School of Statistical Sciences

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The contextual contribution to individual health.

Area of residence and household influences on perceived health among Italian adults

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To my family,

whose contribution to my perceived health

is immeasurable.

List of Acronyms

AIC	Akaike Information Criterion
CI	Confidence Intervals
GDP	Gross Domestic Product
GLS	Generalized Least Squares
HIS	Health Interview Survey
ICC	Intraclass Correlation Coefficient
ID	Index of Dissimilarity
LA	Large Areas
LRT	Likelihood Ratio Test
MOR	Median Odds Ratio
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Squares
NHE	New Home Economics
NHS	National Health System
PAF	Population Attributable Fraction
SD	Standard deviation
SE	Standard error
SES	Socio-economic status
VPC	Variance Partition Coefficient
WHO	World Health Organization

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INTRODUCTION

Health is a "hub" field of research, that stands at the crossroads of many disciplines: not only medicine, genetics, clinical biology, but also public health, epidemiology and demography.

The health domain is one of the areas of interest for demography, insomuch that recently a branch of this discipline has been specifically referred to as *Health Demography* (Kawachi and Subramanian 2005). However, the boundaries of the study of health in demography are generally difficult to outline. This depends on two main factors: i) the scope, the tools and the approach of demography to the study of health evolved greatly over time and ii) the multidimensionality of the health concept which makes it difficult to trace the boundaries of *Health Demography*. If we adopt the broader approach to this discipline, which includes the ultimate health event, mortality, the link with demography is straightforward. The very existence of demography relies on the study of mortality and, according to tradition, it was a systematic study of mortality that gave birth to this discipline in 1662, when John Graunt published what later became known as *the first life table.* The demographic research on mortality has also generously contributed to advances in public health: examples include the fight against infant and maternal mortality during the 20th century, the study of the causes of death responsible for the mortality decline at different stages of the *epidemiological transition* or the evidence of "missing females" in developing countries (Robine and Jagger 2010).

If we define health in a more narrow perspective, focusing on morbidity and disability, physical and mental functioning or self-perception of health status (overlooking the fatal events), its study within demography is more recent, but very profound.

Prevalence of specific morbidities, classification of diseases, frailty models, but also the study of marital status and health, which was pioneered by William Farr already in 1858[1], are unquestionable evidence of the interest of demography in health issues.

[1] Farr studied what he called the "conjugal conditions" of people in France, dividing for the first time the population into categories according to their marital status. He observed relative mortality ratios at different ages for married, celibate and widowed and illustrated for the first time the health advantage of married people, concluding that "Marriage is a healthy estate".

This interest has increased especially in the last decades, as a response to the process of aging, pushed forward by the persistent regimes of low fertility and low mortality in the developed countries. This trend is not confined within the boundaries of developed countries, but it is currently being echoed in developing nations, making aging a worldwide phenomenon (Hayward and Warner, 2005). Deep changes in population age structure, together with the growing role of chronic diseases, have brought to attention the necessity for developing specific investigations on morbidity and health conditions. “As population ages, demographers have turned to health itself as an outcome, including implications for health care need and utilization” (Kawachi and Subramanian, 2005).

Indeed, the aging phenomenon presented researchers with unpredicted scenarios and unexpected new concerns. A key issue was understanding whether declining mortality rates in the older population paralleled the decrease in morbidity and disability rates. In other words, it was unclear whether the years of life gained were characterized by a deterioration of health conditions or represented an expansion of life in good health. In the last thirty years flourishing literature has been debating the issue of *compression or expansion* of poor health, as a response to the increasing life expectancy at old and very old ages (Fries 1980; Crimmins *et al*. 1989; Olshansky *et al.* 1991; Doblhammer and Kytir 2001; Christensen *et al*. 2009).

Specific population measures[2], based on the inclusion of health status in the life table, has been developed to take into account jointly the size and quality of life gained and to monitor population health over time.

Despite the large effort, the debate about the effects of increasing life expectancies on health is still ongoing; one source of confusion being the complexity of the link between aging and health. What the evidence suggests so far is that the link between aging and health exhibits different patterns according to major population subgroups. Typically, improvements in disability are observed before the age of 85 (Christensen *et al.* 2009) and for mild rather than severe disability (Schoeni *et al.* 2001). Amelioration in chronic conditions seldom parallel this trend, and this apparent paradox can be explained by the major effects of those factors which make the illness less disabling, but, incidentally, increase its prevalence in the population, e.g. early diagnosis and improvements in survival (Christensen *et al.* 2009).

[2] A remarkable example is constituted by Healthy Life Years (HLY) and related measures of Healthy Life Expectancies (HLE).

Furthermore, most of the improvements are generally concentrated among the most educated groups (Dalstra *et al*. 2005; Matthews *et al*. 2006; Jagger *et al*. 2007; Cambois *et al*. 2011) and in the countries with higher expenditures for elderly care (Jagger *et al*. 2008).

The interest in health and aging patterns is especially linked to the sustainability of the welfare system. Policies that handle the consequences of population aging are urgently needed and they are expected to be multidimensional, including labor market, health system, housing, education and social protection, to be effective (Castagnaro and Cagiano de Azevedo 2008). In particular, health expenditure and retirement schemes are the most challenging issues posed by population aging. The extent to which they will impact the welfare systems all over the world depends primarily on the health status of the growing number of elderly. Therefore, it has become crucial to understand what factors promote a "Healthy Aging".

This can be ascertained through longitudinal studies on representative sample of the national population, but they are difficult and expensive to carry out. On the other hand, insights can be derived from the cross-sectional observation of how major population subgroups diverge in their health conditions. Frequently, population subgroups differ in unexpected ways and the associations between group specific characteristics and health status shed light on factors influencing the onset or the persistence of poor health conditions.

However, as Rose (1994) pointed out, studying *individual* health can be very different than studying *population* health and it can lead to very different findings. Studies that adopt a population perspective recognize that individuals are embedded in groups, networks, societies and countries and that all these levels of aggregation can potentially influence one person's health. Therefore, they take into explicit account characteristics of these levels in explaining health of individuals, groups and populations.

Demographers and social epidemiologists now recognize that determinants of health operate at different levels (Kawachi and Subramanian, 2005). Hence, any analysis that yearns to be exhaustive can not look solely at the individual but it must include contextual characteristics operating on a hierarchical structure. Furthermore, a solid research on health is expected to investigate the distribution of variance across levels, given that, as Merlo *et al.* (2009) highlighted the goal of health disciplines is "not only to increase the (mean) health of a population, but also to decrease health and health care inequalities (variance)".Although the hierarchical structure of health determinants is almost universally recognized, a handful of studies took it properly into account when they investigated the health subject. As a consequence, findings about the relevance and the characteristics of context that impact population health are sparse and not conclusive.

This thesis stands out from existing research because it intends to respect the hierarchical structure of health determinants and to reproduce it formally in the study of perceived health in Italy. The methodological coherence with the hierarchical structure is obtained by considering data in a nested framework and making use of multilevel models.

Obviously, the hierarchical structure can be analyzed on different spatial scales and from multiple perspectives. However, we knew from existing literature that, over and above the individual characteristics, the main factors affecting health are those related to territorial location (*macro level*) and social proximity (*meso level*).

The relevance of the geography on health has been shown already in 1850s in John Snow's seminal work on cholera. Snow linked the outbreak of disease to contaminated water, by mapping the distribution of cases of cholera in the city of London centred around a public water pump (Snow 1854). In the following two centuries the role of geography on health has been widely documented, although the interest in the topic was not constant over time. In the years running from the second world war to 1990s hardly any discipline studied directly the impact of local environment on health, probably as a consequence of the emergence of strong criticism to ecological analyses (in 1950 the study of Robinson on ecological fallacy first appeared). Beside this aspect, the dominance of individualism and the development of new methodological tools for collect and analyze individual data favoured a micro approach to the study of health (Macintyre *et al.* 2002). An exception were the studies of geographical mortality differentials carried out mainly in Italy and France (Nizard and Prioux 1975; Caselli and Egidi 1979; Caselli and Egidi 1981). Since the early 1990s the study of place effects on health was resumed and became the primary object of analysis for a large number of researches (Diez Roux 2001; Merlo *et al.* 2001; Subramanian *et al.* 2001; Cummins et al. 2005).

International research has also recently illustrated the importance of including in the analysis not only the *macro*, but also the *meso* level, which typically refers to the network of relations binding the individual to the people close to him/her in everyday life (Agneessens *et al.* 2006; Rivellini 2006).

The social/relational network influences individuals in terms of group identity, cultural background, social support; the geographical area of residence is responsible for exposure to environmental risk factors, economic deprivation, social conflicts and, in some cases, uneven health care provision. A limited number of studies about population health has formally made use of a hierarchical structure accounting for both social and geographical levels.

On the one hand, there is a sizeable number of works dealing with territorial inequality through a multilevel approach (Kennedy *et al.* 1998; Kawachi *et al.* 1999; Diez Roux 2001; Lynch *et al.* 2001; Merlo *et al.* 2001; Cummins *et al.* 2005; Olsen and Dahl 2007; Eikemo *et al.* 2008; Kreft and Doblhammer 2012; Pirani and Salvini 2012a, Pirani and Salvini 2012b). These studies consider jointly individuals and geographical areas (neighbourhoods, regions, countries), but the intermediate level of social proximity is generally not included in the analysis. On the other hand, works focused on communities, social groups or families are extremely scarce in the field of public health and they also concentrate on one single level, not considered in a more ample hierarchical structure (Minh *et al.* 2010).

Few studies considering geographical and social levels of aggregation exist, but their main objectives were always very specific. In some cases they just control for contextual effects (Subramanian *et al.* 2003), or they focus on the magnitude of contextual effects, without exploring possible causal mechanisms (Ferrer *et al.* 2005). Furthermore, the most of these studies are settled in Latin American and Asian countries, with once exception for the United States of America. All these countries have familial, territorial and health care organizations that differ substantially from the characteristics of the Italian and European context.

To the best of our knowledge, there are no European researches about contextual health determinants that look jointly to geographical and relational dimensions. This thesis aims at fill this gap, by looking at health determinants for the Italian adult population with a multilevel approach.

The geographical and social dimensions, extensively recognized as very influential, assume even greater relevance in a country like Italy. On the one hand, in fact, *family and community networks* assume for the whole area of Southern Europe including consistently Italy, Spain, Portugal and Greece, particular traits of originality and importance. These countries share common patterns of demographic phenomena, such as transition to adulthood, fertility, intergenerational exchanges, women labour market participation, insomuch that the model has been named after the region as “Southern model”. There are grounded reasons to believe then that the familial level could represent a factor of importance for health as well.

On the other hand, the *geographical area* of residence could also represent a significant determinant health in Italy, particularly from the perspective of health care provision. From 1995 the reorganization of the health care system has produced a decentralization of health financing and programming, with an increasing autonomy to Regions. This process has caused a heated debate on the risk of unequal opportunity of prevention and care for people living in different areas.

According to these premises, in this research the social proximity level was defined based on households, the group of people inhabiting the same house and linked by affective ties; the macro level was built up in order to capture potential differences in health care provision, thus Local Health Care providers (Aziende Sanitarie Locali – ASL) were selected as reference units. These represent the lowest level in the hierarchy of the National Health System, directly responsible for health care management and organization.

The Survey “Health conditions and use of health services 2004/2005” provided the information. Data in this survey are hierarchical structured in a way that is perfectly coherent with our conceptual structure: individuals are selected through a cluster sampling design where the household are the primary units of selection and, for each household, all the individuals are interviewed. Moreover, the sample is representative of the population at different levels of territorial disaggregation. The smallest level is the so-called “Large Area” (in Italian *Area Vasta*), which is a meaningful aggregation of ASL, for which the sample size is sufficient to produce reliable estimation. This territorial level was selected and used across the research, as it was the most appropriate to represent territorial diversities in health care provision.

The main objective of the whole work has been to study population health, valuing at most the information existing on different levels: individual, familial and territorial. This general goal has been achieved through three more specific objectives:

i) shed light on *determinants* of health *at different levels*, in order to produce a complete and accurate picture of what affects health perception among Italian adults;

ii) estimate the *magnitude of the contextual effect* , in order to gain a better understanding of the extent to which the context has relevance on self perceived health

iii) investigate the *household structures* in which familial effects are especially pronounced, in order to improve our comprehension of the mechanisms responsible for familial homogeneity in health.

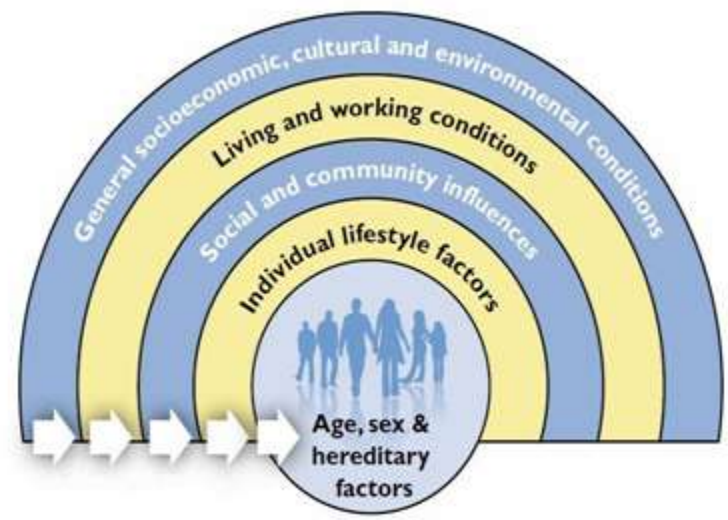
1. THE ROLE OF CONTEXT ON HEALTH

1.1 THE STUDY OF CONTEXTUAL DETERMINANTS OF HEALTH

Among the extensive literature on health inequalities, a salient role is covered by those factors not directly related to the individual, but attributable to what is generally called the "context".

With the word *context* we refer to a very broad and multidimensional concept, whose boundaries cannot exactly be defined. However, a good representation of the contextual factors influencing health is the "Policy Rainbow" (Fig. 1.1) proposed by Dahlgren and Whitehead in 1991.

Fig. 1.1 – The graphical representation of Context in the Policy Rainbow



The authors schematized the context as a series of concentric layers that influence individual health on a progressively wider perspective. At the core of the structure stands the person with his/her *fixed genetic characteristics* that determine the age, the biological sex and all the genetic pool. These characteristics are outside of the individual's personal control. Surrounding the genetic pool there are factors on which the person, or the society, can, in principle, intervene. The second layer is the level of *individual behaviors and lifestyle*: smoking or drinking habit, diet, physical exercise and health prevention are examples of factors pertaining to this dimension. The individual has a remarkable, though not complete, control on these aspects. Mutual support from *family, neighbors and the local community* comes next. At a higher level the *space of living and working* of a person has an influence on health, through the working environment (unemployment, physical or mental working stress, exposure to dangerous environmental factors) and the characteristics of the place of living (housing, food production, green spaces, health care services). Overall we find the *major structural environment*, represented by the socio-economic and cultural background where a person grows up and lives (Dahlgren and Whitehead, 1991). These four levels of influences had a remarkable value in the following studies about health inequality, because they can be seen as correspondent levels for potential policy interventions. To give some examples of level-oriented policies: at the lowest level health education programs can be implemented in order to improve positive attitude towards prevention, to increase screening participation or reduce risky behaviors; at the community level interventions should be aimed at strengthening the ties among families, relatives, friends and community members, which can have an important role in terms of social support. Interventions can improve the material and social conditions where people live and work, such as providing a higher quality of spaces, food and housing conditions, introducing proper measures for employment, social security, health services and welfare. At the top policy level there are all the long term structural changes, which regard the economic policies, the international environmental agreements, culture and norms that regulate the social life of a country (Diderichsen *et al.* 2001).

The study of health determinants has been traditionally approached from two alternative perspectives: the one of demography and that of social-epidemiology. The demographic perspectives, typical of European researches, has looked at factors affecting health at the macro level, whereas social-epidemiology, initially more wide spread in the USA, has focused on the individual risk factors. The two alternative perspectives eventually converged in a shared view of the issue, with the multilevel approach, in recent times (Kawachi *et al.* 2002; Merlo 2003).

The demographic interest in macro determinants of health dates back to the 1970s and 1980s when the first studies about geographical mortality differential emerged for France (Nizard and Prioux 1975), Italy (Caselli and Egidi 1979; Caselli and Egidi 1980) and Europe (Caselli and Egidi 1981). All these studies assumed explicitly that mortality could be affected by contextual factors that increase or, on the contrary, prevent the risk of death and that these factors could, at least partially, depend on the geographical area where the individual lives. These researches shared an ecological approach in which the units of analysis were geographical partitions rather than individuals. Standardized mortality ratios by geographical areas were compared, stratified by gender, age-classes and groups of causes of death, with no control over the individual characteristics. This was due not only to the demographic propensity for the study of populations as a whole, but also to the unavailability of individual data about mortality and health at that time. These studies consistently illustrated very high mortality variations, even at sub-national level, and in some cases they depicted a geography of mortality that was totally unexpected: it is the case of the highest mortality ratios for men in the economically developed and well-off North-East part of Italy (Caselli and Egidi 1979; Caselli and Egidi 1980).

On the contrary, the study of determinants of health inequalities in social-epidemiology at early stages has focused its attention persistently on individual characteristics: the personal network of social support, socio-economic position, life style and behavior. However, from the 1990s the research has gradually moved towards a more comprehensive position, recognizing that "the way we organize communities, working places, and our societies on the larger national and global scale cannot be understood or measured by looking solely at the individual" (Diderichsen *et al.* 2001). This perspective could have already been foreseen in the first stages of the research on health inequalities. In fact, even when research was focused solely on individual characteristics, some of the key findings gave, to some extent, an indication of contextual influences on health. The persistent gradient of poor health according to social position, to give a remarkable example, reflected the person's social standing within the society where s/he lived.

Convincing theories have been elaborated to explain the mechanisms through which the social position can affect health: people from different socio-economic levels can have different probabilities of being exposed to risk factors (*generalized susceptibility* theory by

Syme and Berkman 1976) or can have different levels of social support, barriers to health access and resources to overcome difficult circumstances, i.e. different *social vulnerability* (Cutter *et al.* 2003). Nevertheless the magnitude of the impact of SES on health varies substantially, according to the characteristics of the social context in which the person lives: the level of social stratification, the degree of inequity among groups, the welfare system, the extent of public or familial support.

Therefore, the individual socio-economic position has a very limited significance disregarding the social context that determines it. A cogent example is the relation between the degree of income inequality (at country level) and the magnitude of socio-economic gradient in health (at the individual level): health differences among social classes are more pronounced in countries where the inequality in income distribution is higher, as will be more extensively illustrated in the next paragraph.

1.2 GEOGRAPHICAL AREA AND HEALTH

One of the most straightforward interpretations of context is that of geographical areas. Mortality and morbidity vary dramatically according to geographical areas, even in the most developed and democratic countries. Differences in health among people living in different regions are tangible and persistent whatever the level of territorial disaggregation adopted: from the country level, (Kunst *et al.* 2005), to small areas, such as neighborhoods or census tracks (Stafford and McCarty 2000; Shaw *et al*. 1999).

We have no clear evidence about the factors causing territorial differences. This is partially due to the complex peculiarity of context analysis. The first challenge when investigating contextual inequalities is to disentangle the true contextual effects from compositional effects. In the study of territorial health inequality, this means understanding whether differences in health by area are due to macro territorial (contextual) features or to individual characteristics that are unevenly distributed between the regions (compositional features). This typically happens when people with a similar risk profile are grouped together in the same areas. The only method that allows us for the correct allocation of factors at the right level is a multilevel approach (cf. Chapter 3), which has been extensively qualified as the only proper method to study the effects of context. As Kawachi and colleagues effectively expressed in their Glossary for Health Inequalities: *"Indeed, any research on health inequalities that takes context and place seriously is intrinsically multilevel and cannot be otherwise"* (Kawachi *et al.* 2002).

A number of causal mechanisms have been proposed to explain the effect of residential geographical area on health. We briefly review the most relevant, citing the studies that better elucidated the determinants of health and, at the same time, specifying whether or not they made use of a multilevel approach.

Geographical health inequalities can stem from a wide range of potential determinants, generally grouped in the following three sets: (1) *physical determinants,* such as: air pollution, climate, industrial facilities, provision of green spaces, etc.; (2) *economic determinant,* frequently summarized by average income, rate of unemployment, the level of deprivation, and similar indicators; (3) *social determinant,* generally including levels of social capital, social cohesion and social control (Stafford and McCarty 2000). Furthermore, another set of determinants that has recently gained attention and deserves consideration is that of (4) *Health Care determinants*, which summarizes the health system availability and efficiency at the local level.

1.2.1 Physical Environment and Health

The study of physical environment and health is generally the main objective of environmental epidemiology, that branch of the discipline concerned with environmental exposure that produce an effect (either positive or negative) on health. A broad literature has dealt with specific environmental risk factors for related diseases, such as industrial areas and excess mortality (Martuzzi *et al.* 2002), natural fiber and mortality from chronic obstructive pulmonary disease (Biggeri *et al.* 2004), asbestos exposure and lung cancer (Balletta *et al.* 2012) or air pollution and asthma symptoms (Biggeri *et al.* 2012), just to cite some examples focused on Italy.

However, a limited number of studies, carried out mainly by Pearce and colleagues, have focused solely on an ample range of environmental characteristics of residential areas, to study their influences on health and their role as a potential determinant of health geographical inequalities. This group of researchers developed a first study of this kind focused on the United Kingdom, followed by a second one on New Zealand (Pearce *et al.* 2010; Pearce *et al.* 2011); both countries being characterized by a high level of spatial health heterogeneity. The main elements of novelty of these studies rely on the attempt of the authors to isolate the physical components and to capture in one synthetic measure the multi-factorial nature of the physical environment. They took into consideration a set of physical elements: pollution, geothermal areas, microbial contamination and drinking water, for each territorial unit defined as census tract. The authors found a modest, but significant, relationship between living in physically deprived environment and standardized mortality rates, for overall mortality (external causes excluded) and for cardiovascular and respiratory diseases. The associations remain stable even after controlling for economic deprivation of the neighborhoods. Although innovative, as far as the choice of isolation of physical determinants is concerned, these studies have an ecological approach, from which the variability due to contextual rather than compositional effects can not be detected.

