to analyze the differences (if existing) among firms belonging to groups identified by taking into account different firm-specific features, that is, it would be useful to wonder if the competitiveness model hypothesized and used in order to measure micro-level competitiveness on the whole disposable sample is able to well explain and reproduce the competitiveness structure of different groups of firms having in common certain comparable characteristics (branch of activity, number of employees, geographical area, and so on). In particular, our focus will be on the study of competitiveness development paradigms characterizing two type of firms: those identified on the basis of the economic sector they belong to, and those identified with respect to their economic development levels. Belonging to high-tech manufacturing sector, and those belonging to the KIS (Knowledge Intensive Services) sector[38].

Our aim is to understand if the hypothesized competitiveness second order hierarchical model is able to explain the competitiveness structure of the selected groups of units in a suitable way.

Comparing groups in a latent class context means to define if the detected classes show different behaviors as regards the model parameters.

To this end we will use the PLS multi-group approach, that will allow us to detect on the differences (in terms of model parameter estimates) between the selected groups.

The PLS multi group analysis will provide us with the model parameter estimates for both the selected groups, and with significance tests on the investigated differences among groups. We decided to only display the results concerning the analysis on the statistical significance of the differences between the two groups as they are the core of the PLS multi group analysis; we are not

[38] High-tech manufacturing industries and knowledge intensive services sectors, have been identified by the use of the Ateco 2008 two digit code and its alignment with the Eurostat NACE statistical classification of economic activities that aggregates manufacturing industries in high-technology, medium high-technology, medium low technology and low technology, according to their technological intensity (evaluated by R&D expenditure/value added indicator) and divides services sector into knowledge-intensive services (KIS) and less knowledge services (LKIS) on the basis of the share of tertiary educated persons.

interested in the parameter estimation results for both the groups, we instead aim at understanding if the differences in the parameter estimates are statistically significant. Two kind of PLS multi group test have been used for the analysis: the multi group t-test and the permutation test.

5.8.1 Comparing High-Technology manufacturing and Knowledge Intensive Services firms

Before showing the obtained results, it would be helpful to remember that the first multi-group analysis has been conducted by individuating firms groups on the basis of their membership to the manufacturing or services economic sector; in particular, we focused on the high technology manufacturing firms and on the knowledge intensive services, and we individuate two groups respectively composed of 1505 and 3296 units (only a section of the disposable firms sample has thud been taken into account).

The multi-group PLS-PM analysis conducted on the above mentioned groups showed the result summed up in tables 5.11, 5.12 and in Figure 5.6.

Let’s see them in details. Table 5.11 reports the results of the multi group t-test conducted on the structural parameters linking each competitiveness dimension to the overall micro-level competitiveness construct.

Table 5.11 *Multi Group Structural Model t-Test*

LATENT VARIABLES RELATIONS	DIFFERENCE	t (OBSERVED)	t (CRITICAL)	DF	p-VALUE	SIGNIFICANT
GENDER DIMENSION → COMPETITIVENESS	0,030	0,619	1,960	4799	0,536	**No**
ENVIRONMENT DIMENSION → COMPETITIVENESS	0,131	2,911	1,960	4799	0,004	**Yes**
ECONOMIC DIMENSION → COMPETITIVENESS	0,123	2,057	1,960	4799	0,040	**Yes**
INNOVATION DIMENSION → COMPETITIVENESS	0,146	3,237	1,960	4799	0,001	**Yes**
LABOUR DIMENSION → COMPETITIVENESS	0,026	1,367	1,960	4799	0,172	**No**

It reveals the existence of some statistically significant differences in the structural relationships estimates of the two models. In particular, the just mentioned differences have been found in the relation linking the environmental dimension to competitiveness, in the relation linking the innovation dimension to competitiveness as well in the link of the economic dimension to competitiveness.

As far as the first difference is concerned, by looking at the model parameter estimates it is possible to notice that in the KIS model the environmental dimension has no significant impact (evaluated on the basis of bootstrapped t-values) on the overall competitiveness indicator; it is instead significant in the high-tech manufacturing group. This is probably due to the fact that the services industry is, for structural reason, less engaged in environmental issues than the manufacturing one, that have instead to face most urgent environmental questions not only for social fairness motives, but also for increasing their competitive advantages through costs lowering and through improvements in the production processes and techniques.

Turning the attention to the comparison in the parameters estimates explaining the relations between innovation dimension and competitiveness, and between economic dimension and competitiveness, the PLS-PM multi group analysis revealed that although they are significant in both the competitiveness models, they (significantly) differ in their contribution to the overall competitiveness construct. Figure 5.6 shows the impact of each dimension on the competitiveness indicator, respectively for KIS and high technology manufacturing groups.