1.2.2 Economic Environment and Health

The largest body of studies about geographical inequalities is focused on economic differences between places. Based on the undeniable evidence that at the individual level socio-economic position (whatever the indicator: education, income or occupation) is always associated with a health gradient, many authors paid attention to the study of the same determinants at regional level. These studies frequently make use of synthetic indexes and focus on the average income level (economic deprivation) or the level of inequalities in income distribution (income inequality). Despite this homogeneity in the definition of the economic context, these works present a broad range of health outcomes and apply a variety of methods to quantify the level of inequality (Gini index, Index of dissimilarity, slope index of inequality). However, coherent evidence has been provided in the last two decades.

Pritchett and Summers (1996) have been among the first researchers in showing the macro effects of income on population health. In their article, effectively titled “Wealthier is healthier”, they showed that an increase in a country’s income tends to improve its population’s health. Subsequent studies confirmed this intuition, by showing that the economic development is the macro variable most strongly associated with people's better health, even when the crude GDP is used as an indicator (Beckfield 2004; Fritzell and Lundberg 2005; Olsen and Dahl 2007).

In the same years a parallel line of research focused not just on the level of income, but more specifically on inequality in income distribution as a factor influencing various dimensions of health. Interest in health repercussions of unequal income distribution was engendered by the observation that income inequality was strongly associated with life expectancy among nine OECD nations (Wilkinson 1992). A few years later, Kennedy at al. (1998) illustrated how inequality in the distribution of income has an adverse effect on self perceived health in the 50 states of the United States, and reported that the effect was independent from the individual socio-economic status. Particularly, they demonstrated that the negative effects of an unequal income distribution are not limited to the lowest income group; in fact, in the study people in the middle income group tended to rate their health as poorer if they lived in a state with a high level of income inequality. A limitation of both studies is the absence of a multilevel approach, which obligates the authors to report the state's level of income/inequality as a characteristic of individuals living in that specific state. The study by Kennedy et al. was substantiated three years later using a multilevel approach and including country-level covariates (Subramanian *et al.* 2001). The findings of this new study did not exactly reproduce the previous results. The variation of health between States was found to be significant, but accounted for a very small portion of the overall variability (less than 5%). On the other hand, findings about the interaction of the State's income inequality and the individual socio-economic status showed the other side of the coin with respect to previous findings: the positive effect of income inequality on the most affluent people. High income individuals reported a health advantage from living in high inequality states, confirming the theory that the most affluent are better off in more unequal societies. Income inequality has been investigated also as a possible cause for health inequality between developed countries (Lynch *et al.* 2001). In this ecological study only the infant mortality rate appeared to be associated with the level of income inequality, whereas life expectancy, cause- and age-specific mortality and subjective health showed inconsistent associations with income distribution.

The large body of research about income inequality and health has been revised in 2009, through a meta-analysis of the studies published between 1995 and 2008. Only studies with a multilevel approach were included in the review. Results of this comprehensive review suggested a modest excess risk in mortality and poor health in presence of income inequality. However, the findings were found to be very heterogeneous between studies, one potential explanation being the presence of a threshold. Researchers have long supported the hypothesis that only exceeding a certain threshold of income inequality (Gini coefficient $\geq$ 30) an effect on health becomes appreciable. A merit of the study is the evaluation of the findings in the perspective of population impact: the population attributable fraction suggested that in the OECD countries about 9.6% of deaths (14 millions) could be avoided by leveling the Gini coefficient below the threshold value of 0.30 (Kondo *et al.* 2009).

Results for developing countries are consistent with those of the most developed countries, although the indicators that better highlight the existing inequalities can be very different, such as maternal and child health or rate of infectious diseases in China (Fang *et al.* 2010).

1.2.3 Social Environment and Health

Another set of contextual determinants, potentially very influential for health inequality, are those related to the social environment. The social environment describes the structure and characteristics of relationships among people within a community. One of such characteristics is the well-known *social capital*, a concept that grew out of sociology and proliferated in the study of health disparities. Social capital refers to a variety of social features, such as mutual trust, norms of reciprocity, social and political participation, that facilitate cooperation for mutual benefit and constitute a resource for the individuals (Kawachi *et al.* 1999). The literature posits three main dimensions of social capital: (1) *Bonding*, referring to links between people of a same group, thus, similar for some important characteristics; (2) *Bridging,* referring to links between people who do not belong to the same group and share involuntary associations, such as casual acquaintances, work relationships, daily life contacts; (3) *Linking*, referring to interactions of people across formal and institutionalized structure in the society, where the public authority is involved.

Bonding social capital is high where there is a consistent presence of religious, sport and volunteer associations or where a large proportion of people trusts families and neighbors;

whereas the trust in persons met for the first time or the fairness in payment of taxes are elements improving the *Bridging social capital*. The *Linking social capital* is observed in the extent to which people confide in police, courts and local authorities.

There is general consensus that shared social resources are an asset for health over and above the individual-level network of support. However, the research on this topic is hindered by a lack of standardized definition of social capital and valid international measurements. Different studies vary in the number of item proxies used for the definition of social capital. In order to try to capture the multidimensionality of the concept researchers usually adopt two or three indicators, analyzed separately or jointly in a synthetic measure. Kawachi *et al*. defined social capital for 39 US states by means of three indicators: level of interpersonal trust, reciprocity and membership in voluntary associations. They observed the association of each of these dimensions with self-rated health and reported a strong ecological association between mistrust and poor health (Kawachi *et al.* 1999). They addressed many plausible mechanisms for explaining the effect of social capital on health (e.g. cohesive communities promote health information more rapidly); nevertheless without individual level data they could not provide any conclusive evidence about the contextual effect of social capital on health.

A more comprehensive view was provided in a study by Elgar et al. (2011) where social capital was expressed by 17 items from the World Value Survey (WVS). The items were aggregated and weighted to create 4 main factors synthesizing social capital: Trust, Group Membership, Civic Responsibility and Linking. The authors used these factors to explain individual health differences among 50 countries worldwide, controlling for basic socio-demographic characteristics of individual (age, sex and education) in a multilevel model.

They did not report significant effects of social capital on health *per se*, however they clearly illustrated the moderating role of social capital on some socio-demographic determinants of health: the female disadvantage in health is more narrow in countries where social capital is higher, and the effect of ageing is stronger in low social capital context, whereas education acts as an independent predictor of perceived health, whose effect is not modified by the level of social capital. However, as in many other fields of research, the best practice for the investigation of the causal effect of a contextual factor is the multilevel approach and the longitudinal perspective. A review of perspective multilevel studies on social capital and health have been published recently (Murayama *et al.* 2012). The studies were mainly conducted in the western countries, with American studies focused on community social capital, whereas Scandinavian countries on work place. Results for self rated health were more consistent than for other health outcomes, i.e. mortality hospitalization and health-related behavior, corroborating the previous findings that high level individual and community social capital increase personal health status.

It is worth to remark that the social determinants also have a key role in the causal chain from economic background and health. In fact, when researchers have been asked to elucidate the pathways through which income inequality affects health, one of the most convincing mechanism proposed makes use of the concept of social capital: an unequal distribution of income can be responsible for erosion of social cohesion, and increasing social exclusion and conflict, which in turn have an adverse effect on individual health (Subramanian *et al.* 2001).

1.2.4 Public Interventions and Health

The public interventions are considered as an aspect that stands apart from the economic environment, since their magnitude and the efficacy are generally sparsely related to the overall economic situation of a country. The Health Care System is one of the pillars of any social security system, but the contribution of health care resources on population health status has been much debated (Joumard *et al.* 2008). Berger and Messer (2002) and Or (2000) claim that the health care system has played a remarkable role only until the early 1990s. However, the health resources are a wide concept and its effect on health status depends strongly from the component chose to represent this concept. Among OECD countries physical measures of health care resources are significant in explaining population health when human resources (i.e. *per capita* number of health care practitioners) are considered, but they show no effect if the indicator is the capital equipment (i.e. *per capita* number of beds) (Joumard *et al.* 2008). On the other hand, the monetary measures of health resources is more consistently associated with population health. Significant effect of health expenditure on health status has been reported by Hitris and Posnet (1992), but an increase in health services utilization has been found non influential in lowering population mortality in the USA (Thornton 2002).

An issue is the "value for money" associated with health expenditure. Joumard *et al.* (2008) in their study about OECD countries extensively demonstrated as "no relation exists between relative efficiency performance and the level of health spending." They found among the best performers in terms of efficiency both high- and low- spending countries, such as Australia and Korea, respectively.

The efficiency and effectiveness of a health system vary according to two main aspects: (1) the Welfare Regime typology and (2) the organizational structure of National Health Systems.

The welfare state typologies are especially relevant in explaining the differences between countries, as "it is now widely acknowledged that they mediate the extent, and impact, of socio-economic position on health" (Eikemo *et al.* 2008). As already shown, socio-economic inequalities are the main factors responsible for health inequalities in Europe. The welfare states are designed to intervene on the social stratification, operate economic transfers, by means of income redistribution and providing social services; therefore they are important mediators of the effects of socio-economic position on health. The extent and the modalities of intervention vary greatly from country to country. Researchers have long tried to classify the welfare regimes in broad categories, based on the main characteristics.

Probably the most influential classification is the one provided by Esping-Andersen in "The Three Worlds of Welfare State Capitalism" (1990). He defined three categories of welfare: Liberal, Conservative and Socio-Democratic, according to three principles: *decommodification* (the strength of social entitlements and the degree of immunization of individuals from the market), *social stratification* (the role of welfare states in maintaining or breaking down social stratification), and the *private-public mix* (the combination of state, the family and the market in welfare provision).

Using this classifications, countries can be clustered according to their welfare regime. In a very simplified scheme: Liberal are those countries (United Kingdom, Ireland) characterized by the dominance of the market, minimum levels of social transfers, and an important role played by private insurances. Conservative welfares are distinguished by a wide coverage, but a tendency to maintain existing social patters (e.g. transfers are earnings-related) and social stratification (Germany, Italy, Austria, France). In the Socio-Democratic countries (Scandinavian) there is a universal coverage, the entitlements are very generous and the intervention of government is substantial and oriented at promoting social equality through a redistributive Social Security System.

There are not many studies highlighting the geographical differences in health related to welfare regimes. A remarkable exception is the study by Eikemo *et al*. (2008) about differences in self perceived health between European countries, according to their welfare regimes. In this research the authors first estimated the proportion of inequalities due to the country, and then analyzed whether the types of welfare regimes explain the differences between countries.

In this study the classification of welfare regimes represents a more detailed version of the Esping-Andersen one (5 classes: Scandinavian, Anglo-Saxon, Bismarkian, Southern and Eastern regimes). They found that around 10% of the total variability in health of the European population could be attributed to countries, while the regional intra-country variation was almost non existent. The countries with Scandinavian and Anglo-Saxon welfare regime typology showed better perceived health than countries with Southern and Eastern regimes. The study, however, is not without limitations, since it is well documented that health perception is an indicator affected by cultural circumstances (Jylha *et al.* 1998). Furthermore, the type of Welfare Regime is the only variable included at the country-level. Other not negligible sources of difference between countries do exist and they need to be taken into serious consideration when the aim is to reliably identify what causes international diversities in health. GDP and expenditure on elderly care, for example, have been found significantly associated with Healthy Life Years (HLY) in 25 EU countries (Jagger *et al.* 2008). Furthermore, the information gained from the typology of Welfare Regime is not complete. The Welfare Regimes represent the overall level of social security in a country, but the Health Care Systems has some specificities that can detach themselves, even substantially, from the country's Welfare Regime (e.g. the United Kingdom NHS has a universal compulsory coverage, despite the country Liberal Welfare States). Furthermore the vast majority of developed countries have undertaken a health care reforms from the 1990s, driven by the necessity of containing costs, which have been constantly increasing due to demographic change, population demand and advances in medical techniques. The measures included in the health reform vary substantially from country to country: the main difference is in the fact that some countries have just designed measures to manage rising costs, whereas others have included a "reset of priorities", passing from a prevalent tertiary interventions (curative medicine) to prevention and promotion of public health (OECD 2011).

The second element we mentioned as potentially affecting health is the organization of Health Care System. The main organizational characteristic is the degree of centralization. The health planning, financing and decision-making can be very centralized, disposed by one authority at the national level, or they could be extensively decentralized, distributed to local authorities, with varying levels of autonomy in health planning and financing.

In the last 20 years the issue of decentralization has long been at the centre of debate in many countries, especially in Europe.

The aim of most of the countries is to minimize regional differences in health within their boundaries; however, how the organization of the Health System can contribute to the achievement of this goal remains unclear. Decentralization was originally designed to guarantee more efficiency to the Health Care System, but some researchers think that it increased health inequalities. Decentralization, in fact, can result in an unequal distribution of services between the various regions and, consequently, in diverse opportunities of prevention and cure for citizens, living in different places.

However, the same accusation has been addressed to the over-centralized systems. The Health System of Hungary was heavily criticized in the early 90s, because the extremely centralized health administration and the rigid regional functional structure were seen as responsible for the high geographical health inequality in the country, after the Second World War (Orosz 1990).

Similar criticism have been made about Portugal: this country has experienced about 30 years of a National Health Care System, nonetheless geographical health differences, especially among the elderly, persist within the country. Poor accessibility to health care facilities have been identified as the main reason for these differences: geographical location of health care facilities is uneven in Portugal and it affects the ease of access of the population, influencing utilization patterns (Santana 2000).

In a study published in 1990, the effects of decentralization on health have been painstakingly examined by comparing Finland and Norway (Salmela 1993). The two countries, in fact, have very similar geographical, administrative and demographic characteristics, but different degrees of decentralization of the NHS: Finland has a more centralized government of health, while Norway is characterized by a decentralized structure of the Health System, which gives more independence to municipalities in local decision making. The authors were interested in examining whether a more centralized system, like the Finnish one, was able to provide a higher level of homogeneity in health and a more balanced regional supply of health services. They concluded that there was no evidence of substantial differences in mortality and morbidity between the two countries, despite their differently organized systems. In both countries they reported a non-negligible level of geographical inequality, and, paradoxically, more and better health services where the conditions were best, referring to this phenomenon as the "Inverse care Law".

Although the role of centralization is not clear, the relationship between health outcomes and health supply is undisputed, and this is even more evident in developing countries. In these countries, in fact, the rapid improvement in life expectancies has increased the level of health inequality, and the discrepancies of health care facilities between regions are more pronounced. These two factors have favored the conditions to appreciate the role of health supply in determining individual health. This is particularly evident in the work of Fang (2010), where different health outcomes and different health resources were related through Canonical Correlation Analysis. Among the main findings, maternal and child health in China resulted as being strictly associated with health workforce, health spending and health care services.

This overview shows the deep relevance of geographical area as a determinant of individual health, both at the country and within country levels. Although we do not yet know what characteristics of regions are more influential on health (physical, economic, social or those related to health facilities), we can reasonably assume that residential area jeopardizes people's health.

1.3 FAMILY AND HEALTH

The sociological definition of family is "the unit comprising a man and a woman living together with their children (nuclear family), and potentially with other members (extended family)" (Abercrombie *et al.* 2000). However, Social Sciences have looked at the family more broadly, referring to the ample network of kin and relations that characterized a group of individuals linked by consanguinity, affinity and/or co-residence. This is a very theoretical definition and when researchers need to bring the concept of family into effect they make use of empirical criteria that span from marriage/blood (Census Family in the USA) to co-residence (Household), from spatial distances to frequency of contacts between family members, according to the intent of the research.

Whatever the empirical definition, the family has shown a prominent role in explaining the pattern of various socio-economic phenomena (see the *New Home Economics* , founded by Becker and Mincer in 1960). Despite the many structural changes family has experienced in the last decades, it is still recognized as the first unit of social aggregation, entitled to crucial functions, such as biological reproduction, emotional development, organization of roles and *socialization* (the process that enables children to function as members of their own society) (Lawson and Garrod, 2001). Furthermore, the family is the predominant setting for the inter-exchange of resources finalized to satisfy the individual's needs and to attain wellbeing. In this perspective, the family has always had a key role in supporting its members in those specific critical periods of their lifetime when they need assistance: infancy and childhood, adolescence, state of unemployment, old age and all those periods of life affected by disability/illness (Ongaro and Castiglioni 2000). It is precisely in the family that illness and poor health occur and are potentially resolved. Family can thus be considered as a primary unit in health and health care.

Family members exhibit similar patterns of morbidity over time (Ferrer *et al.* 2005; Van Minh *at al.* 2010), help-seeking behavior (Cardol *et al*. 2005) and utilization of health services (Sepheri *et al*. 2008). The family is, in fact, actively involved in the whole process of defining whether a member is sick or not, appointing the sick and the care-givers roles, providing the first care, precipitating the initial steps for seeking for formal care and utilization of the necessary available care (Litman 1974). Many different factors and patterns are involved in the relationship between family and health.

The Family can affect health in two main areas: the occurrence of illness and the assistance thereof. We can therefore divide the factors into two groups, according to these two areas. Obviously some determinants can operate on both dimensions (e.g. a low socio-economic family status can increase family vulnerability to diseases and, at the same time, can reduce treatment opportunity).

However, in order to have an overall view of previous research in this field, we will follow the aforementioned classification, bearing in mind that the two dimensions do not necessarily exclude each other.

1.3.1 Socio - Epidemiological determinants

Under this group of determinants we consider the hereditary links, causal agents or source of communication of the disease process. The genetic factors are the first and the most intuitive determinants of illnesses, however they cannot be considered as the main agent for similar familial disease patterns. Fairly consistent evidence has reported the highest level of resilience between spouses, rather than siblings or parent-children. This questions the theory that most of the influence lies in genetic factors.

A part from the genetic factors, the family members usually share a similar life-style, in terms of both risk and protective behaviors. The smoking and drinking habits have been shown to have a familial component (Rice *et al.* 1998), and the members of a same family exhibit similar behaviors in nutrition, physical exercise, but also participation in screening programs and preventive care.

Another important contribution stemmed from the *New Home Economics*, that extended the economic approach to many other field of human life and behavior, including family decision, and centered on households rather than on individuals. According to this theory households were assumed to desire different kinds of satisfaction, which are not necessarily economic goods, rather they can take the form of bright and successful children, ample leisure time and relaxation. The NHE posits that households do not purchase these new goods from the market; rather they produce them by combining procured goods and their own time and capacities. In this production process, the ultimate goal is to produce the elements of satisfaction of the family. Health can be seen as one of the elements of household satisfaction, and in this perspective the household can produce health for its member by combining existing resources (clinics, hospitals, screening programs), technologies and information with their (internal) knowledge, skills, norms and behaviors in order to promote, maintain and restore the health of its members (Berman *et al.* 1994).

1.3.2 Formal and Informal care determinants

Given the onset of poor health, the process that defines the patient's illness and leads to care encompasses a series of decisions and events that occur within a family unit. The healthcare seeking behavior, the compliance to the treatment, the utilization of health services strictly depend on the familial approach to health and health care (Schor *et al.* 1987) and a number of studies have clearly illustrated the extent to which also public interventions rely on the compliance of families to become effective. A large body of research, mostly dated from 1970s and 1980s, has focused on the familial pattern of health utilization, providing empirical support to the hypothesis that members of the same family would exhibit similar rates of health-seeking behavior and utilization of health services, especially when children are involved. In the following decades the individualization theory and evidence based medicine have limited the idea of family medicine, and there have been very little research where the family was the unit of analysis. However, in most recent years, some studies have resumed the idea of family as the basic unit for the study of illness and cure. These studies have reported consistent findings of resemblance of family members both in developed and in developing countries, about various health-related phenomena: e.g. the frequency of contacts with general practitioners clusters within families in the Netherlands (Cardol *et al.* 2008), and the individual propensity to seek treatment is jointly influenced by individual and household characteristics in Vietnam (Sepehri *et al.* 2005).

Besides the aspects of utilization of health care, the family can provide direct assistance to its members, through informal care giving. Of special note is the fact that, in this case, just as the family may affect its members' recover, so can the members illness affect the family, in terms of well-being, functioning and health itself. The extent to which illness of one member has an effect on the family's health, is expected to be a function of the nature of the illness itself, the family structure, the intensity of ties and other observable and unobservable familial characteristics.

However this is a largely unexplored field and calls for further investigation.

These two contextual factors engender influences that, although always significant, vary largely worldwide, depending on country specificities. In the following paragraph we illustrate the role of these two elements in the Italian setting.

1.4 CONTEXTUAL DETERMINANTS OF HEALTH: THE CASE OF ITALY

Italy is characterized by several peculiarities both concerning the geographical profile and the family role in an ample set of demographic and social phenomena.

As a consequence, in Italy, both territory and family are found to exert an influence on socio-demographic outcomes that is frequently larger than in other countries. This is primarily due to the marked North-South divide, characterizing the country under various perspectives (including health) and to the solid and influential familial structure, typical of the "Southern Model". In the following paragraphs we describe the core characteristics of the National Health System and its decentralized organization, in order to highlight the importance of investigating the geographical dimension on health. We review the existing evidence concerning the geographical health inequality in Italy and conclude by underlining the lack of specific studies on family and health for the Italian context.

1.4.1 Italian National Health Service: history and characteristics

The Italian National Health Service (NHS) came into existence in 1978, replacing a mosaic of employment-based health insurances, that together constituted the corporate system characterizing Italy for more than three decades after the Second World War. The employment-based health insurances used to differ substantially one from the other in terms of costs, benefits, coverage and economic solidity, leading to an overall health system characterized by many limitations, such as distributional distortion, inefficiency and influence peddling (Taroni, 2011: 66).

The NHS was created with the explicit intent of overcoming these limitations and it was inspired by principles of universality, i.e. the right to health based on citizenship, rather than on working category; *equity* both social and territorial; *integration* of health services into specific local units called Aziende Sanitarie Locali (ASL) and *programming* of health organization, i.e. policies financing and interventions (Egidi and Reynaud 2005).

The National Health System was designed to be financed through universal public taxation, and the monetary contribution of each individual should not be related to his/her risk of illness in any way (principle of *shared risk*).

Although supported by strong ideology and ample public consensus, the Health Reform did not become immediately effective: the mechanisms for the new system to become effective were unclear and the deadlines were fixed with scanty realism. Furthermore, the cooperation of different agents (central administration, regions and local units) was still insufficient, and they were not able to produce reliable health programs, as it was supposed in the Reform. It took more than ten years and two additional reforms to the NHS to become autonomous and functioning.

In 1980s and 1990s Italy, together with the whole Europe, faced a season of important challenges to the welfare system, due essentially to the slow down of the economic growth, after a period of expansion, and to the increasing proportion of elderly over working age population. Both the factors were easily predicted to entail major economic problems to the balance of public transfers.

As a response to the urgent need of reducing public expenditure in 1992 a second health reform introduced principles of managerial efficiency, concurrence and regionalization.