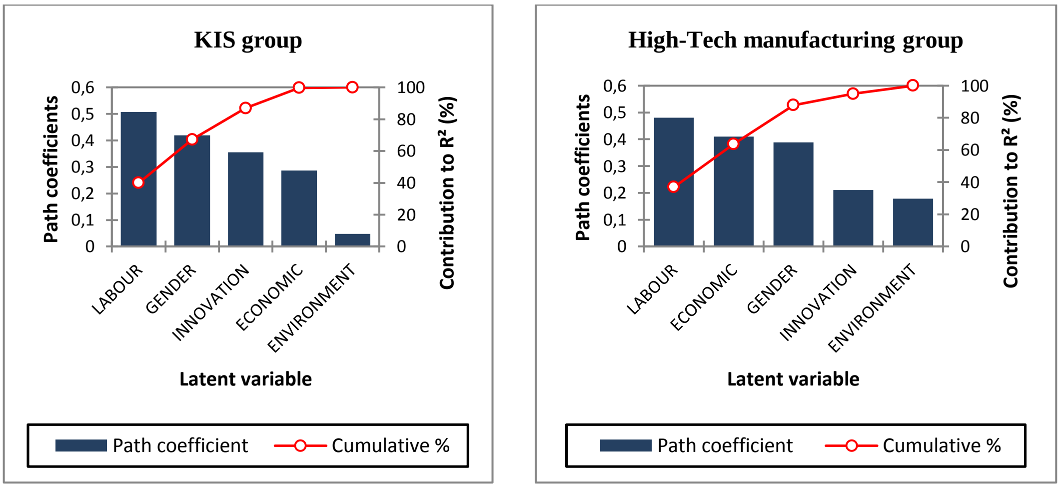


Figure 5.6 *Competitiveness Dimensions Contributions for both KIS and High-Tech Manifacturing Groups*

It is possible to see that, the KIS group structural parameter estimation process brought to a system of weights in which the economic dimension has the lower impact on competitiveness[39], while the most relevant pillars are, in order, the labour dimension, the gender dimension and the innovation one. This is probably due to the fact that intangible resources related to the human capital management of firms, to their internal organization and to their ability to innovate are more important with respect to the economic conditions of firms in determining competitiveness in the sector under analysis, as competitiveness depends on the dynamics through which the firms select their strategic choices. In particular, it is necessary to bear in mind that the most important feature distinguishing manufacturing firms from KIS is in the type of products they supply; that is, the real products of knowledge intensive services are specialized expert knowledge, research and development ability as well as problem solving know-how. These private firms are involved in collecting, processing, generating and distributing knowledge, in order to provide products or services that clients (other enterprises or organizations) are not able or unwilling to develop on their own.

These firms, operating actively in all steps of the value chain, not only contribute to the competitiveness of client firms, but promote their own innovative capacity and their technical and managerial development; thus whereas manufacturing products and processes contain a high degree of codified knowledge, KIS sector contains high levels of tacit knowledge, that has to be gained through a firm organization able to select skilled workforce among a huge, gender balanced pool and to generate and increase technological innovation, in order to foster their competitive advantages.

Looking instead at the structural parameters estimates for the high technology manufacturing group, the contributes of the competitiveness dimensions to the overall competitiveness indicator have a different structure, above all, as revealed by the multi group analysis, with respect to the economic and innovation dimension. In fact, the competitiveness level of the sector under

[39] It would be useful to remember that the environmental dimension in the KIS group showed a non-significant relation with the competitiveness indicator and for this reason it will not be taken into account in the description of the weights structure characterizing the KIS group competitiveness model.

analysis seems to be strongly influenced by the economic dimension, may be because the leading variable explaining it are the export earning on the firms turnover, that are fundamental in determining a manufacturing company competitive advantage. Moreover, as far as the innovation dimension is concerned it has a lower impact on high technological manufacturing sector competitiveness (with respect to the importance this dimension has in determining the KIS group competitiveness), the reasons of this differences probably lie in the structural features of Italian small and medium enterprises; in fact, though the importance of innovation is undoubtedly recognized and innovative processes are often implemented, the competitiveness driver forces are scarcely related to innovation itself. This is probably attributable to the lack of public policies in the field of innovative-related fields, that constraint firms to try to gain competitive advantages trough alternative channels.

The multi group analysis has been also conducted for testing the differences (if existing) among the measurement model parameters. We wanted to assess the relationships of each observed variable with the corresponding competitiveness dimension, both in the KIS and in the high technology manufacturing groups and to use multi group analysis in order to compare them, for understanding if the selected manifest variables are able to measure in a suitable way the competitiveness dimension they have been linked to, both in the KIS and in the high tech manufacturing sectors. Table 5.12 shows the results of the PLS multi group analysis on the measurement model parameters.

Table 5.12 *Measurement Model Multi Group Permutation Test Results*

LATENT VARIABLES	MANIFEST VARIABLES	DIFFERENCE	P-VALUE	SIGNIFICANT
GENDER DIMENSION	Gender Pay Gap	0,072	0,010	Yes
	Leading Women	0,262	0,010	Yes
ENVIRONMENT DIMENSION	End Of Pipe	0,184	0,178	No
	Current Expenditure	0,278	0,782	No
ECONOMIC DIMENSION	Exports	0,056	0,772	No
	Value Added	0,099	0,792	No
INNOVATION DIMENSION	Software	0,252	0,069	No
	R&D	0,502	0,010	Yes
	Patents	0,076	0,743	No
LABOUR DIMENSION	Wages	0,001	0,990	No
	Temporary Work	0,038	0,653	No
	Workers Training	0,021	0,970	No

Three significant differences emerged after the permutation multi group test: the estimates of the manifest variables used in order to measure the gender dimension in both the groups show that they plays a different role in determining the corresponding competitiveness pillar. Specifically in the KIS group the variable measuring the number of women holding managerial positions has a non-significant role in determining the gender dimension variable scores; on the contrary, in the high-tech manufacturing group both the variable (gender pay gap and number of leading women) has a significant link with the gender dimension of competitiveness. The most interesting difference among the groups measurement models lies in the variable representing the R&D expenditure, linked to the innovation dimension of competitiveness. In particular, the link resulted to be non-significant for the KIS group, while in the high tech manufacturing group it is the leading variable in the determination of the innovation dimension scores. This is not a surprising result because high tech Italian manufacturing industry exploits new scientific and technological knowledge obtained through investment in internal, but also in external research and development activities, core of the innovative dimension of firms. In the KIS sector, knowledge is ,instead, the product of the activity of firms, this is the reason why, in order to foster their innovation performance they have to focus the attention on variable related both to intellectual property rights and Information and Communication Technology which, together with the workers skill level, gives the chance to produce and spread knowledge.

The multi group analysis carried out for comparing two groups of firms (respectively belonging to the high tech KIS and to the high tech manufacturing economic sectors) with respect to the previously determined competitiveness models revealed that, although the theoretical second order hierarchic model is able to explain the competiveness structure of both the groups, it is possible to identify a different system of weight for each group; that is, each pillar influence the competitiveness indicator scores to a different extent, depending on the membership of firms to one of the sector-specific groups. The hypothesized heterogeneity has been confirmed by significant differences among parameter estimates measuring the relationships between the elementary indicators and the corresponding competitiveness dimensions.

The above described analysis results let us understand that when dealing with heterogeneous groups of units, identified on the basis of unit-specific features, the Structural Equation Model multi-group analysis allows the researcher to not only investigate on the differences among them, thus confirming (or not) the hypothesized differences, but also to identify in a suitable way, for each group, the model structure revealing the group-specific peculiarities and features.

5.8.2 Comparing firms on the basis of their economic development level

The idea lying at the base of the decision to implement a multi-group analysis for comparing firms groups identified on the basis of their development stages originate from an interesting analysis framework used for measuring competitiveness from a macro-level point of view and specifically adopted by the European Joint Research Centre together with the European Regional Policies department in order to develop the EU Regional Competitiveness Index (RCI, 2010). We will briefly focus on the main features characterizing the above mentioned composite indicator for better understanding the theoretical basis of the multi-group analysis we developed in the present study.

RCI represents the first measure of competitiveness at regional level covering all EU countries. It takes into account both social and economic aspects of regions, including the factors which describe the short and long term potential of their economies; it is thus based on a multidimensional approach to the measurement of competitiveness.

RCI is composed of eleven pillars chosen with the objective of describing different dimensions and aspects of the level of competitiveness and designed to capture short- as well as long-term capabilities of the regions.

The eleven dimensions are in their turn classified into three major groups: the basic, the efficiency and the innovation pillar. The idea at the base of such a partition is that it is fundamental to take into account that regions have different development structures and that as they move along the path of development, their economic and social conditions change and different aspects and features become more important in determining their competitiveness level. This is the reason why, in the first pillar, the elementary indicators that are hypothesized to represent the key basic drivers of all types of economies (institutions, macro-economic condition, infrastructure, health and quality of primary and secondary education) are included; the efficiency pillar is characterized by the factors that enter into play for guarantying advances in competitiveness to developed regional economies (higher education/ training and lifelong learning, labour market efficiency), and the innovation pillar is composed of those elements contributing in increasing the competitive growth of the most developed regions (technological readiness, business sophistication and innovation).