The main features of this reform included the enlargement of ASL autonomy of and changes in their financial organization. The local health care providers (ASL) in fact were titled with legal personality and appointed of specific responsibilities in meet the health care need of their target population. At the same time the economic organization of ASL was re-shaped according to characteristics of the private market, in terms of economic accounting and management (e.g. ASL directors were hired with temporary contracts and managerial functions). More importantly, Regions were appointed with the responsibility of guaranteeing appropriate health assistance to their population and to find resources to fulfill this objective.

The last step of the reform took place in 1999 and became effective from the year 2000. In this passage the central government of health was properly delineated, through the definition of the essential level of assistance (Livelli Essenziali di Assistenza, LEA). These consisted of basic health services that must be ensured to the citizens on the whole national territory. The introduction of LEA was thought to protect the principle of territorial equity. At the same time, however, the third reform expanded the decentralization of the Health care system, increasing regional responsibility in terms of health policy.

At the beginning of the new millennium, two final steps occurred that led to the ultimate asset of the NHS: the first was the fiscal federalism, which entitled the Regions to contribute to their health expenses through autonomous taxation, and to increase the number of available services for their citizens, according to the economic possibilities. The second was the reform of the Italian Constitution (the Title V), which redistributed the legislative functions between State and Regions, and allowed the Regions to produce autonomous legislation for health policy.

The Italian National Health Service resulting by this long process of reforms and institutional changes is structured on three hierarchical levels: two levels of governance (State and Regions) and one level of management (ASL). It is financed by public taxation and it presents a centralized control together with a characteristics of strong federalism. The central governance produces the guidance in term of national health program, defines the priorities and guarantees homogeneity in the basic levels of assistance within the national boundaries; at the same time, the decentralization promotes the regional autonomy in defining, financing and managing the health care facilities. The Region operates through the ASL in transforming the economic resources in public health service for its population.

The decentralization process has alimented a heated debate concerning the risk for territorial health inequality. Designed to guarantee more efficiency, the health reform could incidentally entail increasing differences between regions. The forecast that health expenditure will be entirely financed by Regions, without any national adjustment, has further increased the concern about health equality (Egidi and Reynaud 2005).

1.4.2 Territorial health inequality in Italy: a critical review

Italy is a country characterized by sharp and persistent territorial differences. A North-South divide is generally observed not only for economic aspects, such as productivity, income and employment, but also concerning socio-demographic behaviors as well as environmental and climatic conditions. Health makes no exception, although its geographical pattern is more complex and changes considerably according to health indicators.

A geography of mortality according to Italian Regions (NUTS-2) and provinces (NUTS-3) has extensively been documented (Caselli and Egidi 1979; Lipsi and Caselli 2002, Divino *et al.* 2009): authors consistently reported two very clear spatial trends according to gender. Men were traditionally characterized by higher standardized rates of mortality in the North-East of Italy and more favorable conditions in the South, while women presented the highest mortality rates in Campania and Sicily (Regions from Southern area) and the most favorable conditions in the Centre. These territorial differences especially emerged when the authors made use of NUTS-3 units. The geography of mortality for men exhibits a trend that seems to support the hypothesis of an opposite association between economic development and longevity. However, this result was especially pronounced in the 1970s; later on, substantial improvements in life expectancy occurred with a marked territorial heterogeneity, and contributed to reduce the mortality differences (Lipsi and Caselli 2002). However, territorial inequality seem to persist in terms of avoidable mortality (Prometeo 2001, Quercioli *et al.* 2013), with a geography that overlaps the overall mortality trends. Differently, if we look at the infant mortality rates Southern Regions have an overwhelming disadvantage compared to the Northern ones, with rates that vary from 4.8 deaths per thousand in Sicily to 2.0 in Piedmont (North West)[3].

Territorial differences can be observed also for objective health conditions: e.g. age-specific multi-chronicity prevalence, standardized disability rates and disability-free life expectancy have sharp geographical variations, that come back to depict the traditional North-South gradient (Fig. 1.2 and Fig. 1.3).

[3] Data refer to female infant mortality rate for the year 2009 (source: ISTAT –Health for all)

Fig. 1.2 – Prevalence of 3+ chronic conditions in Italian regions for males (left) and females (right) – 2009

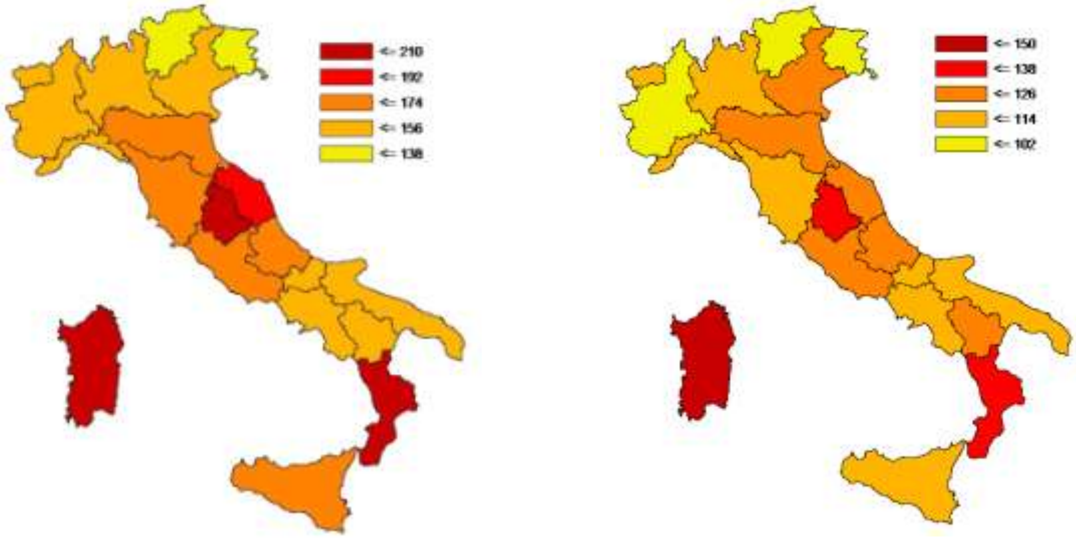
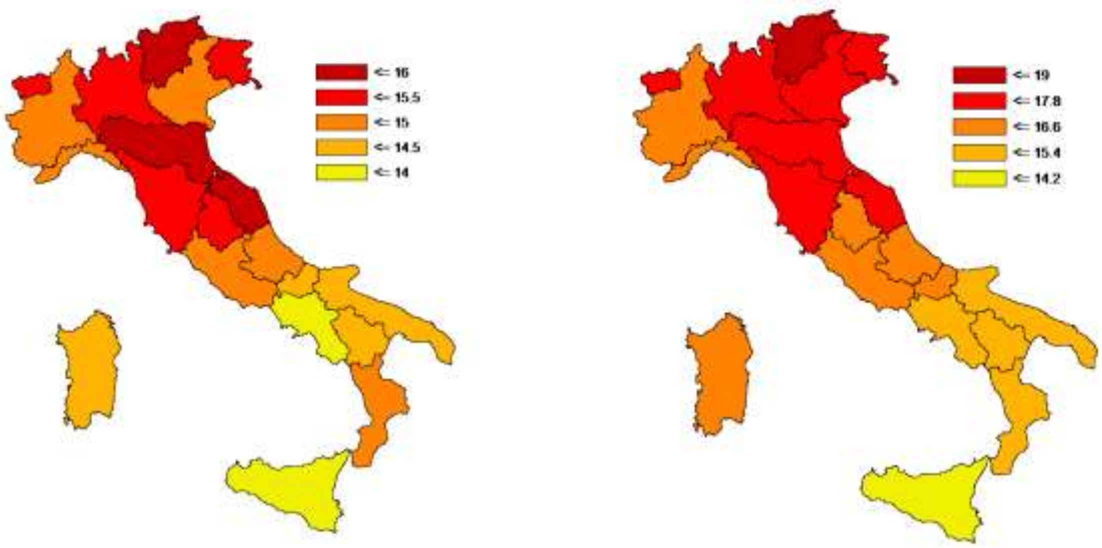


Fig. 1.3 - Prevalence of disability among population 65+ in Italian regions for males (left) and females (right) - 2009



Source: ISTAT – Health for All database

However, the majority of researches about health territorial inequality have focused on self-perceived health, assessed by means of three indicators: Physical Component Summary (PCS), Mental Component Summary (MCS) and Poor Self-Perceived Health (Poor-SPH)[4]. The last

[4] A detailed definition of these health indicators can be found in Chapter 3.

indicator is the most wide spread in literature for its easiness in administration and its consistent predictive power on mortality (Idler and Benyamini 1997; Egidi and Spizzichino 2007).

Self-perceived health exhibits a territorial heterogeneity that can be detected at different levels of disaggregation: differences between Italian macro areas (corresponding to NUTS-1): North-West, North-East, Centre, South and Islands, are consistently found and show a regular spatial pattern. A clear example is the percentage of elderly who report poor and very poor self-perceived health, which is 16% in the North, 22% in the Centre and it peaks in the South with a value of 25% (Pirani and Salvini 2012a). Frequently studies that account for these differences are not limited to the description of geographical trends, but they attempt to isolate and assess the impact of the area through specific explicative analyses with individual data (Egidi and Spizzichino 2007; Ongaro and Salvini 2009). In these works, geographical residence steadily shows a significant negative effect influencing people living in the Centre and in the South compared to those residing in the Northern areas.

From the Regional perspective the result is substantially analogous: in 2005 the lowest prevalence of poor and very poor health (3.1%) is observed in the Northern Region of Trentino, whereas the highest is in Sicily (7.3%) as reported by Mazzuco (2009)[5].

A similar figure is presented by Costa *et al*. (2003) although the differences between Regions are smoothed by the use of PCS and MCS indicators.

Some recent studies further investigated the geographical effect isolating the area of residence from individual confounders, through the use of multilevel models. Regional influences on health are in these studies estimated as autonomous factors, net from the effect of individual differences between areas (Costa *et al.* 2003; Pirani and Salvini 2012a; Pirani and Salvini 2012b).

Results from these works produced a significant extension of our knowledge about territorial health inequality. In fact, although confirming the existence of a geography of health, they consistently prove that a very limited part of variability (ranging from 1% to 3%) is to be attributed to territorial differences (Salvini e Pirani 2012b).

[5] Rates are standardized by age using the population at 2001 Census.

1.4.3 The family in Italy: what role on health?

A huge literature has dealt with the role of family on demographic behaviors. The review of such a vast scientific production would exceed the scope of this research.

What we here intend to underline is that the importance that family ties have demonstrated for well-known demographic phenomena, such as fertility, leaving parental house, economic conditions, can be hypothesized as extendable to health issue.

As already shown[6] for other countries, family members have similar patterns of specific morbidity, health care utilization and health behaviors. Therefore we can expect a major influence of family on health perception as well. Despite the immediateness of this hypothesis, the subject has been hardly ever taken into consideration for the Italian context (and rarely for other countries too). Marital status and patterns of family disruption have been extensively analyzed and they proved to be remarkable predictors of health; however the family as a whole and its role on health did not appear yet in the *health demographer*'s agenda.

An exception is represented by the emerging studies that deal with the burden of care-giving on family members (Ory *et al.* 2000; Bookwala and Shulz 2000; Vlachantoni 2010; Egidi *et al.* 2013). They give a picture of economic and health consequences of care-giving activities, in terms of well being and labor market participation of carers (Vlachantoni 2010) or psychological stressors (Bookwala and Shulz 2000). In other cases, they evaluated more specifically the consequences on health for people living with a person affected by dementia (Ory *et al.* 2000; Egidi *et al.* 2013) giving proof of a non negligible impact on self perceived health especially for people in the youngest age groups, up to age 64, when the demand for care of the dement conflicts with familial and social roles and for couples living alone, for which the burden of care is faced by one single person.

This line of research is quite recent and it paves the street for enriching further developments, however, what has been done so far represents a very specific perspective from which the role of family on health can be observed.

We do believe that a more ample and comprehensive description can be provided, considering the family as a level in the hierarchical structure of health determinants.

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[6] cf. paragraph 2.2

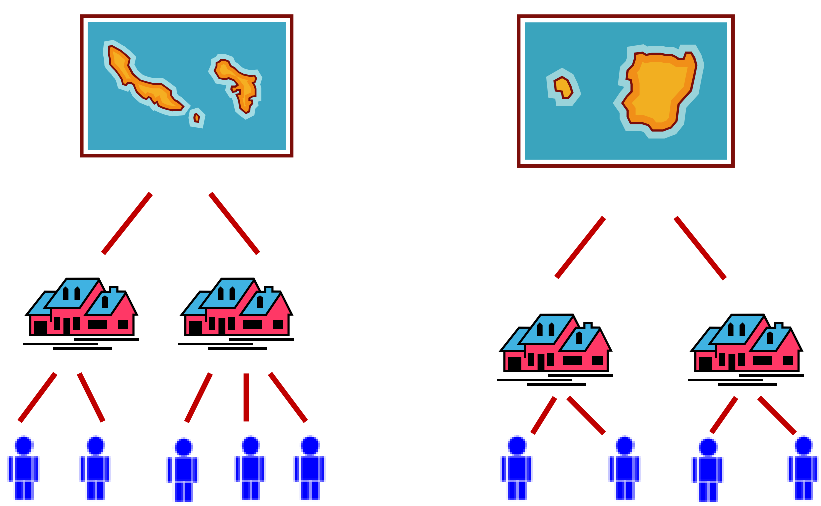
2. DESIGN OF THE STUDY

2.1 OBJECTIVE OF THE RESEARCH

The primary goal of this project is to produce a reliable estimation of the impact of two contextual factors, place of living and household, on individual health. As presented before (cf. Chapter 1) place of living and household are two remarkable dimensions of the conceptual construct of "*Context*". Place of living summarizes the differences between geographical areas in terms of healthcare service availability , socioeconomic environment, social capital, cultural background and exposition to environmental risk factors; household, on the other hand, represents the first social unit, with a prominent influence on health of its members as they share physical and social environment, behaviors and, to some extent, genetic factors. Furthermore, the family is characterized by networks of economic and emotional support, care, affinities and a sense of group identity, which make unique the interfamilial relationships.

Place of living and household can be easily schematized as two nested levels, on a hierarchical structure having at the bottom the individual (Fig. 2.1)

Fig. 2.1 - Conceptual hierarchical structure of context in this research



The magnitude of place of living and household on health can be assessed through the use of Multilevel Models: these tools are, in fact, able to estimate the amount of variability attributable to each level in the hierarchical model (individual, household, area of residence), controlling for compositional biases (e.g. the geographical uneven distribution of individuals by age).

A second objective was to explore the determinants of health, considering jointly individual and contextual characteristics. Again, the multilevel framework rushes in our aid, allowing for estimations of effects which are not biased by the correlation of units in the same group. In particular, within the household level, we wanted to test the hypothesis of the existence of mechanisms of reciprocal influences between the household components, resulting in higher health homogeneity inside the family; this has been done through a focus on the magnitude of health homogeneity by family structure.

Along with these main objectives, there have been more specific goals carried out in the developing of the work. Concerning the geographical distribution of health in Italy, we have also illustrated the overall level of heterogeneity, and its trend through the last decades, with the aim of indentifying whether a health is experiencing a convergence or a divergence process as a response to the decentralization of Health care system.

2.2 DATA CHARACTERISTICS

2.2.1 The Italian Health Interview Survey

The whole research is a population-based, cross sectional study. Data come from the Italian Health Interview Survey, for the years 2004/2005. This survey is carried out by the Italian National Institute of Statistics (ISTAT) with the specific name of “Health conditions and use of health services” (“Condizioni di salute e ricorso ai servizi sanitari”). It is a component of the articulated system of social surveys called “Multipurpose Surveys’ System”, begun in 1993 and designed for the production of comprehensive information on individuals and families. This information produces the informative base about the socio-demographic characteristics of the Country, and, integrated with those drawn from administrative and businesses sources, give a comprehensive picture of the Italian demographic, social and economic characteristics. The

Multipurpose Surveys' System consists of seven surveys covering the most important social issues:

- 1 Survey about Aspects of daily life (*yearly*)
- 1 survey about Tourism (*quarterly*)
- 5 thematic surveys: Health conditions and use of health services, Citizens and Leisure, Safety of citizens, Families and social subjects, Use of time (*rotating on a 5-year period*)

"Health Conditions and use of health services" has the main characteristics of a Health Interview Survey (HIS): it collects data on a broad range of health topics, through personal household interviews. Health Interview Survey (HIS) are carried out in all the most developed countries[7] and in many developing countries. HIS are especially relevant for that information that cannot be gathered routinely though registers or sentinel surveillance programs, but can be collected directly from the general population. From the '80s the European Union is especially promoting the developing and harmonization of the Health Interview Survey, in order to have comparable information for developing communitarian health programs.

The Italian HIS provides data concerning health status, health care utilization, prevention and risk factors, as well as social, demographic and structural information about the family and its components. Properly trained interviewers collect information about all the members of the household through face to face personal interviews at the family's house. Data related to health conditions and sensitive questions are collected though self-reported questionnaires.

The survey has a data collection structure based on quarters, covering a one-year time frame (from October 2004 to September 2005), in order to control from seasonality of some health phenomena. The sample selection follows a two-stage stratified sample design, based on municipalities and households. Municipalities are stratified in two groups depending on the population size: auto-representatives and non-auto-representative[8]. The former are always

[7] With some exceptions: HIS are not carried out in Greece (only regional surveys), Luxemburg, Ireland and Iceland (Hupkens 1999).

[8] Autorepresentatives and Non-autorepresentatives municipalities are defined on the base of a minimum number of residents (λ), varying between the sampling domains – r -according to the minimum

In the second stage, for each selected municipality, ISTAT operates a cluster sampling, with clusters represented by household. They are selected randomly from municipalities' registries. The non response rate is 14%.

The final sample is representative of the population at National and Regional (NUTS-2) levels. However, from 1999 the sample size has been considerably increased, passing from 24.000 to 60.000 families, in order to extend the representativeness at sub-regional level. The sub-regional domain had been identified as "Large Areas": a territorial unit, based on Local Health Care provides, constituting a unit for health planning.

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number of families to be interviewed(m_r), the average size of the families (δ_r) and the sampling fraction (f_r) of each domain

2.2.2 *Definition of the contextual levels: Household and Large Areas*

Our levels of analysis have been defined in order to represent the level of social proximity and that of territorial aggregation. Data from the Italian HIS provided data that fulfill coherently this conceptual framework. We therefore defined the two levels of the hierarchical structure as:

- *Household*: the group of people cohabiting and related by marriage, kinship, adoption or sentiment (a definition commonly referred to as Cohabiting Household)[9]. Institutionalized people are therefore not included in the analysis, as well as people living together with no sentimental relationship (e.g. cohabiting formal caregivers).
- *Large Areas* are projected to be an aggregation of neighboring Local Health Providers (Aziende Sanitarie Locali - ASL), constituting a unit for local health planning. However, this criterion was relaxed when these domains were practically identified: Large Areas are currently obtained as an aggregation of different kind of administrative units: Local Health Care Providers (ASL), which in many cases correspond with the territorial boundaries of Italian provinces a(NUTS-3)[10].

There are 68 Large Areas characterized by statistically comparable population size (Fig.2.2): the average size is 850,000 inhabitants, ranging from a minimum of 120,000 in Valle d'Aosta (the Region at the top North-West) to a maximum of 2,474,376 in Lombardia_2 (the area corresponding to the hinterland of the city of Milan).The list of Large Areas with population dimension is reported in Appendix A1.

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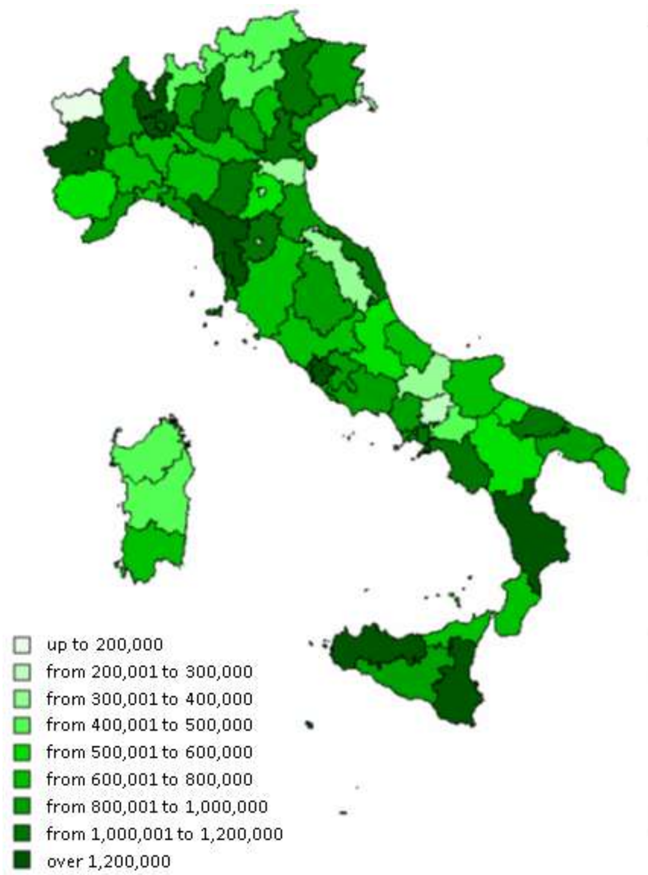
[9] This definition was introduced with the *Regolamento Anagrafico* (Residential Registry Regulations) of 1989 and substituted the previous definition that, including aspects of the household's economics, presented problems of comparability.

[10] An exception are Large Areas Marche_1 and Marche_2 where the criterion of aggregation of ASL was the municipality's altitude.

Fig. 2.2 - Large Areas by population size



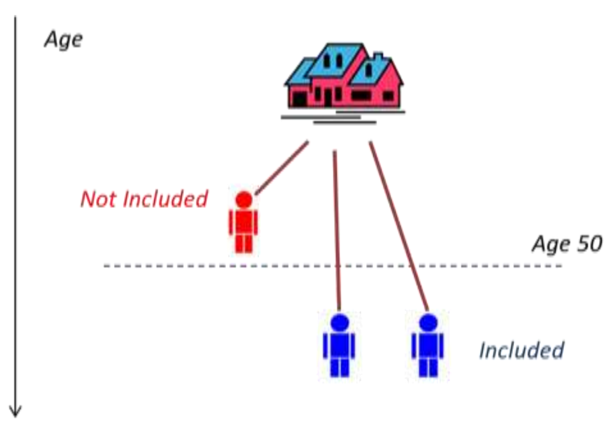
Source: our adaptation from: ISTAT, Methodological notes to the Multipurpose Survey 2004

2.3 SAMPLE SELECTION

We operated a sample selection including people aged 18 and over, living in households with at least 2 components. The reasons for this selection rely on data characteristics and on research conceptual assumptions.

People living alone were excluded from the analysis as they did not fit the research objective of investigating the effects of household on health. Concerning age, selection of age 18 was selected as a compromise between two requirements going in opposite directions. The first requirement was to keep age as low as possible to include the most of the family members, without loosing any information dropping out individuals from the household; on the other hand, age had to be sufficiently high to guarantee reliability of the variables in the study. Self-rated health (as many other variables in the questionnaire) is, in fact, not accurate for child ages, as parents act frequently as respondents on behalf of their children. Thus, we selected age 18 as threshold to guarantee personal reports on the questionnaire. The age of 18 is in Italy the age of majority, when legal control and responsibilities of parents formally terminate. We expect from that age onward the risk of proxy responses to be negligible (or comparable to the rest of the sample). Furthermore, many social covariates, such as unemployment and education, are collected only from age 18 onward.

Fig. 2.3 – Inclusion criteria according to age



2.4 SELECTION OF VARIABLES

2.4.1 Health outcome measurements

The research is focused on population heath, therefore we sought for an outcome that could properly capture the multidimensionality of this phenomenon (Patrick, 1993), but at the same time that was handy, easy to understand and to administer in a large sample setting.

Both in the field of public health and in more specific clinical studies, a large number of measurements have been developed for tracking population health status.

Although the World Health Organization (WHO) defined health very broadly as long as a half century ago, health has traditionally been measured narrowly and in the negative direction (Centers for Disease Control and Prevention 2000). What was traditionally measured was ill health in its severe manifestations, those which are verifiable through physical examination and other objective procedures or tests. Mortality and morbidity have been the main measurements of health for a very long period. Such traditional measures provide information about the lowest levels of health, but they reveal little about other important aspects of an individual's or a community's level of health, including dysfunction and disability associated with diseases, injuries, emotional status and quality of life.

From the 1980s, these approach to health was found insufficient and researchers begun to look for measurements to supplement the lack of information about health. A more positive perspective about health developed rapidly, and the domain of health was widened, including new components such as physical functioning, emotional and cognitive status, and perceptions about present and future health.

Health indicators are gaining acceptance and are now regularly introduced in health survey and surveillance systems, as reliable assessment of service need in the population and health interventions outcomes.

Although literature did not converged on a single indicator summarizing population health, a number of accurate and reliable positive-oriented health measurements are now available, to be selected and used according to different research needs.

Each indicator is able to highlight a particular dimension of health and can be more suitable for specific context (e.g. VAS scale for pain is particularly useful for specific-disease patients, whereas Activity Daily Living scale – ADL is suitable for predict elderly need for assistance).

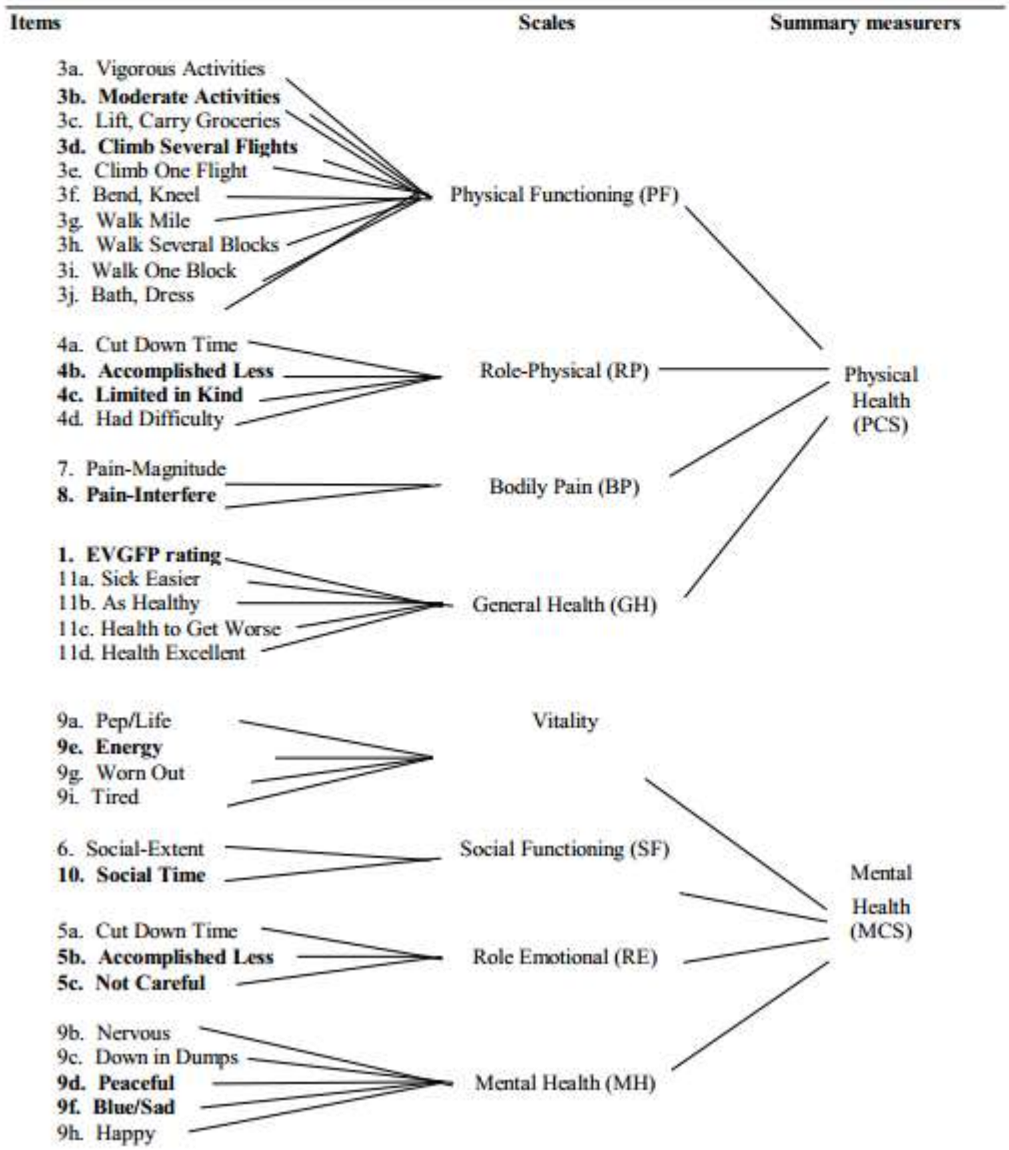
We used different indicators of health in order to disentangle health dimensions that can be diversely influenced by contextual and individual determinants. Specifically we selected three measures:

- Short Form Health Survey (SF-12) - Physical Component Summary (PCS)
- Short Form Health Survey (SF-12) - Mental Component Summary (MCS)
- WHO - Self perceived health (SPH)

The first two health indicators used in this phase are both derived from the *Short Form-12 Health Survey* (SF-12). The SF-12 is a subset of the *36-item Short Form Health Survey* (SF-36), a psychometric questionnaire produced as part of the Medical Outcome Study, to evaluate health-related quality of life of chronic disease patients (Stewart and Ware, 1992). It is composed of 36 items on 8 different scales: physical functioning, social functioning, role limitation (physical), role limitation (emotional), bodily pain, mental health, vitality and general health.

In 1994, researchers discovered, through the use of factorial analysis, that 80-85% of the variability of the overall questionnaire could be explained by 2 components: PCS – Physical Component Summary and MCS – Mental Component Summary. This was true both in analyses on specific patients groups than in representative samples of the population of the United States and other Countries. The physical and mental components could be reproduced with a smaller number of questions, by selecting the most informative items out of the total 36 items and scaling them with proper weights. The new version of the questionnaire composed of the 12 items shown in Figure 2.4 was named SF-12.

Fig. 2.4 - Selected items from SF-36 to SF-12



The advantage of using PCS and MCS relies on the fact that they are quantitative assessment of health; therefore more structured and consistent models can be applied to this typology of outcome, especially in the multilevel framework.

The other indicator of health used was Self-Perceived Health. Self perceived Health occurs in literature also under a multiplicity of names: self-rated Health, self-assessed health or self evaluated health. To use a unique terminology we will always refer to “self-perceived health (SPH)” in this study. SPH is the individual’s global evaluation of health status, in the broadest possible perspective, not framed into any specific dimension of health.

There are different options to assess self perceived health: the majority of health survey uses a single item, but multi-items scales also exist. In most cases the question is posed without any comparison group, but alternatively the respondents can be asked to rate their health compared to a group of peers (similar age/disease). Modalities for the answers can also differ: from categorical classes to numerical scales anchored at the end by “best” and “worst” imaginable health status.

The most widely applied measure of SPH is a single-item question proposed by the World Health Organization (WHO), which asks: “*How is your health in general?*” (De Bruin et al, 1996). Eligible answers are on five points- Likert scale: very good, good, fair, bad, very bad. For the purpose of this research, the five categories are grouped to create a dummy variable (SPH) with value 1 indicating “poor health” (bad and very bad categories) health and value 0 for “not poor health” (fair, good and very good). This transformation is due to the very unbalanced frequency distribution of respondents on the 5 categories: very small proportion of the population are in the extreme categories (very good/very poor); therefore analyses considering these categories independently can produce very different estimations for these extreme groups under consistent conditions, this turns out in a loss of reliability of the estimations.

Finally, the choice of poor health as the outcome derives from what we already know about determinants of health. Poor health and good health are not affected by the same factors with just inverted direction; indeed they have a different profile of determinants.

Poor health is primary affected by objective health status (functional limitations, diseases, and chronic conditions), low education, economic deprivation, isolation, whereas good health has shown to be more sensitive to mood, self-esteem and attitudes (Shields, 2001). Therefore, information we have available from Health Surveys are more efficient in explaining poor than good health. Although this indicator is very simple and general, it has been proved to be a very good independent predictor of mortality (Idler et al., 1992; Idler et al. 1997), even across different Countries. Italian based studies have confirmed the stronger predictive power of SPH compared to objective measures gained by Health Examination Survey (Egidi et al. 2006).

Although, the three variables assess a very similar phenomenon, the perception of health, they have a different characterization, both conceptually and methodologically. PCS and MCS asses a more specific construct (physical domain and mental domain, respectively) and they are continuous measurements of health, whereas SPH has a very general connotation, and is a binary variable. We believe that consider the three variables jointly offer an opportunity to look in a comprehensive way to health determinants, and it consents to overcome some methodological issues, comparing outcomes obtained by different typologies of response variables.

2.4.2 Individual covariates

We considered in the analysis demographic and social characteristics (age, gender, education and occupational status), objective health status (disability, multichronicity) and a variable for the burden of disease due to disability of family members (Cohabitation with disabled). All the variables are included as categorical.

Age

Age was treated as a categorical variable because we hypothesized that the relation between age and health is not fixed over the life course. Including quantitative age would force the model to find a regularity (linear, quadratic, polynomial,) in the relationship between the independent variable (age) and the dependent one (health). In other words, the effects of age on health would have been supposed to follow a specific trend. Literature has shown that there is not a homogeneous pattern between age and self perceived health: the negative effect of ageing on health is sometimes counterbalanced by an improvement in health appraisal, due to a progressively diminishing of the expectations over time. In fact, life course can be pictured as a sequence of "life stages", defined by substantial changes in socio-demographic conditions (retirement, widowhood, grand parenting), where health expectations could differ greatly.

Adopting this approach, age was divided into 4 categories: <50, 50-64, 65-74, 75+. The classes reflect our primary interest in investigating health with a focus on people older than 50. People younger than 50 are considered as one single class, since we did not expect substantial differences prior to this age. From this age onward we hypothesized three steps where the relation age-health can e differently characterized.

Gender

In the study of health, gender has always played a key-role. The "gender paradox", i.e. higher morbidity but lower mortality in women, has puzzled researchers for decades and not an exhaustive explanation has been proposed yet (Wingard 1984). Differences persist using subjective and objective measures of health and they are not fully explained by women's attitude to over report minor health problems (Singh-Manoux *et al.* 2008). Although the mechanism of this influence is still undiscovered, gender is one of the most consistent independent predictor of health outcomes.

Disability

The Italian Health Survey assesses disability according to the OECD *Long-Care Disability Questionnaire*: a 16-item, multidimensional questionnaire that measures the impact of disability on essential daily activities. The set of items identifies 4 domains of disability:

- Confinement (3 items: confinement at home, on a chair, in bed)
- Difficulties in movements (3 items: walk, climb stairs, stoop)
- Difficulties in Activity of Daily Living –ADL (7 items describing basic daily activities)
- Difficulties in Communication (3 items: permanent limitations in hearing, sight and speech)

The respondent is classified as disable when he/she declares the highest limitation grade (even using health appliances) in at least one of the items listed, excluding temporary limitations.

Multichronicity

In order to study the chronic morbidity, interviewees were asked to indicate the diseases they were suffering from a pre-codified list with twenty-four chronic illnesses. From the aforementioned list, the 18 most severe diseases (or class of diseases) are selected by ISTAT and provided in the dataset (Table 2.1).

Diseases can be distinguished into three typologies:

- Chronic diseases that are <u>incurable</u> (e.g. Alzheimer, diabetes or osteoporosis), for which only one yes/no answer is included in the questionnaire
- Chronic diseases with for which exists the possibility of <u>recovery</u> or symptoms attenuation (e.g. asthma, chronic arthritis), for which two questions are included: one referred to the disease in the past (yes/no) and one for current disease (yes/no)

- acute events that generates a chronic condition (e.g. myocardic stroke), for which the interviewee is asked whether s/he has experienced the event in the past.

All the incurable diseases and the acute events that result into a chronic condition are considered in our multichronicity variable, whereas curable diseases were included only if affecting the person at the moment of the interview. The only exception is cancer, which is included also when affected the person in the past. This is due to the fact that, even when the patient achieve a full remission from this condition, s/he cannot be considered healed, unless remission is maintained for a long period. Furthermore, for long period after cancer remission an individual has to undertake periodic medical examinations and controls, which affect the quality of life and physical and mental health. The whole period during which the person is exposed to this situation can be assimilated to a status of chronic condition.

Multichronicity is the state in which the person suffers from more than one long-stand pathological illness. We defined *multichronicity* as having 3 or more diseases out of the 18 listed in Table 2.1.

Table 2.1 - Chronic pathologies for determination of the multichronicity variable

1	Asthma
2	Diabetes
3	Hypertension
4	Myocardic stroke
5	Heart diseases
6	Ictus/cerebral haemorrage
7	Chronic Bronchitis/Enphysema
8	Chronic Arthrits
9	Osteoporosis
10	Gastric/duodenal ulcer
11	Cancer (including lynphoma and leukemia)
12	Cancer in the past
13	Chronic anxiety and depression
14	Alzheimer disease
15	Parkinson disease
16	Liver/gall/kidney calculus
17	Cirrhosis of the liver
18	Thyroid diseases

This definition of multichronicity is oriented to the study of elderly: in fact, this segment of population is characterized by a pronounced multi-morbidity, which required us to define multichronicity with 3 pathologies in order to discriminate between an average condition and more severe objective health states.

Education

The research concerning the relationship between health and socio-economic-status (SES) dates back to the 19^{th} century (Cutler et al., 2008). The SES-health gradient, although extensively documented in research, has extremely difficult interpretation, because of the unclear direction of causation (from SES to health, rather than from health to SES). SES is traditionally measured by means of education, occupation or income. Our selection of education as a proxy for SES has some advantages: it is universal to all adults and it is stable through the life-course; furthermore education is the most exogenous of the three indicators and it is less likely to be influenced by poor health, than occupation or income.

We selected three categories for education: Low (primary education or lower), Medium (lower secondary), High (upper secondary education or higher).

We are aware that the meaning of this variable is not the same for different age groups: for people aged more than 50, high education denotes a positive selection (i.e. only a small percentage of individuals, with more economic, social, cognitive resources stand out from the average education reaching the High level); for the last generations the meaning of education is reversed, and people with low/medium education are generally negatively selected. Although this worsening of the meaning, the direction of the indicator is unchanged and it works for both groups as a good predictor of health. Even when we tried the interaction-effect with age we didn't detect any significant discontinuity. Therefore we kept education as a 3-level categorical variable for all the analyses.

Cohabitation with a disable

We created a new variable from the dataset labeled "Cohabitation with Disabled" with value 1 when the individual has any other member of the household (even younger than 18) reporting a disability. The disable him/herself has the value 0, unless he/she lives with another person with disability in the same household. The variable is intended to capture the burden of disability of one household member on the rest of the family. Disability can impact family through diverse pathways: on one side, the emotional/psychological distress, on the other the care-giving effect: being a care giver has been shown to be a "per se" factor of health deterioration.

Table 2.2 Individual variables included in the analyses

Level	Variables	Description	Categories
1	**Gender**	Sex of the respondent	*0* = male 1= female
1	**Age**	Age group	1= 18-50 *0* = 50-64 2 = 65-74 3 = 75+
1	**Education**	Highest school attainment	0 = Upper Secondary / Higher 1= lower secondary 2 = primary or lower
1	**Disability**	1 or more limitation OECD scale	0= no 1= yes
1	**Multichronicity**	3 or more chronic conditions	0= no 1= yes
1	**Cohabitation Disable**	Having a disable member in the household	0= no 1= yes

2.4.3 Household level covariates

In the multilevel models we included covariates related to household, in order to investigate which characteristics of the family affect the health status of the components. After preliminary analysis of the best predictors we selected the following variables:

Economic Resources Perception

We wanted to include a variable that gave the dimension of current disposable income of the household. The Health Interview Survey did not provide any objective information about income; the only information available is the variable “Economic resources evaluation”, which reports the subjective judgment about the adequacy of income for family’s needs (0= good/satisfactory, 1=inadequate). This variable was deeply inspected before inclusion, because we suspected it to give the same information as the outcome, both expressing a subjective evaluation of current situation and both influenced by personal attitude. However, the two variables (Economic Resources and Health Perception) did not show any strong association, confirming that they produce related but autonomous information.

Housing conditions

Beside the income, we were interested in a variable that captured the physical environment of the households, and this has been done through the assessment of housing conditions. Housing conditions can also be seen as a proxy for the wealth of the family, which is a remarkable, although often ignored, dimension of health inequality (Baum, 2005). The survey provides a summary index obtained by 6 indicators of inadequate housing conditions: absence of bathroom, absence of heating, inadequate size, damp patches, poor general conditions and less than 1 room for each component. The index assumes numerical values according to the number of elements of house deterioration. However, the frequency distribution of this variable is markedly skewed, with a vast majority of the population reporting good housing conditions, and a very small proportion presenting more than 2 housing problems. Thus, we recoded the index in 3 categories: Good (no items of inadequacy), Fair (1-2 item), Bad (more than 2 items), naming the variable Housing Condition.

Household size

The size of the household was considered as a categorical variable (2-3; 4; 5+ components), expecting large families to report lower levels of poor health, because they share the burden of care of one ill member, provide each other a more exhaustive network of support, and suffer less of influences of poor health one with the other. Besides this hypothesis, we also expected the negative influence of poor health perception to be much stronger in small families, and especially in couples living alone, where the exclusivity of the relation makes ties tighter and reciprocal health influence more intense.

Household structure

In the last years there has been a flourishing of literature concerning living arrangements effects on health, especially for the elderly with a focus on cognitive functioning (Hays, 2002). In our study we have found household structure, in terms of the network of relations between members, to be more consistent in predicting health than individual marital status. This has different explanations: firstly the marital status do not detect people stably cohabiting with the partner, who have behaviors, characteristics and a risk profile which is more similar to married couples than to single/ever married persons. Secondly, it is likely than the structure of the family affects all the family's components in a similar way. Therefore we need a household-level variable to better capture this effect, rather than the individual marital status.

The *Household structure* variable has 2 categories: *Couple-headed* families are the reference group (0) and *single-headed* families are opposite to them (1). A couple-headed family is any nuclear family formed by a couple with or without dependent children. On the other side the single-headed households are those with a single-parent and his/her children. In the case of multi-nuclear families, the classification is based on the presence of the couple in the main family unit.

This selection derived from the preliminary analysis on how the family structure had an impact on health. We did not found a clear pattern of differences between household members classified according with their role. The detailed structure of the family (couple with children, couple childless, single-parent, multi-nuclear family) did not show consistent differences between categories either. The only groups that exhibited persistent differences were coupled-families VS single-families.

City size

The size of the town where the family resides was also considered, with 2 classes based on the threshold of 50.000 inhabitants.

2.4.4 Large Area level covariates

Geographical area

The macro geographical zone of residence (North, Central, South or Islands) was included in the multilevel analysis as a characteristic of Large Areas.

Table 2.3 Household and Large Area variables included in the analyses

Level	Variables	Description	Categories
2	**Economic Resources**	Subjective Evaluation of household economic situation	0 = Good 1= Inadequate
2	**Housing Condition**	Number of elements of inadequate conditions	0= Good (no elements) 1= Fair (1/2 elements) 2= Bad (>2 elements)
2	**Household Size**	Number of household members	0 = 2/3 persons 1 = 4 persons 2 = 5+ persons
2	**Household Typology**	Household structure	0 = couple no children 1 =couple with children 2 = other families
2	**City size**	Number of inhabitants of the municipality	0= >= 50.000 1= <50.000
3	**Geographical Area**	Territorial macro-area where Large Area is located	0 =North 1= Centre 2=South 3=Islands

3. METHODS AND MODELS

The whole research project was designed to achieve a better understanding of what determines self perceived health, giving importance to both individual and contextual factors. A second objective that directly stems from the first was to estimate the magnitude of the effect of context on perceived health is, when it is correctly examined within a hierarchical setting.

We started from a descriptive analysis of geographical health heterogeneity in Italy and made use of synthetic indexes to summarize the overall level of health inequality. We then proceeded with the development of multilevel models, which are the tool specifically designed to analyze jointly micro and macro dimensions and to disentangle contextual effects, controlled for any differences (observed or unobserved) at the individual level. In this chapter we describe the conceptual framework of multilevel models, their main features, according to different kind of health outcomes, and conclude with specific methodological issues arised from the use of multilevel models in the context of this research.

3.1 ANALYSIS OF GEOGRAPHICAL INEQUALITIES

The basic assumption underlying the study of contextual influences on health is that the health status changes according to contextual circumstances (different Large Areas/ Households). This can easily be tested in case of geographical units, as these are in a manageable number and they can be graphically represented. Although there is already a body of evidence about health geographical gradient in Italy (Costa *et al.* 2003), we decided to perform some preliminary analyses in order to enlighten the geographical distribution of health and the overall level of inequalities, with the most recent available data.