It is thus possible to hypothesize that there exist some elements and aspects that, depending on the development stage of regions, plays a different role in determining their competitiveness performances. From a composite indicator construction perspective this entails using an exogenous weighting scheme assigning to each pillar different weights, on the basis of the level of development of the regions taken into account. Specifically, if regions are characterized by low level of development, the basic pillar variables will contribute in defining competitiveness to a greater extent than the variables measuring both the efficiency and innovation pillars; regions with a medium development stage should be characterized by a competitiveness structure assigning stronger weights to the basic and efficiency pillar with respect to the innovative ones, and the level of competitiveness of the most developed regions should take into account to a larger extent their innovation capability as a key driver for their economic and social advancement. Such a weighting scheme has the clear objective of not penalizing regions on factors where they lay too far behind, thus providing a composite measure allowing for fair comparisons among heterogeneous units.

A fundamental phase for the construction of a composite indicator taking into account heterogeneity among the analyzed regions is thus the identification of their stages of development, on the basis of a fixed criteria.

In the European Regional Competitiveness Index, regional economies are divided into medium, transition and high stage of development. The development stage is computed on the basis of the regional GDP at current market prices (year 2007) measured as PPP per inhabitants and expressed as percentage of the EU average.

EU regions are then classified into three groups of medium, transition or high stage according to a GDP percentage respectively lower than 75%, between 75% and 100% and above 100%[40].

The system of exogenous weights determining the final composite indicator is built in the following way: by starting from the idea that regions characterized by different development levels have different competitiveness structures, for each region, the stage of development is assessed and three sub-indices corresponding to the three groups of pillars previously described are computed as simple average of their elementary indicators.

For the computation of the overall RCI index, each pillar is then weighted differently to reflect its relevance in defining the final index on the basis of the regions development stage. For medium economies the set of weights is: 0.4 for the basic pillar, 0.5 for the efficiency pillar and 0.1 for the innovation pillar. This

[40] The threshold which defines the level medium (t1=75% of EU average) is the value defined by the EU Commission to identify regions eligible for the Convergence objective. This threshold is highly relevant as it affects EU policy funding. The second threshold, t2= 100%, is instead established in an arbitrary way.

reflects a situation where, given that the economy is mostly driven by basic and intermediate socio-economic factors, the first and second groups of pillars are assigned almost all the weight (90%), while the innovation related group is assigned the lowest weight (10%). For intermediate economies, the set of weights is: 0.3 for the basic pillar, 0.5 for the efficiency pillar and 0.2 for the innovation pillar. With respect to the medium-stage, the role of the third pillar is given more relevance. For high-stage economies weights are defined as: 0.2 for the basic pillar, 0.5 for the efficiency pillar and 0.3 for the innovation pillar. In this type of economies basic factors have the lowest relevance while the innovative group of elementary indicators is assigned a relatively high importance.

It can be seen that for all development stages the highest weight is assigned to the second pillar. The importance of the first pillar decreases going from medium to high stage of development, while the last pillar correspondingly gains importance.

Table 5.13 resumes the above described exogenous weighting scheme.

Table 5.13 *RCI Exogenous Weighting Scheme*

		STAGE OF DEVELOPMENT		
		Medium Stage	Transition Stage	High Stage
PILLARS	Basic Pillar	0,40	0,30	0,20
	Efficiency Pillar	0,50	0,50	0,50
	Innovation Pillar	0,10	0,20	0,30

Turning again the attention toward the objectives of our study, we decided to adopt a structure of analysis similar to the just described one in order to develop a competitiveness measure able to take into account the heterogeneity characterizing the firms sample used in course of the research.

Although the analysis framework developed for the measurement of regional competitiveness is appealing and innovative, it has a fundamental limit: the system of weights determining the final composite indicator is established in an *a priory* fixed way.

Our aim was to overcome that limit, by endogenously estimating the system of weights to be attributed to each competitiveness dimension, on the basis of the level of development of the Italian firms.

To this end we used a Structural Equation Models approach that allowed us to initially test the hypothesis that firms characterized by different development levels have different competitiveness structures and to subsequently estimate the weights to be assigned to each competitiveness dimension, on the basis of the level of development of firms.