Health was investigated both in terms of perception (self perceived health, Physical Component Summary and Mental Component Summary) and in its severe manifestations (disability and multichronicity). For all these indicators we firstly observed the geographical distribution through maps of the Italian territory partitioned in Large Areas.

In a second step, we applied two synthetic inequality measures (Index of Dissimilarity-ID and Proportion Attributable Fraction-PAF) to the aforementioned indicators, to quantify the level of heterogeneity between large Areas in Italy. The analysis was performed only for the territorial level, because of the too large number of households.

The *Index of Dissimilarity* (ID) is an indicator that captures the overall level of heterogeneity by telling how many people in different groups diverge (positively and negatively) from the average level of the health indicator used (e.g. poor health).

It is defined as:

$$ID = \frac{1}{2}\sum_{i} \left| \frac{p_i H_i}{\overline{H}} - p_i \right| \tag{3.1}$$

where:

- p_i is the proportion of people in Large Area i
- H_i is the number of people in poor health in i
- $\overline{H}$ is the average number of person with poor health in the overall population.

The factor ½ ensures the index variation between 0 and 1.

Another measure that summaries the level of inequality, derived from epidemiology, is the *Population Attributable Fraction* (PAF), which tells us what proportion of a poor-health outcome (severe illness, disability, poor self-perceived health) can be avoided if all the population had the same rate of illness as the best health status group (Anand *et al.* 2001).

The measure is given by the ratio between the “excess” of poor health outcome (numerator) and the overall level of the health outcome (denominator):

$$PAF = \frac{\sum_i p_i (RR_i - 1)}{\sum_i p_i RR_i} \tag{3.2}$$

3.2. MULTILEVEL LINEAR MODELS

3.2.1 The micro and macro dimensions of research

In many fields of research, and especially in social sciences, researchers have been concerned with the integration of micro and macro perspectives of analysis. On the one hand we find the analysis of the context with its characteristics influencing individuals' decisions, behaviors, and relations; on the other hand there are studies on individuals and their personal properties, collectively shaping the context, in terms of analytical (compositional) variables (i.e. those variables referred to the macro level, but derived from the aggregation of individual characteristics. (e.g. percentage of illiteracy, percentage of conservative voters, percentage declaring poor health status).

The contrast between the 2 dimensions finds its peak in sociology, at the end of the last century, with the consolidation of macro-sociology. This branch of sociology assumes that social structures determine individual behaviors, thus it focuses on the whole society and its aggregated subgroups with a collectivistic perspective. This position has long been opposed by methodological individualism, which claims that social phenomena must be explained by showing how they result from individual actions. Émile Durkheim and Max Weber are traditionally identified as the promoters of the two approaches in the social discipline.

The two perspectives have characterized many other disciplines and both positions have shown their strengths and weaknesses in the following decades of research. In fact, before the advent of multilevel approach, the strategy for jointly analyzing context and individuals was to move all variables by aggregation or disaggregation to one single level of interest, followed by an ordinary multiple regression. Analyzing variables coming from different levels to one single level leads to two different kinds of problems: firstly, statistical problems, which arise when we *aggregate the data*, because individual information are lost and the statistical analysis loses power. When operating *disaggregation*, on the other hand, we can encounter difficulties too: in this case, in fact, if we have N groups, each group value is attributed to all the individuals in the group, which means that the same value is repeated identically for many units, considered as being independent. The correct sample size for contextual variables would be the number of groups (N), however by disaggregation we consider as sample size the number of individuals (n), resulting in smaller standard $(\frac{\sigma}{\sqrt{n}})$ and spurious significances.

Another set of problems is conceptual and concerns the interpretation of results when cross-level inference occurs, i.e. when data are investigated at one level and conclusions are drawn at a different level. When macro associations are interpreted at individual level we refer to as *Ecological Fallacy,* whereas when individual relations are observed and the very same relation is attributed to aggregated data we have the *Atomistic Fallacy*. A remarkable example of Ecological fallacy was provided by Robinson (1950): he measured the ecological correlation between percentage of black people and percentage of illiterate in nine geographic divisions of the USA in 1930, and found this correlation to be 0.95 at the macro level. This result induced to conclude that blacks were more illiterate than whites. Robinson cautioned against deducing conclusions about individuals on the basis of population-level, or "ecological" data. In fact, the same relation tested at the individual level resulted in an association of only 0.20. Robinson showed that the higher correlation at the level of state populations was because blacks tended to be settled in states where the native population was more illiterate.

The same mistake can derive from extending individual relations to macro levels. The atomistic fallacy arises because associations between two variables at the individual level may differ from associations between the same variables measured at the group level. For example, a study on individuals may find that increasing individual level income is associated with decreasing coronary heart disease mortality. If from these data we infer countries' higher per capita income is associated with lower rates of coronary heart disease mortality, we are committing the atomistic fallacy, because across countries, increasing per capita income may actually be associated with increasing coronary heart disease mortality (Diez Roux 2002).

The issue of studying data on different levels is one aspect of dealing with hierarchical structured data.

3.2.2 Hierarchical data and the integration of different levels

We can represent the research setting where micro and macro dimensions occur simultaneously as a hierarchical structure: units at the first level are nested into groups (second level), which could be in turn nested into higher level clusters (third level).

In this research the hierarchical structure is represented as follows: individuals at the bottom of the hierarchy (first level), nested into their respective households (second level), which are eventually nested inside the Large Areas (third level), according to the place of residence.

When the data have such a structure one of the basic hypotheses of the ordinary regression models is not fulfilled: the independence of units at the lower levels. A consequence of this unmet requirement is the bias in estimations; more specifically standard errors are frequently underestimated, entailing spurious significances for the regression coefficients.

The traditional models, in fact, do not take into account the more complex structure of the variability that characterizes the data with a hierarchical structure. When dealing with such data the whole variability can be decomposed in two parts: *between groups* (variance among the mean values of the different groups) and *within groups* (variability between the units of each group).

The Multilevel approach, whose methodological aspects are presented in details in paragraph 5.2.3, is that which precisely allows us to analyze the variability in its different components, integrating information coming from different levels.

Differently from other approaches used for the integration of micro and macro dimensions, e.g. comparative macro analyses followed by micro analyses for causality, aggregation and disaggregation procedures (Racioppi *et al*. 1996), Multilevel approach is the only technique that models not only the average, but also the variances, decomposing the variability of the outcome variable on the different levels of analysis (individual, households and Large Areas).

Mesures of variation in multilevel models constitute complementary information to traditional measures of associations (regression coefficients or Odds Ratios). They provide knowledge of the relative importance of each level in determining the individual outcome (Merlo 2003). Therefore the advantage of using MM relies not only in producing correct estimates, but also in gaining more sophisticated information about the relative importance of each level of analysis. Studies that do not account for this further information can produce a false impression about the influence of administrative boundaries on health. These analyses, in fact, by looking solely to significant associations between contextual determinants and health, produce a misleading picture in cases when the relevance of the context is very small, and encourage public interventions that will largely be ineffective (Merlo *et al.* 2012).

3.2.3 Multilevel Models: methodological aspects

The basic idea behind Multilevel Models is quite simple: the main parameters in the regression equation (intercept and slopes of the explanatory variables) are not fixed for the whole population, but they can vary between groups, allowing for different average levels of the phenomenon (*intercepts*) and different effects of the explanatory variables (*slopes*) between groups. We will present the formalization of a multilevel model for the simplest case with 2 levels; however relations and formulas can easily be extended to the case of 3 and more levels.

Let us consider a population of N individuals, nested in J groups, each one with a different number of individuals (n_j).

Individuals (i) and groups (j) are modeled in this approach as 2 different hierarchical levels. The multilevel regression model can be built up for one outcome variable measured at the lowest level[11] (Y_{ij}) and as many explanatory variables as we need at any level of analysis.

In order to understand the multilevel logic, we can proceed by steps, starting from the ordinary regression equation generic unit i in the group [12]:

$$\mathrm{Y_{ij}} = \beta_{0j} + \beta_{1j}\mathrm{X_{1ij}} + \mathrm{e_{ij}} \tag{3.3}$$

where:

Y_{ij} = outcome variable (continuous)

β_{0j}= intercept

X_{1ij}= the 1st individual covariate

β_{1j} = regression coefficient for the 1st individual covariate

e_{ij} = residual error at the individual level, normally distributed $\sim N(0, \sigma_\varepsilon^2)$

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[11] The outcome variable can be continuous or binary/categorical. In this paragraph we assume the outcome to be a continuous variable. The case of a binary outcome is exposed in Paragraph 5.3.1.

[12] The rationale for a 3-level model is not different from the 2-level model, thus we [therefore] adopted the 2-level notation for the sake of brevity and simplicity. Vice versa, When the two models present methodological differences these are clearly pointed out in the text.

The multilevel model allows the intercept (β_{0j}) and the slope (β_{1j}) to vary across the groups, which means, respectively, that the average level of the outcome and the average effect of the explanatory variable (X_1) can be different among groups. These assumptions referred to the present research could be phrased as: Large Areas can have different levels of average health status (different intercepts), and the effect of a specific individual characteristic (e.g. education) on health can be stronger in one Large Area and smaller in another (different slope for Education).

However, not all the parameters need to vary simultaneously in a multilevel model: we can design models with random intercept only, random slope only or random intercept and slope (full models). In all these models, the basic goal is to predict the variation of the parameters (intercept and slopes) across groups, and to explain this variation through group-level covariates.

Random intercept model:

In a Random intercept model the only parameter we let vary between groups is the intercept β_{0j}, which is expressed by:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} Z_j + u_{0j} \tag{3.4}$$

where:

γ_{00}= average value of the intercept across groups (when the covariates are set at zero)

γ_{01}= effect of the group-covariate Z in predicting the average level of the intercpet

u_{0j} = residual error term at group level, normally distributed $\sim N(0, \sigma^2_{u0})$

Example: consider that Y_{ij} is the Physical Component Summary (continuous measure of physical health status) and Z_j is the household-level variable: *size of the household*. A positive value of the parameter γ_{01} means that the health status in large families is better than the health status in small families; on the contrary a negative value of γ_{01} would indicate that the health in small families is on average better than in large families.

The random error u_{0j} represents the residual effect of the group, net of the effect of the covariates included in the analysis: groups with a positive value of u_{0j} are those where the observed value of the outcome is higher than expected (given the value of the covariates for that group), group with a negative $u_{0j}$are those where the observed values are smaller than what they should be according with the model predictions.

Specific assumptions can be made about the variance-covariance matrix of residuals within each group. In fact, as we stated before, the main assumption behind the multilevel model is that the units are not independent; rather observations in the same group are supposed to be correlated. This means that units pertaining to the same group share a quote of residual variation, that is expressed precisely by the group level variability (σ^2_{u0})

$$\mathrm{Cov}\left(Y_{ij}, Y_{i'j'} \middle| \underline{X}, \underline{Z}\right) = \begin{cases} 0 \text{ per } j \neq j' \\ \sigma^2_{u0} \text{ per } j = j' \end{cases} \tag{3.5}$$

At the same time, the individual residual variance is given by the sum of level-one and level-two variance:

$$\mathrm{Var}\left(Y_{ij} \middle| \underline{X}, \underline{Z}\right) = \sigma^2_{\varepsilon} + \sigma^2_{u0} \tag{3.6}$$

This is true for all the groups, so we end up by having the same Variance-Covariance matrix in all the groups (this is why such a structure is called *exchangeable*), and a covariance of zero for any couple of observations pertaining to different groups, as represented in Figure 3.1.

Fig. 3.1 - Matrix of variance and covariance of residual terms (exchangeable)

S		1	1	1	2	2	2	2	3	3	3
	P	1	2	3	1	2	3	4	1	2	3
1	1	$(\sigma_u^2+\sigma_e^2)$	σ_u^2	σ_u^2	0	0	0	0	0	0	0
1	2	σ_u^2	$(\sigma_u^2+\sigma_e^2)$	σ_u^2	0	0	0	0	0	0	0
1	3	σ_u^2	σ_u^2	$(\sigma_u^2+\sigma_e^2)$	0	0	0	0	0	0	0
2	1	0	0	0	$(\sigma_u^2+\sigma_e^2)$	σ_u^2	σ_u^2	σ_u^2	0	0	0
2	2	0	0	0	σ_u^2	$(\sigma_u^2+\sigma_e^2)$	σ_u^2	σ_u^2	0	0	0
2	3	0	0	0	σ_u^2	σ_u^2	$(\sigma_u^2+\sigma_e^2)$	σ_u^2	0	0	0
2	4	0	0	0	σ_u^2	σ_u^2	σ_u^2	$(\sigma_u^2+\sigma_e^2)$	0	0	0
3	1	0	0	0	0	0	0	0	$(\sigma_u^2+\sigma_e^2)$	σ_u^2	σ_u^2
3	2	0	0	0	0	0	0	0	σ_u^2	$(\sigma_u^2+\sigma_e^2)$	σ_u^2
3	3	0	0	0	0	0	0	0	σ_u^2	σ_u^2	$(\sigma_u^2+\sigma_e^2)$

3.2.4 Multilevel model development

Given the high number of parameters and covariates in a full multilevel model, a reasonable strategy for analyzing hierarchical data is a step-by-step procedure: we started from the simplest model and then added parameters in successive passages, controlling,_at each level, which parameters were significant and how much unexplained variation was left on the different levels.

Step 1: empty model

This is a model where no covariates are included at any level, therefore the variance is not explained, but only decomposed on the different levels. This model appears in literature under a plurality of names: intercept-only model, null-model, random effects analysis of variance. However, all these names refer to a model composed only of the overall intercept and 2 random parameters: the group and the individual residuals

$$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij} \tag{3.7}$$

This model is extremely useful as a first step in the development of a Multilevel approach, as it offers information about the basic partition of variance between the two levels. In fact, as we saw in (3.6) the total variance of the outcome is:

$$\mathrm{Var}(\mathrm{Y_{ij}}) = \mathrm{Var}\left(\mathrm{u_{0j}}\right) + \mathrm{Var}\left(\mathrm{e_{ij}}\right) = \sigma^2_{\mathrm{u0}} + \sigma^2_{\varepsilon} \tag{3.8}$$

which is composed of the *between group* (σ^2_{u0}) and the *within group* (σ^2_{ε}) variance. Therefore a way to see the contribution of the grouping structure on the outcome is to compare the variance between groups to the total variance:

$$\frac{\sigma^2_{u0}}{\sigma^2_{u0} + \sigma^2_{\varepsilon}} \tag{3.9}$$

This ratio is called Variance Partition Coefficient (VPC), as it represents the proportion of variance attributable to differences between units on a specific level. It is good practice to compute the VPC at the beginning of a multilevel analysis, as it gives information on whether the multilevel approach is adequate or not. In fact, if the VPC assumes not significant values, a multilevel approach is not requires.

The same ratio has also another interpretation, which stems from the variance and covariance definition in (3.5) and (3.6).

- The <u>denominator</u>: $(\sigma^2_{u0} + \sigma^2_{\varepsilon})$
  is the residual variability of both Y_{1j} and Y_{2j}(*variance*)

- The <u>numerator</u>: σ^2_{u0}
  is the residual variation shared by Y_{1j} and $Y_{2j}$for the fact that they pertain to the same group (*covariance*)

From these equations we derive that the VPC also expresses the correlation between the residuals of 2 units in the same group. In fact, if we randomly drawn 2 individuals from the same group j, and refer to them as Y_{1j} and Y_{2j}, then:

$$Corr\ (Y_{1j}, Y_{2j}) = \frac{Cov\ (Y_{1j}, Y_{2j})}{\sqrt[2]{Var(Y_{1j})} * \sqrt[2]{Var(Y_{2j})}} =$$

But $Var(Y_{1j})$ and $Var(Y_{2j})$ are both equal to $(\sigma_{u0}^2 + \sigma_\varepsilon^2)$ for (3.6), therefore:

$$Corr\ (Y_{1j}, Y_{2j}) = \frac{\sigma_{u0}^2}{\sqrt[2]{(\sigma_{u0}^2 + \sigma_\varepsilon^2\ )^2}} = \frac{\sigma_{u0}^2}{\sigma_{u0}^2 + \sigma_\varepsilon^2} \tag{3.10}$$

This correlation holds for each pair of individuals randomly drawn form the same randomly selected group. For this reason the ratio is also referred to as Intraclass Correlation Coefficient – ICC (often represented by the Greek letter rho - ρ).

This identity, expressed for 2-level models, becomes more complicated when the number of level is higher. When the hierarchical structure has 3 levels of analysis, the Variance Partition Coefficient (VPC) maintains the original structure, while the ICC is generally computed by adding to the numerator the variance of any higher level.

E.g. A 3-level variance structure (indexes omitted for sake of simplicity):

$$\mathrm{Var}(\mathrm{Y_{ijk}}) = \mathrm{Var\ (w)} + \mathrm{Var\ (u)} + \ \mathrm{Var\ (e)} = \sigma_\mathrm{w}^2 + \ \sigma_\mathrm{u}^2 + \ \sigma_\varepsilon^2 \tag{3.11}$$

Where:

w = Large Area variance

u = Household variance

e = Individual variance

The proportion of variability between households (Variance Partition Coefficient for level 2) has the following structure:

$$VPC = \frac{\sigma_u^2}{\sigma_w^2 + \sigma_u^2 + \sigma_\varepsilon^2} \tag{3.12}$$

while the ICC is expressed by:

$$ICC = \frac{\sigma_u^2 + \sigma_w^2}{\sigma_w^2 + \sigma_u^2 + \sigma_\varepsilon^2} \tag{3.13}$$

The ICC is designed to express the correlation between two units randomly drawn from the same cluster. This correlation depends on the fact that the units belong to the cluster itself, but also on the (possible) correlation at any higher levels. Going back to our example: two persons pertaining to the same households, necessarily live also in the same Large Area, thus their overall correlation is given by the correlation at the household level plus the correlation at the Large Area level.

However in this research we adopted a different approach to estimate the intraclass correlation coefficient. When we studied the Household ICC, in fact, we were not interested in the overall correlation between 2 units (i.e. correlation due to Household + correlation due to Large Area), but we wanted to estimate the correlation specifically due to the Household level, and adjusted for the effect of health similarity due to Large Area. Therefore we computed the ICC according to the formula 5.12 and refer to it as *2-ICC*:

$$2 - ICC = \frac{\sigma_u^2}{\sigma_w^2 + \sigma_u^2 + \sigma_\varepsilon^2} \tag{3.14}$$

The 2-ICC expresses the degree of homogeneity between 2 units in the same households (numerator), over the total variability (denominator) and net from the effect exerted by Large Areas (σ_w^2 is included in the denominator). It is worth noting that the ICC expressed by equation (3.14) exactly corresponds to the VPC in (3.12). This is not surprising as the 2-ICC gives the same information as the VPC: the higher the degree of similarity *within groups* at one level (net from the effect of higher levels), the larger the proportion of variability *between groups* at the same level.

Step 2: Individual level covariates

When the null model had confirmed that the variability at higher levels was statistically significant, we adopted the multilevel approach. We proceeded by adding individual level covariates, trying to explain the variability observed in the null model.

The research questions at this point were:

Are individual characteristics explaining differences between groups?

And in case what individual characteristics have an influence on health?

The model formulation is:

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + e_{ij} \tag{3.15}$$

In this step we assessed the contribution of each explanatory variable, and control whether the individual and group variability change after adjusting for individual covariates. It is important to underline that, with the introduction of individual covariates, both the individual unexplained variance and the group unexplained variance can change, the latter due to compositional effects. Generally, the introduction of individual characteristics contributes to the explanation of the health outcome, so the residual (unexplained) variance is expected to decrease at each level. However, in some cases the household (Large Area)-level variance can increase, in case the individual characteristics were hiding differences in the health between groups.

Step 3 : Group level covariates

If the group variability was still significant after controlling for individual characteristics, this means that the differences between households and Large Areas were not due to individual characteristics, rather they originate from heterogeneity between these groups, which deserves further investigation.

The research questions at this point were:

What Household/Large Area characteristics might explain differences between groups?

Group level variables only explain the variability between groups: the residual variance at the group level can either decrease or remain unchanged.

Model formulation:

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + u_{0j} + e_{ij} \tag{3.16}$$

This expression can be seen as composed of 2 parts:

Fixed part:

γ_{00}= average value of Y in the whole sample, when X and Z assume the value zero.

γ_{10}= effect of X on Y, when Z is zero

γ_{01}= effect of Z on the average level of Y,

γ_{11}= impact of Z on the effect of X on Y.

Random part:

ε_{ij}= level-one residual for the individual i in group *j*

u_{0j} = level-two residual for the group *j*

These residual terms are not estimated directly, rather they variability is produced as an output:

σ_{ε}^2 = residual level-one variance, after controlled for the covariate X

σ_{u0}^2 = residual level-two variance in the mean value of Y, after controlled for X and Z

3.2.5 Estimation procedures

The parameter estimation in a linear multilevel model is realized through the Maximum Likelihood method (ML). This method maximizes the Likelihood function, that is the probability of observing a specific realization of the data (X_{obs}) , given the values of the parameters to be estimated (θ)

$$L(\theta|X_{obs}) = P(X_{obs}\,|\theta) \qquad (3.17).$$

The value of the parameter θ that maximizes the likelihood function ($\hat{\theta}$) is, in fact, the value of the parameter that is *more likely* to have generated the observed data.

ML produces asymptotically efficient and consistent estimates. In addition, when the sample size is numerous, it also provides parameter estimations that are robust against small violation of the assumption of normality for the distribution of the error terms.

The Maximum Likelihood can be applied through two functions: the full maximum likelihood (ML) and the restricted maximum likelihood (RML). The basic difference between the two is that RML estimates the random parameters taking into account the loss of degrees of freedom due to the estimation of fixed parameters, while the ML does not.

In this work we have used the ML method, because it allows us to perform the Likelihood Ratio Test for nested models, in order to evaluate the improvements of the model when a new covariate is added. However, for large samples, as in our case, the difference between the two methods is negligible (Snijders and Bosker 1999).

3.2.6 Goodness of fit

In order to evaluate the goodness of fit of the models created, we made use of two indexes:

- Likelihood ratio test (LRT)
- Akaike Information Criterion (AIC)

The ***Likelihood Ratio Test*** is a statistical test designed to select the model that better perform between two competing models nested one in the other, respectively called the *null model* and the *alternative model*. Generally the null model is the model without any covariates, while the alternative model is the complete model, with all the covariates we wish to include; however, the LRT can be used with any couple of nested models. Models are nested if both contain the same terms and one of them (the alternative) has at least one additional term.

Example:

$$Y_{ij} = \gamma_{00} + u_{0j} + e_{ij} \tag{A}$$

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + e_{ij} \tag{B}$$

Model A is nested in Model B; therefore Model 1 is the null model and model 2 is the alternative for the Likelihood Ratio Test.

The LRT compares maximum likelihood of the null $(\hat{L}_0)$ and the alternative $(\hat{L}_1)$ model and evaluates whether the difference between the two models is statistically different. This is achieved by building the ratio between the two maximum likelihoods:

$$L = \frac{\hat{L}_0}{\hat{L}_1} \tag{3.18}$$

applying the logarithm transformation

$$\ln \frac{\hat{L}_0}{\hat{L}_1} = \ln \hat{L}_0 - \ln \hat{L}_1 \tag{3.19}$$

and then considering that, under the null hypothesis, i.e. if the maximum likelihood of the null and the alternative models are not statistically different, we have:

$$-2(\ln \hat{L}_0 - \ln \hat{L}_1) \sim \chi_p^2 \tag{3.20}$$

where χ_{p}^2 is a chi-squared distribution with p degrees of freedom and p is the difference in the number of parameters between the 2 models.

Finally, we can fix the value of α based on which we accept/refuse the null model against the alternative model. This value as been set at 0.05 for the whole development of this research. In general terms, given a fixed number of parameters, the higher the likelihood of the alternative method, the higher the value of the LRT and therefore the probability to reject the null hypothesis in favor of the alternative one.

The notation for LRT is: $-2\ln \mathrm{L}$, whose equivalence with (5.20) can easily be derived from (3.18) and (3.19).

The ***Akaike Information Criterion*** – AIC, first developed by Hirotugu Akaike (1974) under the name of "an information criterion", then named after his creator, is a statistic for model selection, obtained as:

$$AIC = -2\ln L + 2p \tag{3.21}$$

where p is the number of parameters in the model. AIC has the same structure as LRT, but with a penalization term proportional to the number of parameters in the model ($2p$). In fact, it gives a measure of the tradeoff between accuracy and complexity of the model tested.

The AIC decreases as the likelihood increases, and it increases with the number of parameters. Thus, given a set of candidate models, the one with the lowest AIC is the one to be preferred. It is worth noting that AIC does not test a null hypothesis and it does not provide absolute information about goodness of fit: the value of AIC is meaningful only for comparison between models built on the same set of data. The good feature of this test is that the models can be completely independent (they do not need to be nested). This makes this test very flexible and largely used.

3.3 EXTENSION OF MULTILEVEL MODELS TO BINARY OUTCOME

3.3.1 Modeling a binary outcome

The models described in the previous paragraph assume the outcome to be continuously distributed. However, there are also a number of situations where the dependent variable is binary and denotes only the presence/absence of a specific characteristic. This kind of outcome is very common both in social sciences and in medical/epidemiological studies and it cannot be properly approximated by a continuous distribution. In order to satisfy this necessity hierarchical generalized linear models have been developed. Within this group of models stands the logistic multilevel model, which was the one used in this research to model poor self perceived health *(poor-SPH).*

In this setting the outcome variable is thought to assume only two values:

$$Y_{ij} = \begin{cases} 0 \ \ (absence\ of\ \ poor\ health) \\ 1\ (presence\ of\ poor\ health) \end{cases}$$

Therefore the outcome variable is assumed to be binomially distributed:

$$Y_{ij} \sim Bin\ (1, \pi_{ij})$$

With a binary outcome the link function can not be the identity, like in the ordinary regression model, as it allows, in principle, to predict values outside the range (0-1). Therefore, the link function is assumed to be the logit function, which is defined as the logarithm of the odds of the probability (π_{ij}). This function is typically applied to transform values in the 0-1 range into a continuous scale. The model is referred to as *Multilevel Logistic Regression*, and it is expressed as follows:

$$Y_{ij} = \pi_{ij} + \ \varepsilon_{ij} \tag{3.22}$$

$$\ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + \beta_1 X_{1ij} + u_{0j} \tag{3.23}$$

As already seen for the linear case β_0 is the average level of the intercept for all the 2-level units, while u_{ij} is the specific distance of group j from this overall intercept, with $u_{0j} \sim N(0, \sigma_{u0}^2)$. Differently from the linear models the individual residuals ε_{ij} cannot be hypothesized with a normal distribution, because:

$$Y_{ij} = \pi_{ij} + \varepsilon_{ij}$$
$$E(Y_{ij}) = \pi_{ij}$$
$$Var(Y_{ij}) = \pi_{ij}(1 - \pi_{ij})$$

And, consequently:

$$Var\left(\pi_{ij} + \varepsilon_{ij}\right) = \pi_{ij}\left(1 - \pi_{ij}\right) \tag{3.24}$$

The variance of ε_{ij} is not independent from the probability of success π_{ij} . Furthermore the 2-level variance (σ_{u0}^2) is measured on a logistic scale, thus, it is not directly comparable with the 1-level variance σ_{ε}^2 Therefore, the Variance Partition Coefficient formulation is not as straightforward as it was for the linear e. However, some procedures have been proposed to overcome this issue: (1) model linearization using Taylor expansion, (2) simulation methods, (3) approximation through the normal distribution and (4) the latent variable approach.

All these procedures have they benefits and shortcomings, and the selection of the most appropriate primarily depends on the research characteristics. In this study we selected the *latent variable approach*. According to this approach the dichotomous outcome Y is conceived as the result of an underlying non-observed continuous variable, that assumes the value of 1 when a certain threshold is exceeded (Goldstein 2011). It seemed reasonable to assume that the observed variable poor-SPH (0,1) could derive from an underlying latent continuous process (health status deterioration) so that 1 was observed when a certain threshold of health deterioration is exceeded. Under this hypothesis the level- 1 residuals of the unobserved latent variable have a logistic distribution, whose standard mean is 0 and standard variance is $\pi^2/_3$= 3.29. One advantage of this approach is in that the residual variance at the individual level is comparable with the residual variance at the group level, because they are both on a logistic scale. On the contrary, a disadvantage relies in the fact that the absolute values of the regression coefficients (and their corresponding Odds Ratios) can not be compared between different models. This limitation stems from the constraint that residual variability at level-1 is fixed at 3.29. In fact, as clearly explained by Snijders and Bosker (1999), if a multilevel logistic model has been estimated and, then, a new individual variable x_{r+1} is added to the model, this would lead to a decrease in level-1 residual variance. However, level-1 residual variance cannot decrease, as it is fixed at 3.29. As a consequence level-2 variance and the regression coefficients of the other covariates tend to become larger, in order to keep meaningful their ratio with the unexplained random variation at level-1. This means in a multilevel logistic model the absolute values of regression coefficients and residual variances are not meaningful in their own. What is properly meaningful, in fact, is the ratio between parameters at the individual and group level. Consequently regression coefficients (and their corresponding OR) coming from different models cannot be compared.

Obviously we are aware that alternatives to ICC for multilevel logistic regression exist. One of the best performing is the Median Odds Ratio - MOR (Larsen and Merlo 2005), around which the scientific consensus has coalesced for its ability to combine a strong methodological structure to an extreme facility of interpretation. MOR translates the group level variability into the Odds Ratio scale. The clear advantage for this measure is the facilitation in the interpretation of group effects: MOR can directly be interpreted as the average increase in risk (of poor health) that an individual would experience by passing from a group with lower probability to a group with higher probability.

However we preferred the ICC because it allowed comparisons with the other health outcomes (PCS and MCS) and permitted the cross-validation of results of the binary outcome through these comparisons.

3.3.2 Parameters estimation: Adaptive Gaussian Quadrature

For the logistic multilevel models, as already seen for the linear multilevel models, the parameters estimation is obtained through the maximum likelihood method. However, in the case of linear multilevel models, the likelihood function could be expressed in a closed form, while for nonlinear multilevel models, also called generalized linear mixed models (GLMMs), the likelihood function does not have a closed form. Different likelihood approximations, with varying degrees of accuracy and computational complexity, have been proposed for these models. The most common procedures are based on the approximation of the non-linear link with a *quasi-linear* function through the Taylor Series Expansion (to the first or second order). The estimations are then obtained with an iterative procedure: in each iteration, the parameters are more accurately estimated and they constitute the base for the following iteration, until the convergence is reached. The estimation procedure can include the sole fixed part of the model (Marginal Quasi Likelihood) or it can include both the fixed part and the estimations of the higher level residuals (Penalized Quasi Likelihood). With these methods the quasi-likelihood function to be maximized is not the real likelihood function, hence, the test based on the Likelihood (LR test and AIC) are not very accurate.

An alternative method which is based on the likelihood function, without these shortcomings, is the numerical integration of the likelihood function. With this procedure the likelihood function to be estimated is the real function and all the tests based on the deviance remain valid.

We preferred such an approach and selected, as a method for the integration, the Adaptive Gaussian Quadrature. This method considers the marginal likelihood function:

$$L(y) = \int \prod_{j=1}^{J} \prod_{i=1}^{n_j} f(y_{ij}|u_j) f(u_j) du_j =$$

$$= \prod_{j=1}^{J} \int \prod_{i=1}^{n_j} f(y_{ij}|u) f(u) du \qquad (3.25)$$

The likelihood function is expressed as the product of the contribution of each of the J groups. For each group j the evaluation of the marginalized likelihood involves integrating out the function in (3.25), so the computation of j integrals is needed. The Adaptive Gaussian Quadrature articulates in two steps: (1) numerical approximation of the integral and (2) maximization of the likelihood function using the values of the integral obtained in the previous step. The numerical approximation of the integral uses the Gauss-Hermite formula:

$$\int_{-\infty}^{+\infty} e^{-x^2} f(x)\, dx \approx \sum_{i=1}^{n} f(p_i) w_i \tag{3.26}$$

where p_i are the points used for the quadrature of the integral and w_i are the associated weights. This procedure is called *Non Adaptive Gaussian Quadrature*, and its accuracy depends on the number of integration points used. This method, however, is inappropriate when the integrand function have marked peaks or it is unimodal (Lesaffre and Spiessens 2001). In these cases the non adaptive quadrature would necessarily evaluate the function close to 0, however the function is concentrated around its mode $\hat{\mu}$. When $\hat{\mu}$ lies remote from 0 and the number of quadrature points is small, the estimations will be inaccurate. In those cases it is required an adaptive quadrature method, that takes into consideration the characteristics of the function to be integrated. The Adaptive Gaussian Quadrature shifts the quadrature points (p_i) and re-locates them under the function peaks. As pointed out before, the accuracy of this procedure is a function of the number of quadrature points. In our analyses we used Adaptive Gaussian Quadrature with 7 integration points. We checked the sensitivity to the number of quadrature points in a preliminary analysis by increasing the number up to 12, without finding any substantial differences.

3.4 SPECIFIC METHODOLOGICAL ISSUES OF MULTILEVEL MODELS IN THIS RESEARCH

3.4.1 Small cluster size for households

It is fundamental to remark that some methodological issues arise in Multilevel analysis when the cluster size is small (Austin 2010). This is the case when we consider households as clusters, as they have a range of 2-8 individuals, with an average size of 2.5 units per group. A specific part of the work for this project has been devoted to a better understanding of consequences and limitations due to this particular condition in the analysis. As far as we know, there are no distortions in the estimations of parameters for continuous outcomes (PCS and MCS), even when the cluster size is small; however, some biases are expected in logistic multilevel models (SPH) under the same conditions (Raudenbush 2008). The potential bias is mainly related to the estimation of the variance of random parameters, rather than the estimation of the fixed part of the model. Results from this model have always been considered in the light of results from PCS and MCS, which are more consistent, and also constitute a cross-model validation of SPH results.

3.4.2 Sample survey data

The issue of weights when using survey data has long been debated in the last twenty years and no universal guidance has been provided up to date. There is a total agreement about the use weights for *descriptive inference*, i.e. when we want to estimate some descriptive parameters of the population; the issue becomes more complex for *analytic inference*, i.e. when the aim of the analysis is the way in which a variable is associated with other variables. In these situations *design-based* and *model-based* approaches conflict: the former asserts the necessity of sampling weights to incorporate individuals' unequal selection probabilities, the latter rejects the universality in the use of weights. Model-based researchers, in fact, claim that "a sample that is a biased representation of the population does not necessarily lead to bias in the estimation of parameters" in a model correctly specified (Snijders and Bosker 1999). What gained scientific consensus, however, is that weights must necessarily be considered if they are related to the response even after conditioning on the covariates in the model (*informative survey design*). This is typically the case when weights incorporate not only the different selection probabilities, but also correction for nonresponse (Rabe-Hesket and Skrondal, 2006). The Italian Health Interview Survey makes use of these weights, which are calculated in order to:

- correct for unequal selection probabilities
- correct for nonresponse
- calibrate to population totals: i.e. make the estimations of some key variables coherent with respect of population totals obtained from other sources (e.g. proportion of males aged 65-74, in Region A)

The use of weights would therefore be recommended; however it has not widely been adopted by analysts when they deal with complex survey data (Carle 2008).

The main reasons for this limited use are substantially two:

Firstly, sampling weights are treated differently in multilevel models than they are in standard models such as OLS regression. The difference relies in that *weighted multilevel analysis* requires the component weights from each level of sampling. In other words, weights need to be included at each level of the hierarchy, expressing the probability of inclusion, conditional to the fact that the higher level has already been selected. In a two stage sampling where groups are randomly selected and then individuals are selected within groups, what is required for a multilevel analysis of these data are w_{ij} - the inverse of probability that group *j* is selected, and $w_{i|j}$ - the inverse of the probability that individual i is selected, conditional of group j already been selected. Moreover, most of the dataset, regardless of the design, contains only an overall inclusion weight (w_{ij}) for each observation in the data, and in such situations to use the weights in a multilevel setting is hampered**.**

Secondly, even in the most fortunate case, when weights are available at each level, another basic issue needs to be considered: *scaling of the weights*. The basic idea is that the individual weight is unique to the group, so that the group-to-group magnitude of these weights needs to be normalized, in a way that makes them “consistent” on the whole dataset. That is, not only the relative sizes of the weights at lower levels matter, the scale of these weights matters also. Scaling is not an exact science and it has fostered the research about multilevel analysis the last decade (Grilli and Pratesi 2004; Asparouhov 2006; Rabe-Hesket and Skrondal 2006).

In our data we have a quite peculiar sampling design that can be described as follows:

- *Large Area* weights $w_h = 1$, because all the large Areas are included in the sample.
- *Household* weights conditional to Large Areas $w_{j|h} = w_j$ because the probability of inclusion of LA=1
- *Individual* weights conditional to the household already been selected $w_{i|j} = 1$, because data come from a cluster sample where cluster (households) are considered either completely or not at all.

Under these conditions there is no need to rescale the individual weights, as they are already comparable between groups.

The household weights w_j are available from the survey[13], and the only passage that was still required is their normalization through the formula:

$$c_j = w_j * \frac{n}{N}$$

where:

n = is the number of household in the sample (*sum of all the households in the sample*)

N = is the number of households in the population (*sum of all the household weights)*[14]

In this way we rescaled the weights to the sample size, which makes computations easier and avoids potential distortions on the significance of models' coefficients.

[13] In order to obtain coherent estimations for individuals and households, the Italian National Institute of Statistics provides weights defined so that each household j and each household member in j (ij) have the same weight (Istat, Nota metodologica). This is equivalent to define the household weight w_j and to fix the individual weight conditioned to household (w_{ij}) equal to 1.

[14] The ratio n/N for households is exactly equivalent to the same ration for individuals, where n = sample size and N = population size, since the weights for households and individuals correspond (cf. note 13)

The use of weights in our situation was recommended, but has some remarkable shortcomings, such as the impossibility to compare nested models through the Likelihood ratio Test, because the weighted multilevel analysis uses Pseudolikelihood function.

However, in analytic inference, estimates from unweighted and weighted models do not differ significantly, as it has been shown both by methodological (Carle 2009) and empirical studies realized under very similar conditions (Salvini and Pirani 2012a).

We applied both the procedures and compared the results through sensitivity analysis.

As the results were highly similar, we decided to present the easier case, i.e. the unweighted data results, according to the principle of parsimony. Nonetheless results of the sensitivity analysis are reported in the results.

4. THE ROLE OF CONTEXT ON HEALTH: RESULTS

In this chapter we present the most relevant results concerning the effects of context, namely area of residence and household, on health outcomes, defined by means of three variables: Poor Self-Perceived Health (Poor-SPH), Physical Component Summary (PCS) and Mental Component Summary (MCS). These analyses have been placed in the more exhaustive framework of the study of health determinants: thus, individual variables, always included in the analyses, are not exclusively treated as confounders, rather they are complementary information, contributing *on a par* with contextual determinants to describe the health phenomenon in its entirety.

Furthermore, a special interest was directed to the estimation the magnitude of the effect of context on perceived health is, when it is correctly examined within a hierarchical setting.

When we have found these contextual effects (e.g. household effects) to be extremely relevant, we deepened the analysis by looking at the conditions under which these effects were especially pronounced and proposed hypotheses for their explanation.

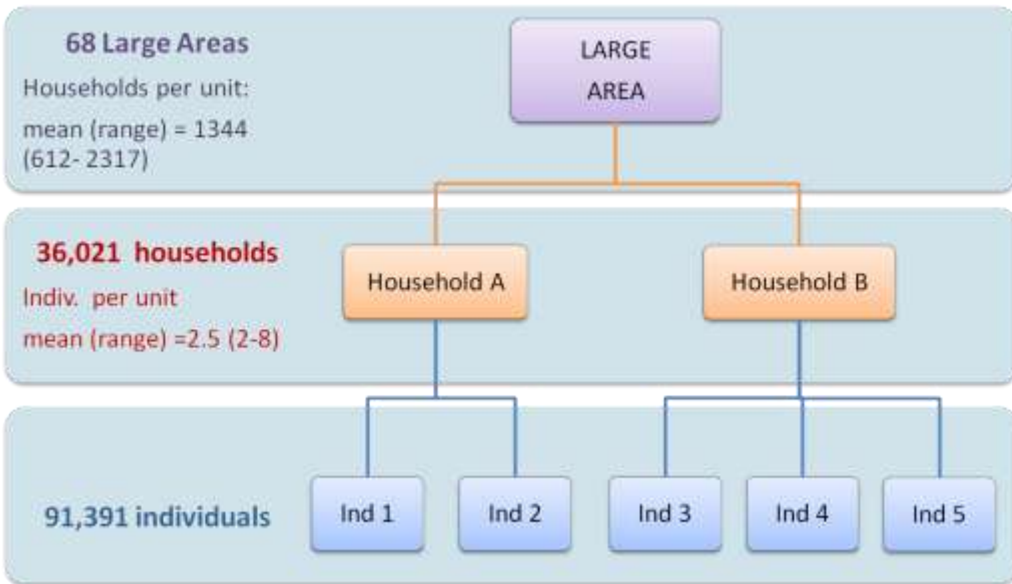
The first paragraph is devoted to the description of sample, the illustration of health distribution in the population and its association with individual characteristics. Paragraph 2 illustrates the geographical distribution of Health by Large Areas and synthesize the level of territorial health inequality. Paragraph 3 estimates the proportion of variability in health attributable to the context and explores which individual and contextual determinants give significant contribution in explaining health differences through multilevel models on a 3-level structure: Large Areas, Households and Individuals. All the models were run with the three outcomes (PCS, MCS, SPH), comparing the profile of predictors for different measures of health. The following paragraph is devoted to a sensitivity analysis between the models reported in paragraph 3 (unweighted) and their corresponding weighted version, through which we illustrate the very limited variation of estimates between weighted and unweighted models. Paragraph 5 is entirely aimed at comparing the magnitude of Large Areas and Households residual variability (internal homogeneity) after controlling for individual and contextual characteristics, and discussing the magnitude of effects for the Large Area and Household. The effect of household is further investigated in Paragraph 6, which focuses specifically on the homogeneity of health within households, and its variability by different household structures (couples, couples with children, single-parent households, …), in order to test whether the hypothesis of reciprocal household influences has empirical support.

4.1 DESCRIPTIVE AND EXPLORATIVE ANALYSIS

4.1.1 Characteristics of the sample

The final sample has a 3-level hierarchical structure graphically represented in Figure 4.1.

Figure 4.1 - Hierarchical structure of the sample and



After the sample selection[15] we disposed of 91,391 individuals satisfying the eligibility criteria, nested in about 36 thousands households, which are, in turn, grouped together into 68 Large Areas. Collectively Large Areas are representative of the Italian population, as they are mutually exclusive and collectively exhaustive portions of the Italian territory.

Each Large Area includes a number of households varying from 612 to 2,317. The number of household is proportional to the share of Italian people living in the area itself.

The household dimension ranges from 2 to 8 individuals, with an average of 2.5 people.

It is worth to underline that data come from a cluster survey design, therefore when a household is sampled, all the household members are surveyed.

The research sample has the characteristics shown in table 4.1, according to the covariates included in this study. The distribution is quite balanced for the most of the

[15] Details about the sample selection are provided in Chapter 2.

individual covariates, with only Disability and Cohabitation with disable presenting categories with a frequency lower than 7%.

Table 4.1 - Sample Characteristics: individual covariates

Level	Variables	Description	Categories	Counts	Proportions (%)
1	**Gender**	Sex of the respondent	0 = male	45,172	49.43
			1= female	46,219	50.57
1	**Age**	Age group	1= 18-50	51,271	56.1
			0 = 50-64	21,920	23.98
			2 = 65-74	10,999	12.04
			3 = 75+	7,201	7.88
1	**Education**	Highest school attainement	0 = Upper sec / higher	33,672	36.84
			1= lower secondary	33,381	36.53
			2 = primary or lower	24,338	26.63
1	**Disability**	1 or more limitation OECD scale	0= no	87,494	95.74
			1= yes	3,897	4.26
1	**Multichronicity**	3 or more chronic conditions	0= no	81,497	89.17
			1= yes	9,894	10.83
1	**Cohabitation Disable**	Having a disable member in the household	0= no	85,078	93.09
			1= yes	6,313	6.91

Concerning households and Large Areas characteristics, the categories of the different variables are adequately represented in the sample(Table 6.2); the least frequent condition is to live in a households with 5 or more members (3.2%). It is worthy of note that the two variables related to household economic situation, Economic Resources (proxy of income) and Housing Conditions (proxy of wealth) have a very different profile. Almost 30% of the sample experience inadequate economic resources, while poor housing conditions affect less than 5% of the sample population. This induce to think that the two variables are actually providing complementary information about the economic conditions of the household. This was actually confirmed by a specific analysis of the association of the two variables (results not shown).