We decided to identify the level of development of firm by using their turnover values. We classified Italian firms into three stages of development, the basic stage, the intermediate stage and the high stage on the basis of the percentage of firms turnover per employee on the average turnover level computed on the whole Italian sample. The threshold values determining the stages of development have been chosen according to the RCI perspective; therefore firms with a turnover percentage lower than 75% were assigned to the basic stage of development, firms with a turnover percentage between 75% and 150% were assigned to the intermediate stage of development and the remaining firms, with a turnover percentage greater than 150% were assigned to the high stage[41].

As said before, the idea of the present analysis is that different competitiveness aspects have different impacts on the overall phenomenon, depending on the development levels of the firms taken into account. We therefore identified three groups of competitiveness dimensions, by borrowing the RCI structure that we found to be in line with the micro-level competitiveness theoretical hypotheses described in the course of the research.

The first pillar (basic pillar) coincide with the economic competitiveness dimension that includes variables considered strictly necessary for the basic

[41] The second threshold value differs from the one used in the macro-level approach, we in fact opted for a greater value for trying to guaranty a distribution of firms among the last levels of development as near as possible to the real situation and condition of Italian small and medium firms. Table 4. shows the final distribution of firms among the identified groups.

functioning of any firm. The second pillar (efficiency pillar) includes both the labour and the gender dimensions that describe a firm structure which is more sophisticated, with a higher potential skilled labour force and a structured labour market. The last pillars (innovation pillar) comprises the innovation as well as the environment dimension, both characterized by variables that are fundamental in explaining the competitiveness levels of the most developed firms. Figure 5. shows the competitiveness model obtained by putting together the competitiveness dimensions used in the course of the research in order to obtain three pillars containing different aspects of the phenomenon that are hypothesized to have different impact on competitiveness, depending on the firms level of development.

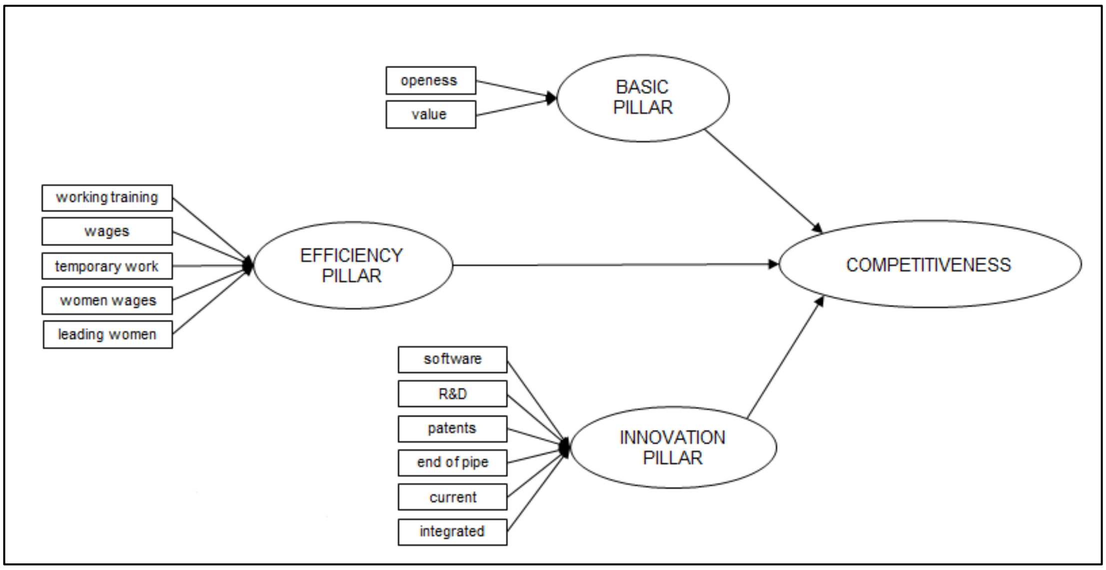


Figure 5.7 *Three Pillars Competitiveness Model for Multi Group Analysis*

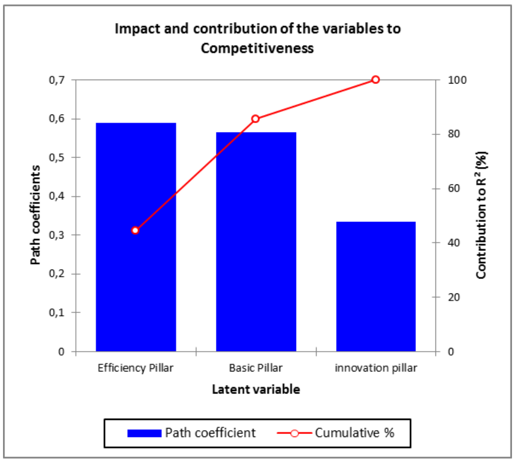
Our aim was to use a Structural Equation Models approach in order to estimate the competitiveness model parameters for each group of firms identified on the basis of their development level and to understand, by using statistical tools, if significant differences among the three groups exist.