Table 4.2 - Sample Characteristics: Household and Large Area covariates

Level	Variables	Description	Categories	Counts	Proportions (%)
2	**Ec Resources**	Evaluation of household economic situation	0 = Good	64,358	70.4
			1= Inadequate	27,033	29.6
2	**Housing Condition**	Number of elements of inadequate conditions	0= Good (no elements)	54,762	59.9
			1= Fair (1/2 elements)	32,359	35.4
			2= Bad (>2 elements)	4,270	4.7
2	**Household Size**	Number of members of the household	0 = 2/3 persons	52,337	57.3
			1 = 4 persons	36,132	39.5
			2 = 5+ persons	2,922	3.2
2	**Household Typology**	Family structure	0 = couple no children	21,689	23.7
			1 =couple with children	57,302	62.7
			2 = other families	12,400	13.6
2	**City size**	Number of inhabitants of the city	0= >= 50.000	32,672	35.8
			1= <50.000	58,719	64.3
3	**Geographical Area**	Macro area where the household lives	0 =North	37,453	41.0
			1= Centre	16,356	17.9
			2=South	27,271	29.8
			3=Islands	10,311	11.3

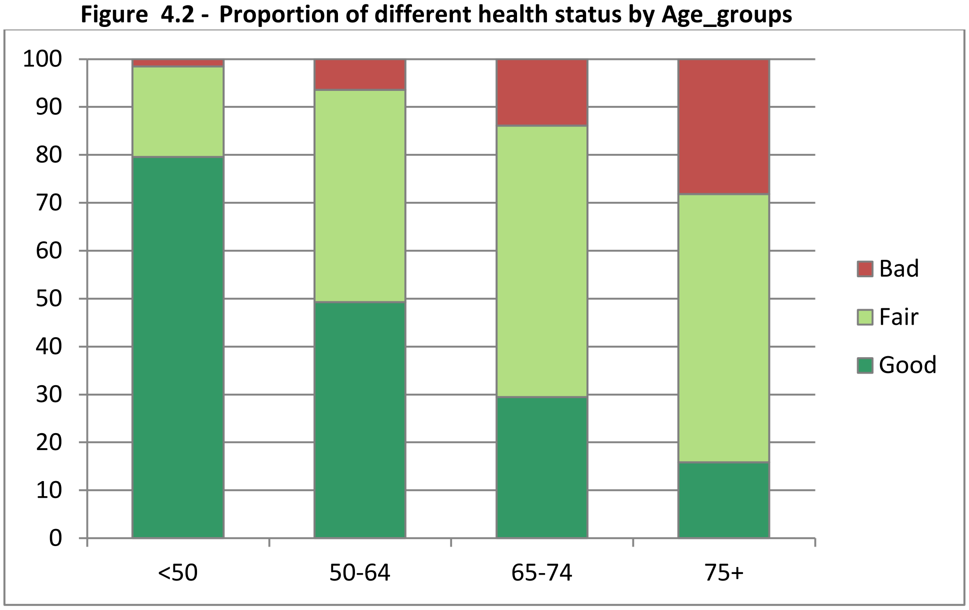
4.1.2 The health distribution and its association with individual covariates

In this preliminary analysis we describe the distribution of health in the population and highlight the most interesting associations of health and individual characteristics. Furthermore we shade light on the relationships between the three health outcomes, both in an overall perspective and across the life course.

For all these preliminary analyses we applied sampling weights to produce correct population estimates.

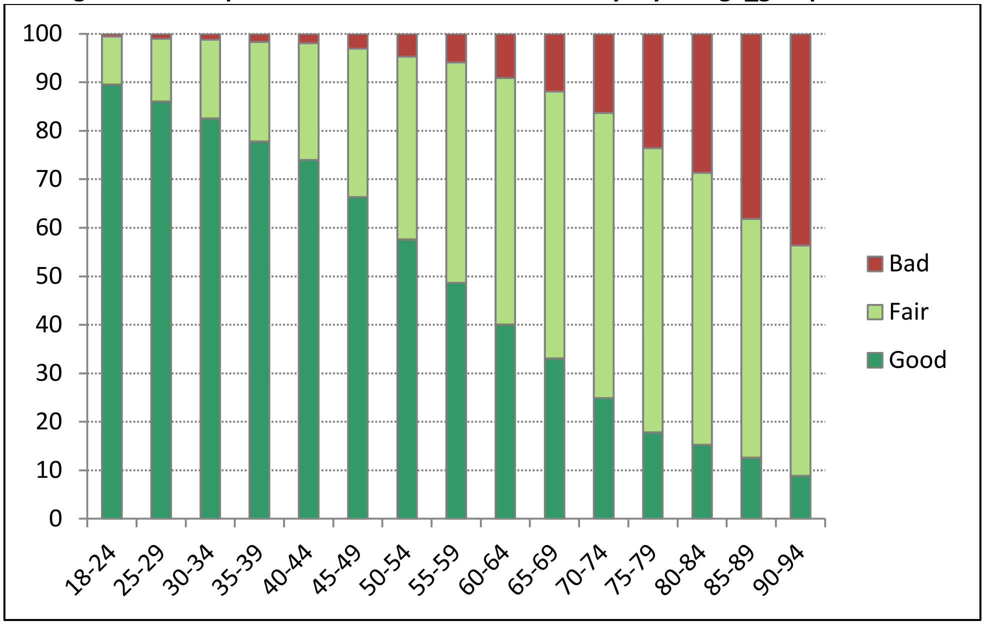
Whatever the measure adopted and the context of study, health is primary affected by the *ageing process.* For this reason in our population, which presents a wide age span (18 – 90+), we expected health to be extremely variable. The proportion of poor health ranges from 1.6% in the youngest group to 27.8% in the oldest group (Table and Figure 4.2).

Figure 4.2 - Proportion of different health status by Age_groups



If we look at the trend of SPH by more detailed age groups, we can see a more gradual change, leading to the same remarkable variation between extreme age groups (Fig 4.3).

Figure 4.3 - Proportion of different health status by 5-year age_groups



Similarly, the summary scores from SF12 questionnaire presented an extremely large range of variation: 11-68 for the physical component and 7-72 for mental component (Table 4.3).

Table 4.3 - Summary statistics for PCS and MCS

Variable	Obs	Mean	Std. Dev	Min	Max
PCS	91391	50,4	9,3	11,1	67,8
MCS	91391	49,9	9,6	7,5	72,3

However, for both the indicators the width of the range did not seem to be strongly dependent on age: the size of the variation was comparable across the age groups, and in the case of MCS, interestingly, the minimum score (worst mental condition) is observed among the youngest and the maximum (best mental status) across the oldest segment of population (Tables 4.4 and 4.5).

Table 4.4 - Summary statistics for PCS by Age_Groups

Age Group	Obs	Mean	Std. Dev	Min	Max
< 50	51,271	53.6	6.3	14.6	67.8
50-64	21,920	49.6	8.8	14.1	67.2
65-74	10,999	45.0	10.5	11.1	67.2
75+	7,201	38.1	11.5	11.5	64.0

Table 4.5 - Summary statistics for MCS by Age_Groups

Age Group	Obs	Mean	Std. Dev	Min	Max
< 50	51,271	51.0	8.7	7.5	70.4
50-64	21,920	49.4	9.6	7.6	72.0
65-74	10,999	48.2	10.3	7.5	72.3
75+	7201	45.6	11.7	11.1	71.1

Given that the three indicators are assessments of the same phenomenon by different perspectives, we were interested, in this preliminary explorative analysis, in a better understanding of the interrelation among SPH, PCS and MCS.

One of the most interesting point was to establish whether the continuous indicators (PCS, MCS) were significantly related to the general health perception (SPH), and whether they can constitute a reliable and informative alternative to SPH, in those cases where a binary indicator is unsuitable or insufficient (*e.g. logistic regressions for very unbalanced distribution of the outcome; multilevel logistic regressions when the cluster size is small*).

We assessed the average physical status (PCS) and mental status (MCS) in 2 groups: (1) people reporting poor perceived health (*Poor SPH*) and (2) people reporting good perceived health (*Good SPH*)[16]. The hypothesis was that the 2 groups had different levels of PCS and MCS, with people in *Poor SPH* group reporting significantly lower physical and mental conditions than people in *Good SPH*. We adopted a T-test for comparison groups means, and selected the one-tailed T-test because we wanted to check differences in one precise direction (PCS in "Good SPH" > PCS in "Poor SPH"; MCS in "Good SPH" > MCS in "Poor SPH").

[16] The groups are defined based on the variable SPH: value 1 is poor and very poor health; value 0 is fair, good or very good health.

Table 4.6 - Mean PCS by SPH and relative test for difference

Group	Obs	Mean PCS	Std. Err	95% CI	
Good SPH	85588	51.8	0.0	51.8	51.9
Poor SPH	5803	29.9	0.1	29.7	30.1
difference		*21.9*		*21.7*	*22.1*

Diff= mean (Good) – mean (Poor) **T-test = 213.6**

H0 : diff=0 **p-value < 0.0001**

H alt: diff>0

Table 4.7 - Mean MCS by SPH and relative test for difference

Group	Obs	Mean MCS	Std. Err	95% CI	
Good SPH	85588	50.8	0.0	50.7	50.8
Poor SPH	5803	36.6	0.2	36.3	36.9
difference		*14.2*		*14.0*	*14.4*

Diff= mean (Good) – mean (Poor) **T-test = 117.7**

p-value < 0.0001

H0 : diff=0

H alt: diff>0

The values of the test were extremely significant for both the indicators, pointing out that the physical and mental dimensions of health captured by PCS and MCS are strongly associated with the general self-perceived health. Given that SPH has shown to be age-dependent whilst MCS was not dependent from age, we wanted to check whether the relations of PCS/MCS And SPH were consistent over age. We plotted average PCS and MCS for people in Good SPH and in Poor SPH over the ages, to check whether the relation of SPH and SF-12 indicators was stable over the life course (Fig. 4.4 and 4.5)

Figure 4.4 - Average PCS score by good/poor health status over age.

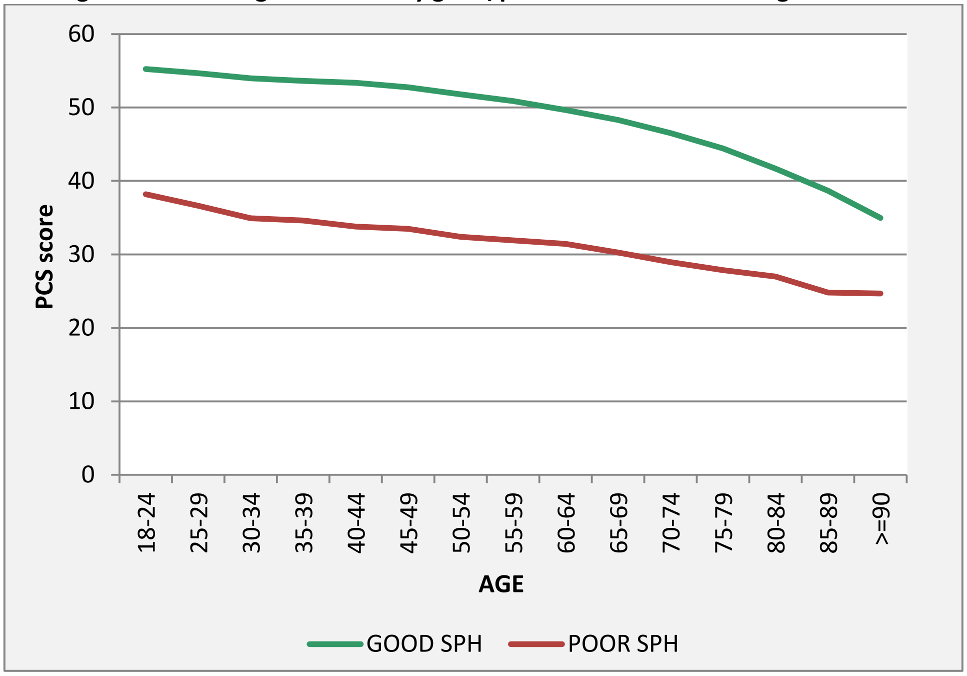
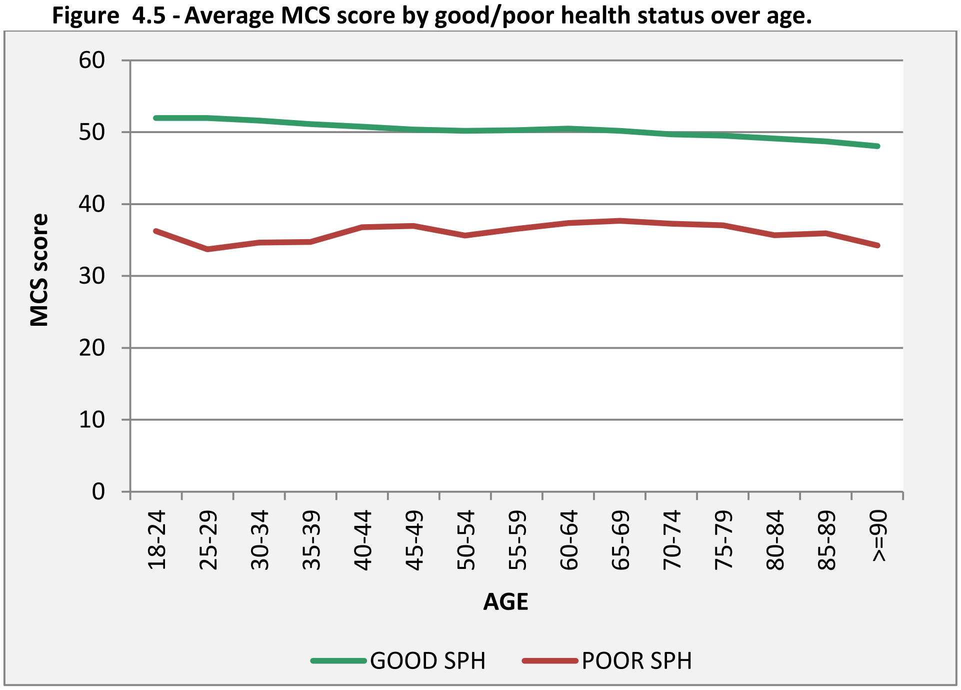


Figure 4.5 - Average MCS score by good/poor health status over age.



Both PCS and MCS reproduce the difference between a fair/good general health status from a poor health status, with a distance of about 10 to 15 points on their scale. What is interesting to note is that the distance between good and poor perceived health is the highest among the youngest, both for physical and mental dimension of health, whereas it reduces over ages. This suggest that for an individual rating his/her health can differ over the life course:

Another point of relevance is the, already anticipated, apparent independence of mental health from age: there is not any pattern over ages as illustrated clearly by Figure 4.5 where the lines for mental health are almost flat, showing a complete different pattern from Physical health, where the decreasing trend over time is undoubtedly evident. The data remarked that relations between health indicators is complex, and, even if they refer to the same concept, they cannot be treated as alternatives one to the other.

Already from these simple descriptive statistics we deduced that health has a strong variability in the sample: even though the mean values (and the proportions for the binary outcome) indicate the expected negative trend over age for all the indicators, SPH shows this trend very clearly, whereas the physical and mental summary scores display a more complicated pattern, where presumably other factors than age play an important role.

We took into consideration the other factors potentially affecting health in a preliminary analysis of association of health perception with individual social characteristics.

When health was expressed by means of the binary outcome (SPH), Pearson's Chi-Squared Test assessed the significance of the association between health and the individual characteristic; when health was assessed through quantitative indicators (PCS, MCS), one-tail T-Test (Anova) were used to highlight significant differences in the values of PCS and MCS between 2 (or more) categories of the covariate of interest.

More specifically the T-test gave us information on the significance of the difference in health between the categories of the variable of interest (e.g. difference in mean PCS between disabled and healthy individuals). When the categories were more than 2 the Anova analysis was used, with post hoc estimation to detect the groups for which the differences were significant.

The first individual characteristic we investigated was the *gender*.

We knew from existing literature that women are more likely to report poor health status compared to men, even after controlling for important factors of possible distortion (age, education or objective health conditions). This result was confirmed in our data. The distribution of health by gender, reported in table 6.7, showed a percentage of poor health at 7% for females and 5% for men (not controlled for other variables). Though the frequencies of poor health were not dramatically different between the two sexes, the association of gender and health was statistically significant. The differences shown by PCS and MCS between men and women were significant too, with men always favored.

Table 4.8 - Mean PCS, mean MCS and % Poor SPH for individual covariates and tests of association

COVARIATES	PCS mean	*T test p value*	MCS mean	*T test p value*	POOR SPH %	χ^2 *p value*
Gender						
Male	51.3	<0.001	51.1	<0.001	5.4	<0.001
Female	49.9		48.7		7.3	
Education						
High	53.4	<0.001	51	<0.001	2.1	<0.001
Medium	51.6	<0.001	50.4	<0.001	4.5	
Low	45.2		47.6		15.3	
Disability						
no	51.5	<0.001	50.3	<0.001	4.02	<0.001
yes	30		39.2		58.56	
Multichronicity						
no	52.1	<0.001	50.7	<0.001	3.02	<0.001
yes	37.9		42.5		33.81	
Living with disable						
no	50.9	<0.001	50.1	<0.001	5.62	<0.001
yes	46.1		46.1		16.16	

The health gradient according to *Education* was in the direction expected. We found of particular interest the consistent pattern of education and health across the age groups. In particular, we observed a stable association of SPH and education in the different age groups. Low education did not seem to have a stronger negative effect for people younger than 50. This is surprising if we consider the different meaning of low education for the generations born before and after the II World War: for the oldest generation being what we defined "low educated" (no school/ primary) was the average condition, while, with the arise of Public Education programs after 1945, this condition became more and more rare, and it tended to mark individuals negatively selected (experiencing very low socio-economic status, poor health condition, mental retardation or exclusion). Hence, we expected the association of low education with poor health to be stronger in the youngest generations. Although the meaning of education has changed profoundly during the XX century, apparently its gradient on health has kept very similar features.

The objective conditions of health (*disability and multichronicity*) were obviously strongly associated with health perception, whatever the measure. In particular, disability presented the most intense association with poor SPH: about 58% of individuals with a disability reported to be in poor health, versus 30% of individuals affected by chronic conditions. Both the objective conditions of health status have a larger effect on the physical dimension (PCS) than on emotional aspects (MCS).

The last individual characteristic analyzed with respect to health was the co-residence with a person affected by disability. We registered an impact of living with an impaired person of comparable magnitude for PCS and MCS (score of 50 for people living in “healthy households” versus 46 for those living in “households with disability”). The effect of living with a disabled person is much more evident in SPH, where people living in a household with a disabled member report poor health in a proportion of about 16% versus 5% of their peers living in healthy household (Fig. 6.7). Disability is confirmed as one of the major challenge to good health status, with a tremendous direct and indirect effects. More than a half of people directly affected by physical limitations perceived their health as poor or very poor. Remarkably, also indirect effects of disability are significant: among healthy people those who live in the same household with a disabled report their health to be poor in 1 case over 5, whereas only 1 over 20 report poor health in households without disability[18].

[18] All results are 2-way associations not corrected for other possible covariates. Therefore they need to be interpret only as an explorative analysis of the characteristics associated with health.

Figure 4.6 - Proportion of poor health according to presence of disability (Direct effect)

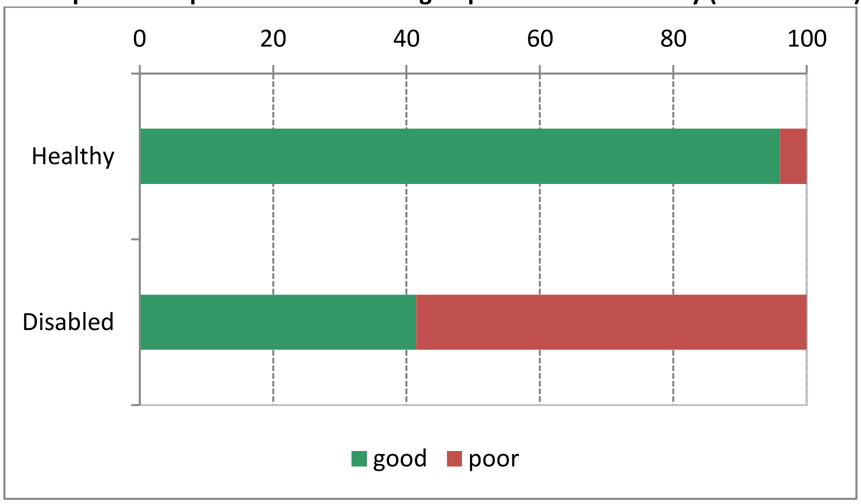
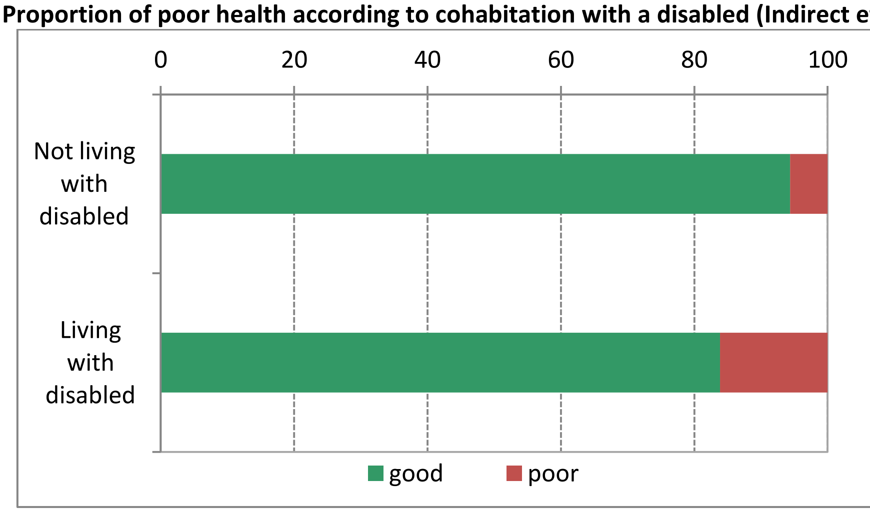


Figure 4.7 - Proportion of poor health according to cohabitation with a disabled (Indirect effect)

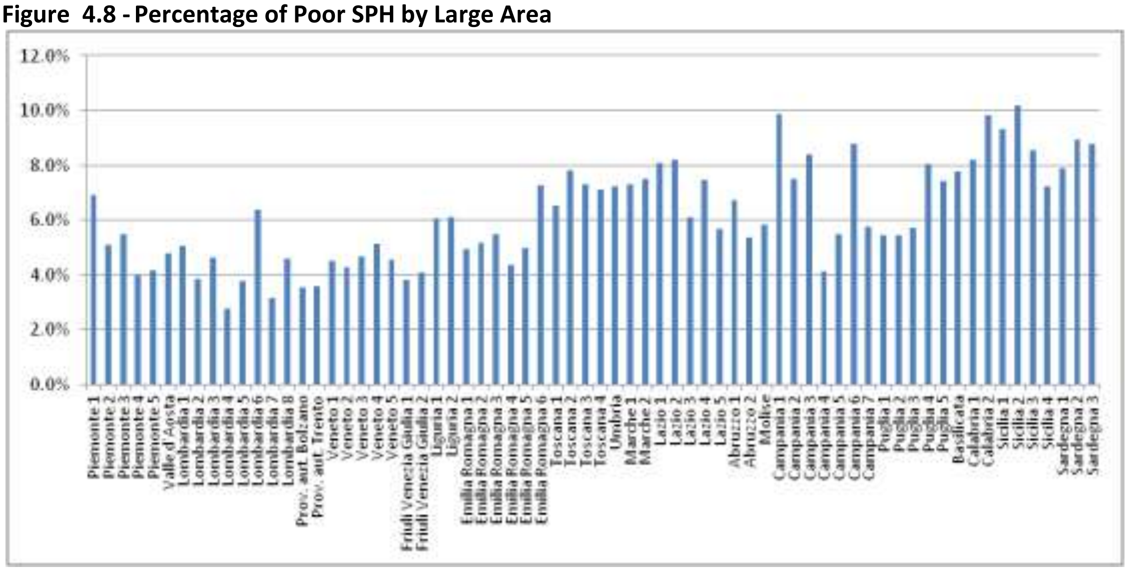


4.2 GEOGRAPHICAL INEQUALITIES IN HEALTH

Differences in perceived health by Large Areas are more pronounced when we look at the prevalence of poor-SPH than when we observe mean physical and mental summaries: the age-standardized percentage of people reporting poor-SPH spans from 2.8% to 10.2% respectively in *Lombardy_2* (which corresponds to the province of Milan) and *Sicily_4* (covering the very Southern part of Sicily) , whereas standardized mean scores for PCS and MCS vary from 48 to 52, confirming the North-South divide, as the highest levels are registered in Northern areas (Bolzano and Friuli-Venezia-Giulia) while the lowest score consistently appear in the South (*Puglia_5* and *Calabria_2*) (detailed values in A2).