The existence of such differences would justify the use of a system of weight assigning different values to the three competitiveness pillars, depending on the firms development levels. The system of different weights could be obtained by using the structural parameter estimates of the competitiveness model computed for the three development groups, thus guarantying the objectivity of the weighting scheme.

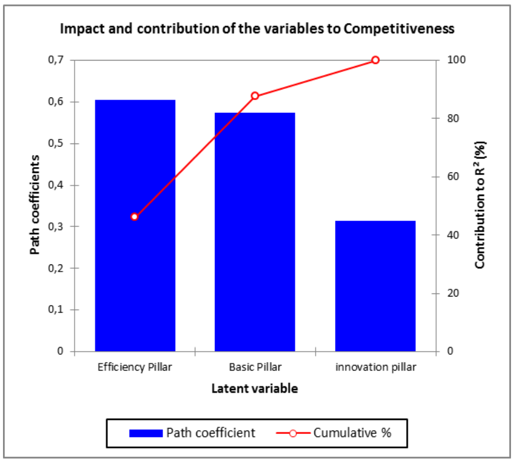
The use of a multi-group approach to the Structural Equation Models let us simultaneously reach both the objectives.

The parameter model estimates computed on the three group of firms are statistically significant, the relations between the three competitiveness pillar and the overall competitiveness construct showed the same structure in all groups: the pillar contributing to a greater extent in determining the competitiveness levels is the efficiency one, followed by the basic and the innovation pillar. Figure 5.8 displays the impact of each pillar to competitiveness, for the three groups of firms, followed by table 5.14 showing the significance of the models parameters estimates.

Basic Stage



Intermediate Stage



High Stage

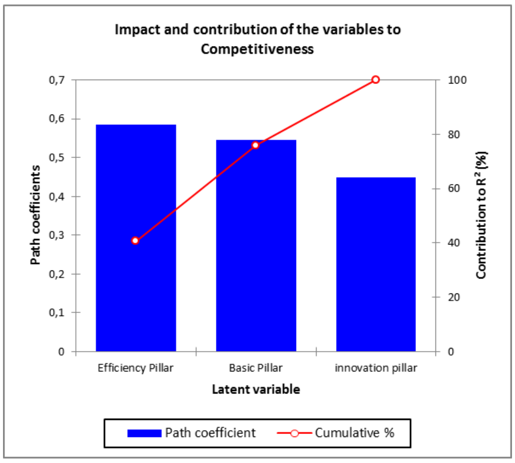


Figure 5.8 *Pillars Contributions to Competitiveness by Firms Development Level*

As said before we were interested in testing if significant differences exist among the competitiveness model estimates computed for each group of firm identified on the basis of the firms development level. The multi-group permutation test showed interesting results.

The comparison between the firms groups characterized by low and intermediate stages of development revealed that there are not significant differences in the structural model parameters[42]. The comparison between groups of firms respectively belonging to the low and the high stages of development showed that the competitiveness model parameters estimates are statistically significant, in particular with respect to the innovation pillar. The same results have been obtained by the comparison between the firms groups characterized by high and intermediate levels of development. The above listed results are reported in table 5.14

[42] The lack of significant differences in the model parameters estimates of the groups of interest, , may allow us to hypothesize the presence of only two heterogeneous groups: the group of firm with a basic/intermediate stage of development and the group of firm with high development levels.

Table 5.14 *Multi Group Structural Parameters Comparisons by Development Level*

LOW vs MEDIUM

Latent variables	Difference	P	Significant
Basic Pillar -> Competitiveness	0,008	0,614	No
innovation pillar -> Competitiveness	0,021	0,614	No
Efficiency Pillar -> Competitiveness	0,016	0,386	No

LOW vs HIGH

Latent variables	Difference	P	Significant
Basic Pillar -> Competitiveness	0,021	0,307	No
innovation pillar -> Competitiveness	0,114	0,010	Yes
Efficiency Pillar -> Competitiveness	0,006	0,822	No

MEDIUM vs HIGH

Latent variables	Difference	P	Significant
Basic Pillar -> Competitiveness	0,029	0,069	No
innovation pillar -> Competitiveness	0,135	0,050	Yes
Efficiency Pillar -> Competitiveness	0,022	0,297	No

The results of the Structural Equation multi-group analysis revealed that it does makes sense to hypothesize a composite competitiveness measure whose weighting structure reflects different patterns of competitiveness development, depending on the development stage of firms, in particular with respect to the dimension taking into account their innovative ability. It is therefore possible to describe the weighting structure by using the structural parameter values obtained through the estimation of the competitiveness models for the three groups of firms.

Table 5.15 shows the estimated weighting scheme for micro-level competitiveness.

Table 5.15 *Endogenous Competitiveness Weighting Structure by Development Level*

		STAGE OF DEVELOPMENT		
		Basic Stage	Intermediate Stage	High Stage
PILLARS	Basic Pillar	0,60	0,60	0,50
	Efficiency Pillar	0,60	0,60	0,60
	Innovation Pillar	0,30	0,30	0,40

By comparing the weighting results based on the macro-level approach system (table 5.13) it is possible to notice that, in both the competitiveness analysis, even if developed at a different aggregation level, the pillar with the greater impact on competitiveness in all the analyzed groups is the efficiency one, the pillar with the smaller impact is instead the innovation one. The multi-group analysis results, obtained by means of an objective, endogenous estimate of the micro-level competitiveness composite indicator are thus very similar to those exogenously hypothesizes at macro level; it therefore does make sense to assert that analyzing and studying micro-level competitiveness is fundamental for understanding the main structures characterizing the phenomenon at a different level of aggregation, that is, from a macro-oriented perspective.

Although the multi-group Structural Equation Models analysis allowed us to obtain interesting results, above all considering the explorative nature of the analysis objectives, it is necessary to underline the limits of the approach used for creating a composite measure taking into account the heterogeneity characterizing the Italian firms. The most important element to be highlighted is the subjectivity characterizing the choice of the threshold values determining the composition of the groups of firms on the basis of their development level; it is undoubted that different results could be obtained by using different thresholds. In order to overcome this limit it would be useful, for example, to use statistical tools for investigating on possible sources of unobserved heterogeneity (in a PLS-PM framework a suitable tool is represented by the REBUS algorithm) or to use clustering techniques for the objective definition of groups showing heterogeneous features.

Although the above present analysis have been developed in an embryonic form, with purely explorative and comparative purposes, it would be interesting to go more in depth with the research of suitable statistical methods allowing to compute multidimensional measures by using a system of weights able to objectively take into account the heterogeneity characterizing the units of analysis, in order to obtain fair indicators as less as possible influenced by differences among units.

Final Remarks

The novelty element of our study, strictly related to the interpretation of the phenomenon under investigation, lies in the idea to conceptualize competitiveness as a huge, multidimensional and latent concept characterized by several tangible and intangible aspects. The study of economic theoretical and empirical studies on competitiveness gave us the chance to go in depth with the knowledge of the multidimensional phenomenon, therefore allowing us to trace the theoretical grounds of our study as well as to identify the variables to be used in order to conduct the empirical analysis.

As a matter of fact, to deal with a multi-dimensional concepts, means to specify which are the single aspects (dimensions) to be taken into account for the comprehensive description of the concepts themselves and to establish which are the most suitable indicators to be used in order to measure each of these aspects.

The analysis of the economic literature clarified that competitiveness is to a large extent determined by the enterprise culture, the ability of management and human resources to adapt to changing conditions, influence the firms environment, innovate, develop or explore new technologies and markets. We therefore hypothesize competitiveness to be influenced by five dimensions: the economic dimension (providing information on the economic status of firms), the labour dimension (providing information on the workforce composition, on the contractual typologies and on the firms skills level), the gender dimension (providing information on the gender equality measures implemented by firms), the environment dimension (providing information on firms environmental management strategies), and the Innovation dimension (providing information on the innovative ability of firms, by including measures of intangible assets considered fundamental in determining the firm ability to innovate). We specified a competitiveness model grounded on the hypothesis that each competitiveness dimension (conceptualized as a latent, multidimensional construct and measured through a series of observable variables describing their multifaceted nature) is directly linked to the overall competitiveness indicator, thus originating a hierarchical second order model (the first order level being composed of the five competitiveness dimension and the second one by the overall competitiveness latent variable). The specified model has been used for the empirical analysis conducted on the small and medium Italian enterprises sample in 2008.

We estimated the model parameters (indicator weights) by means of a Structural Equation Models non-parametric approach and found that the main drivers of competitiveness are the labour and gender dimensions, followed by the economic, the innovation, and the environment pillars. Better explaining, despite all the dimensions specified in the model significantly contribute in affecting firms competitiveness levels, some of them have a greater influence. In particular, the results of the structural parameters estimation process let us understand that firms investing both in human and organizational capital, by means of on-the-job employees training, fair wages polices as well as by the ability to adapt to the ever-changing external environment conditions through flexible form of workforce recruitment, and in gender equality policies, giving women the chance to advance their career and remunerating them to the same extent of men, are more likely to be competitive.

Improving firms competitiveness means to assign different levels of priority to firms policies implementation; in particular investments in human resources, and a fair and dynamic management of human capital seems to be the unavoidable element for companies to be competitive. The parameter estimation results confirmed that the hypothesized hierarchical second order model is able to explain the complexity characterizing the multidimensional nature of competitiveness, moreover it has been possible to prove the hypothesis, already supported by a series of empirical studies, that among the categories composing the concept of intellectual capital, the most relevant in determining firms competitiveness is the one concerning the human capital management.

The model parameter estimation phase allowed us to obtain both the competitiveness dimensions and the model-based competitiveness composite indicator scores for the Italian sample. We used them for trying to trace the profile of the most competitive Italian firms.

The competitive Italian firm-type emerging from our study is located on the north-east of Italy, develops its activities in the high-tech manufacturing sector by employing a number of workers greater than 50, is a firm with a wealthy economic situation, investing on human capital, careful to gender policies and able to adapt its productive processes to ever changing environmental external conditions.

In the second part of the empirical application we used a multi-group Structural Equation approach for assessing the existence of different classes showing heterogeneous behaviors inside the Italian firms sample as well as to deal with the issues of group-specific effects. The decision of using such an approach originated from the reflection on the importance of investigating on heterogeneity among units for guarantying the quality of the results of statistical analyses. From a micro-level competitiveness framework point of view, we wanted to analyze the differences (if existing) among firms belonging to groups identified by taking into account different firm-specific features, that is, we wondered if the competitiveness model hypothesized and used in order to measure micro-level competitiveness on the whole disposable sample was able to well explain and reproduce the competitiveness structure of different groups of firms having in common certain comparable characteristics (branch of activity, number of employees, geographical area, and so on). Our focus has been on the study of competitiveness development paradigms characterizing two type of firms, respectively belonging to the high-tech manufacturing sector and to the KIS (Knowledge Intensive Services) sector.

The multi group analysis revealed that, although the theoretical second order hierarchic model is able to explain the competiveness structure of both the defined groups, it is possible to identify a different system of weight for each group; that is, each pillar influences the competitiveness indicator scores to a different extent, depending on the membership of firms to one of the sector-specific groups. The hypothesized heterogeneity has been confirmed by significant differences among parameter estimates measuring the relationships between the elementary indicators and the corresponding competitiveness dimensions.

The above described analysis results let us understand that when dealing with heterogeneous groups of units, identified on the basis of unit-specific features, the Structural Equation Model multi-group analysis allows the researcher to not only investigate on the differences among them, thus confirming (or not) the hypothesized differences, but also to identify in a suitable way, for each group, the model structure revealing the group-specific peculiarities and features.

The last empirical analysis carried out by means of a multi-group Structural Equation Model approach had the aim to compare group of firms identified on the basis of their level of development. The idea borrowed from the macro-level approach to the construction of a regional competitiveness indicator at EU level (RCI, 2010), has been to individuate a micro-level competitiveness indicator by using an endogenously determined weighting structure that would be able reflect the hypothesis that different competitiveness dimension have different impact (different weights) on the overall phenomenon, depending on the development level of the firms taken into account. The multi-group analysis showed that a different weighting scheme depending on the firm development level should be used with reference to the innovative dimension: firms lying at different stages of the development path show different competitiveness structures above all with respect to innovative policies.

Although the above described approach has been developed in an embryonic form, with purely explorative and comparative purposes, it would be interesting to go more in depth with the research of suitable statistical methods allowing to compute multidimensional measures by using a system of weights able to objectively take into account the heterogeneity characterizing the units of analysis, in order to obtain fair indicators as less as possible influenced by differences among units.

The research on micro-level competitiveness furnished interesting results both on the phenomenal and on the methodological point of view, several open scenario would however be taken into account. A possible development would be to in-depth analyze methodological issue related to composite measure sensitivity analysis, in order to reduce as much as possible the influence of subjective choices characterizing some composite measures computation phases.

Moreover, starting from the hypotheses that competitiveness is the result of a number of factors interacting among each other as well as with the surrounding environment, and that elements characterizing competitiveness such as trade, labour mobility, technology and knowledge diffusion are a sources of geographical dependence among firms, it plausible to assume that competitiveness levels of firms influence and are in their turn influenced by the performance of the surrounding firms, giving rise to spillover effects. Interesting developments would therefore arise from a spatial analysis, carried out in a non-parametric Structural Equation Models framework, for exploring the potential spatial structures, with the final aim of detecting clusters of high or low performers among firms.

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