Large Areas in Figure 4.8 are ordered according to their geographical location: from areas in the North East (on the left side) to areas of South and Islands (on the right side). We can easily detect a spatial pattern, although with some irregularities, mostly due to the consistently higher levels of poor perceived health in the Large Areas corresponding to large metropolitan areas within each region.

Figure 4.8 - Percentage of Poor SPH by Large Area



The Index of Dissimilarity for poor-SPH is 12%, meaning that the heterogeneity among the groups is slightly more than ten percent, whereas the Proportion attributable fraction is 55%, which is the percentage of poor self-perceived health that could be avoided if all the groups had the same rate as the group with the best health status. It is worth noticing that both these measures of health heterogeneity do not account for individual confounders, therefore they are an overall level of variability that needs to be refined through the multilevel approach.

Since PCS and MCS are quantitative measures we looked at range (maximum – minimum values of the distribution) and variance to evaluate the overall level of inequality. We observed a range of 3.7 points for PCS and 4.2 for MCS, with variances of 0.48 and 0.52. These differences are not extreme in their absolute values, however we know from previous studies (Costa *et al.* 2003) that values of PCS and MCS are very concentrated around the mean value of the scales (50), therefore we can assume that even small variations can be the result of significant differences.

We therefore tested these differences through an ANOVA analysis to detect whether differences between Large Areas represent real variation or they are just observed by chance.

The overall ANOVA test showed significant results, thus we proceeded through a post hoc estimation in order to detect which Large Areas differ significantly one from the other. A clear patter emerged in which the Area of the province of Milan (*Lombardy_2*), Bolzano and Areas of Friuli differed significantly from Large Areas in Basilicata, Calabria and Sardinia. These results reproduce the well-known geography of Italy by macro zones (NUTS-1): North West, North East, Centre, South and Islands.

However significant differences have been observed even for some specific neighboring Large Areas. It happens especially in the South for the areas of *Calabria_2* and *Sicily_1* for PCS and *Puglia_2* and *Puglia_3* (intra-regional differences) for MCS.

4.3 INDIVIDUAL AND CONTEXTUAL DETERMINANTS OF HEALTH

The proper way to investigate jointly individual and contextual predictors of health is the multilevel approach, where each factor operates from the most appropriate level, and the relative weight of each level in determining health can be estimated. As extensively exposed in Chapter 3, we followed the classical steps in developing a multilevel model, slightly adapted to the peculiarities of this research: firstly, we estimated the magnitude of each level (Individual, Households, Large Areas) in affecting individual health, secondly, we introduced individual covariates in the model in order to investigate possible compositional effects (whether the differences between groups were made up or hidden by individual characteristics), then we added Household and Large Area covariates to explain the differences in health between groups by means of different characteristics of the groups themselves. In this step we also checked how much unexplained variability persist between groups after controlling for all these structural variables.

4.3.1 Taking account of context: the empty model

The empty model, i.e. the multilevel model without any covariates, served us as a starting point. In this model, in fact, the variance is not explained but only decomposed on the three levels (variance between and within groups). This model allowed us to observe how much variability in individual health was attributable to differences between geographical units and between households, for each of the three health outcomes. This has been done through the Variance Partition Coefficient (VPC), that expresses precisely the proportion of variability at each level[19]. The VPC of households when the outcome is SPH need to be considered with caution. In Multilevel models with binary outcome and small cluster size , the estimation of random parameters could be biased[20]. However results for SPH are always cross validated through PCS and MCS.

[19] The other interpretation of this coefficient is the degree of resemblance between units in the same cluster (*intraclass correlation coefficient* – ICC). This interpretation is conceptually different, but methodologically related to the VPC: the higher the similarity of units inside the groups, the larger the proportion of variability attributable to differences *between* groups (for a detailed description of ICC interpretation refer to Chapter 3).

[20] For more methodological details see Chapter 3, Paragraph 3.4.1.

Table 4.9 - The 3-level empty model for PCS

PCS				
FIXED PARAMETERS	COEFF	S.E.	95% CI	
Intercept	50.36	0.09	50.19	50.53
RANDOM PARAMETERS				
Var (Large Area)	0.42	0.09	0.28	0.63
Var (Household)	20.22	0.40	19.45	21.02
Var (individuals)	65.83	0.40	65.05	66.62
VPC per level				
VPC (Large Areas) %	0.48	0.10	0.29	0.68
VPC (Household) %	23.38	0.36	22.69	24.08

Obs	**Log-LIkelihood**	**df**	**AIC**
91391	-331,288.6	3	662,583

Table 4.10 - The 3-level empty model for MCS

MCS				
FIXED PARAMETERS	COEFF	S.E.	95% CI	
Intercept	49.85	0.10	49.65	50.05
RANDOM PARAMETERS				
Var (Large Area)	0.60	0.12	0.40	0.89
Var (Household)	30.32	0.44	29.46	31.19
Var (individuals)	60.72	0.37	60.01	61.44
VPC per level				
VPC (Large Areas) %	0.66	0.13	0.40	0.92
VPC (Household) %	33.08	0.33	32.45	33.72

Obs	**Log-LIkelihood**	**df**	**AIC**
91391	-331,867.5	3	663,741

What immediately stands out from tables 4.9 and 4.10 is the very small contribution that the Large Areas give to the overall variability in health between individuals: less than 1% of the differences in physical and mental conditions are linked to the Large Area of residence. This contribution of health administrative units to individual health is, however, significant (the 95%

confidence intervals do not include the zero). Thus, the individual health is affected by the area of residence, but in a very small proportion with respect to other possible factors that occur at the household and at the individual level.

The picture was not substantially different when we looked at SPH (Table 4.11).

Table 4.11 - Intercept-only Model for SPH

	SPH			
FIXED PARAMETERS	OR	S.E.	95% CI	
Intercept	0.028	0.001	0.025	0.031
RANDOM PARAMETERS	VARIANCE			
Var (Large Area)	0.07	0.01	0.05	0.10
Var (Household)	2.20	0.11	2.00	2.41
Var (individuals)	3.29			
VPC per level				
VPC (Large Areas) %	1.24	0.26	0.82	1.88
VPC (Household) %	39.52	1.09	38.65	42.92

Obs	Log-LIkelihood	df	AIC
91391	-20,926	3	41,859

The proportion of variability to be accounted for at the territorial level is now 1.24%.

This proportion is relatively higher than PCS and MCS and, in fact, self perceived health exhibited more territorial variation than PCS and MCS already in the descriptive analyses.

However, the reflections we elaborated about PCS and MCS can be extended to SPH. The geographical component has a much smaller weight than lower level factors in explaining why individuals differ one from the other in terms of health[21]. To sum up we could look at table 4.12 where we have the percentage of variability at each level and for each indicator.

[21] Through the formula already discussed in Chapter 3 (paragraph 3.2.4), we computed the Variance Partition Coefficient for SPH by assuming an individual variance fixed at 3.29

Table 4.12 - Proportion of variance on the 3 nested levels

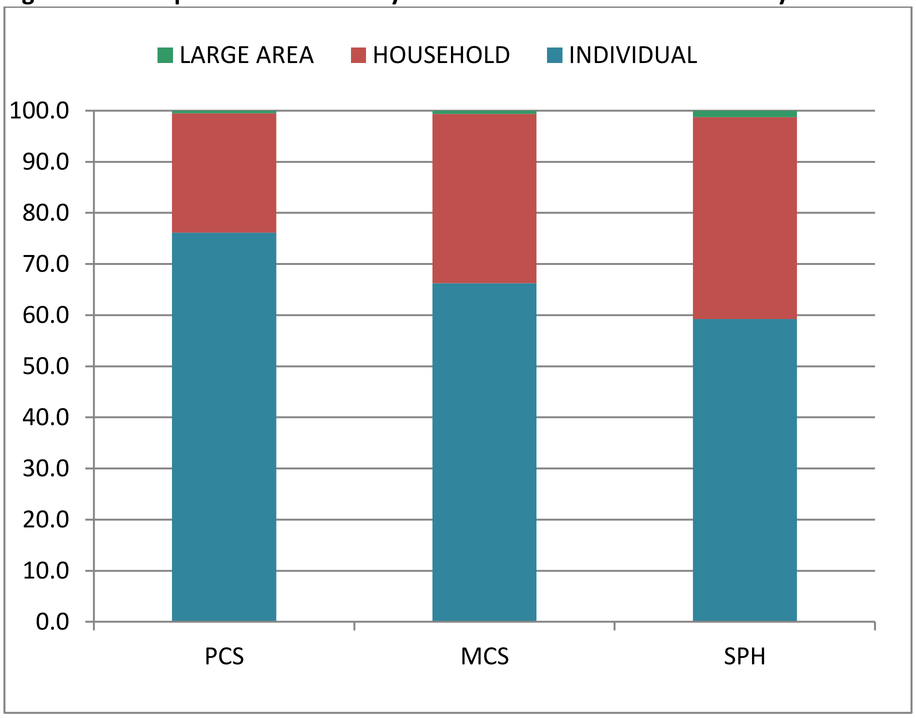
LEVEL	HEALTH OUTCOME PCS	MCS	SPH
LARGE AREA (%)	0.5	0.7	1.2
HOUSEHOLD (%)	23.4	33.1	39.5
INDIVIDUAL (%)	76.1	66.2	59.3
TOTAL (%)	100	100	100

The proportion of variability attributable to Large Areas was extremely small for all of the three measures: from 1.2% for Poor Self-Perceived Health to about 0.5% for the Physical Component of the SF-12 (Table 6.12), suggesting that the Large Areas contribution to health differentials is generally limited.

Although it is a general opinion that in Italy health differences by area of residence do exist, when we explore the phenomenon through indicators of health and in a multilevel approach, it seems that the Area of residence does not have a remarkable effect compared to household and individual factors. This result is in line with findings from similar studies conducted in Italy, where the authors reported a contribution of health administrative units, precisely Regions and Large Areas, lower than 3% of the total variability of self-perceived health among the elderly (Pirani and Salvini, 2012b).

Differently from Large Areas, households exhibit a substantive effect on individual health: the proportion of variance due to household grouping structure is about 23% for PCS, 33% for MCS and 40% for self-perceived health. Not surprisingly PCS is the indicator less affected by contextual factors, while MCS and SPH are similarly influenced by what is over and above the individuals. The Physical Component Summary, in fact, is the indicator more strictly linked to objective conditions. Although it is based on self-perception of physical conditions, PCS concerns mainly aspects of activity and role limitations, physical pain and loss of productivity, that are obviously less affected by contextual factors.

Figure 4.9 - Proportion of variability for each of the three level of analysis



We considered some hypotheses for interpreting the large disproportion of variability attributable to Large Areas and to Households. A first hypothesis was methodological: the different variance between Households and Large Areas could depend on the different characteristics of the 2 levels. Households are small clusters, with an average of 2.5 individuals, whereas Large Areas are ample units, including about 1,300 households on average. Therefore we could expect to observe more homogeneity *within* households (and consequently more variation *between* households) and less homogeneity *within* Large Areas (corresponding to less variation *between* Large Areas). Furthermore the total number of Households and Large Areas is also very different: households exceed 30,000 units in our dataset, while Large Areas are 68: this could explain the higher heterogeneity observed between Households compared to Large Areas. This interpretation is quite intuitive and supported by methodological evidence, however, results of several researches on international health inequality cast doubt on it. In these studies, which explores health differences between countries, the size of the level-2 units (countries) is significantly larger than the size of Large Areas, nevertheless the variability at the country-level is estimated at 9-10% of the total variability in health perception (Eikemo *et al.* 2008), (Elgar *et al.* 2011). The different cluster size of level-2 and level-3 units, therefore, can not entirely explain the differential in the variability registered at the household and at the geographical level. Other explanations need to be considered, based on the body of knowledge about geographical health inequalities in Italy. Geographical variability in Italy has traditionally been observed in mortality rates (Caselli and Egidi, 1980), specific cause mortality and health objective measures (Osservasalute 2008). However, small evidence exist about health perception. Perceived health, in its multidimensional assessment by physical and mental components (PCS, MCS) and overall health status (SPH) could be characterized by smaller variation than other health indicators. Another interpretation of our result could therefore be in this direction: the geographical gradient observed in Italy for mortality and objective indicators of health (e.g. disability free life expectancy – DFLE) could be not equally reproduced by self perceived health. This hypothesis an it is better investigated and discussed along this research project, although it needs to be supported by further evidence.

Since the geographical differences were small but always significant, we kept the 3-level hierarchical structure in all the following developments of the models and, as a further step, we considered the individual characteristics in the analysis. With the inclusion of individual covariates we expected the magnitude of contextual effect to be exposed to change: variability between Households/Large Areas could either decrease or increase, depending on whether the individual characteristics were making up or masking the differences between contextual units.

4.3.2 The Compositional effect: model with individual covariates

Individual covariates were included in the model, in particular: age in classes, gender, education, objective health conditions (disability, multichronicity) and cohabitation with disable were considered as predictors of perceived health status.

The reference for Age has been set at 50-64, because we intended to investigate health differences and relative determinants focusing on old-adult population, and because they represent a more stable class to be assumed as a reference compared to the ge <50, where poor health is a very rare phenomenon.

The interpretation of the effects across the three indicators (PCS, MCS, SPH) requires some attention, because the quantitative measures derived from SF-12 (PCS, MCS) are positively-oriented (a higher score corresponds to better health), whereas the SPH indicator is negatively oriented, designed to capture poor health status[22]. The covariates in the model with SPH will exhibit coefficients with opposite directions than those referred to PCS and MCS.

The model for PCS is illustrated in Table 4.13.

[22] Reasons for the choice of negative oriented SPH are discussed in Chapter 2.

Table 4.13 - Random intercept model with individual covariates for PCS

	PCS			MCS		
COVARIATES	COEFF	95% CI		COEFF	95% CI	
FIXED PARAMETERS						
Intercept	52.7	52.5	52.9	51.8	51.6	52.1
Age in classes						
< 50	2.3	2.2	2.4	0.7	0.6	0.9
50-64 (ref)	*0.0*			*0.0*		
65-74	-2.0	-2.2	-1.9	0.4	0.2	0.6
75+	-5.0	-5.2	-4.7	0.3	0.1	0.6
Gender						
Male (ref)	*0.0*			*0.0*		
Female	-0.9	-1.0	-0.8	-2.0	-2.1	-1.9
Education						
High (ref)	*0.0*			*0.0*		
Medium	-1.0	-1.1	-0.9	-0.4	-0.5	-0.2
Low	-2.4	-2.5	-2.2	-1.0	-1.2	-0.9
Disability						
no (ref)	*0.0*			*0.0*		
yes	-13.0	-13.2	-12.7	-7.4	-7.7	-7.1
Multichronicity						
no (ref)	*0.0*			*0.0*		
yes	-7.8	-8.0	-7.7	-5.3	-5.5	-5.1
Living with disable						
no (ref)	*0.0*			*0.0*		
yes	-0.1	-0.3	0.1	-1.9	-2.2	-1.7

	PCS			MCS		
RANDOM PARAMETERS	VALUE	95% CI		VALUE	95% CI	
Var (Large Areas)	0.15	0.10	0.23	0.49	0.33	0.74
Var (Households)	7.22	6.82	7.65	25.90	25.15	26.67
Var (Individuals)	42.65	42.15	43.16	54.94	54.30	55.60
VPC Large Areas (%)	0.30	0.19	0.47	0.61	0.41	0.90
VPC Households (%)	14.74	13.96	15.55	32.45	31.67	33.23

Statistics of the model

PCS	df	Log-LIkelihood	LR Test value	LR Test p_value	AIC
	14	-307,398.4	47,402	0.00	614,824.8
MCS					
	14	-326,739	10,032	0.00	653,506

The majority of the variables selected for the analysis have shown a significant effect in predicting PCS. Particularly Disability and Multichronicity appear as the main drivers of a low perceived physical condition, as they produce a decrease of the index of respectively 13 and 7.8 points. Ageing causes a steep deterioration of physical conditions, with a decrease of PCS of about 2 points passing from an age group to the older age group-

The relation of gender and health is also confirmed, with women reporting on average almost 1 point less than men in PCS, other things being equal.

Education shows also a notable impact: the gradient is almost linear, with the PCS decreasing of 1 point as the level of education is lowered of one class (from High to Medium, and from Medium to Low). The cohabitation with a person affected by disability does not seem to have effect on individual physical health. Although a physical impact of living with a person with disability could also be expected, since the burden of disease or the caregiver activity can affect healthy members of the family also on the physical profile, however, we expected major effects for the other two indicators, more sensitive to the emotional and psychological aspects.

Concerning the weight of the context: Large Area's relative impact is lowered by the introduction of individual covariates and reaches a level of 0.3% of the total variability. We can remark that, though very low, this value is still significant (the 95% Confidence Interval do not include the value of 1). Nevertheless, with this result we can conclude that the "pure" effect of place of living accounts for a very limited proportion in explaining individuals diversities in health status.

The variability between households registered in the Intercept-only model revealed to be the fruit of a strong compositional component: when we introduce individual explicative variables the inter households variability decreases from 23% to 15%. However, the values adjusted for individual characteristics are still remarkably high and strongly significant.

Overall, the model with individual covariates performs , as we would expect, better than the empty model as suggested by the Likelihood Ratio Test (LR test) and the Akaike Information Criterion (AIC): the introduction of information at the individual level significantly improve the fit of the model.

The *Mental Component Summary* exhibits a completely different profile than the Physical Component Summary (Table 4.13).

The main socio-demographic characteristics influence both the indexes, but with a very different intensity. Gender is more influential on mental health (with men benefiting of about 2 points on average), while age is not significant for MCS, indicating that emotional well-being is not strictly connected with age. Education is still significant for MCS, but less importantly than for physical health.

What is especially relevant for the perspective of this research is the impact of the variable Cohabitation with a disabled, that in this model has now a remarkable effect on individual health. Living with a disable decreases the mental score of 1.9 points and, as expected, its negative influence is largely more evident on Mental health, that it affects by means of emotional burden, psychological distress and mental weariness.

Large Areas and Household variability is not substantially modified by the introduction of individual characteristics. Both decrease of 1 percent point: the former from 0.7% to 0.6%, the latter from 33% to 32%. This result can be read as follow: individual characteristics explain variability between individuals, but they are globally equally distributed in households and Large Areas, therefore the differences we found at the contextual level are not moderated by the introduction of individual characteristics. The pure values of variance, however, denote that the individual predictors did not explain a large part of variability at the individual level either.

In the interpretation of results for SPH we need to bear in mind that in a multilevel logistic model coefficients (or their exponential version: odds ratios) have a meaning only within the model, in relative terms, but they cannot be compared with coefficients of another nested model[23].

Therefore, the absolute values of the odds ratio can not be interpreted straightforwardly as in an ordinary logistic regression.

[23] For more methodological details on this issue see Chapter 3, Paragraph 3.3.1

Table 4.14 - Random intercept model with individual covariates for SPH

COVARIATES	COEFF	STD ERR	Z	Pr>Z	95% CI	
FIXED PARAMETERS						
Intercept	0.01	0.00	-52.35	0.00	0.01	0.01
Age in classes						
< 50	0.45	0.03	-13.91	0.00	0.40	0.50
50-64 (ref)						
65-74	1.23	0.07	3.78	0.00	1.11	1.38
75+	1.31	0.08	4.33	0.00	1.16	1.48
Gender						
Male (ref)						
Female	1.19	0.04	4.76	0.00	1.11	1.29
Education						
High (ref)						
Medium	1.60	0.09	7.99	0.00	1.43	1.80
Low	2.48	0.15	14.85	0.00	2.20	2.80
Disability						
no (ref)						
yes	24.08	1.67	45.79	0.00	21.02	27.59
Multichronicity						
no (ref)						
yes	9.36	0.47	44.93	0.00	8.49	10.32
Living with disable						
no (ref)						
yes	1.40	0.09	5.57	0.00	1.25	1.58

	COEFF	STD ERR	95% CI	
RANDOM PARAMETERS				
Var (Large Areas)	0.12	0.03	0.08	0.19
Var (Households)	1.91	0.13	1.68	2.17
Var (Individuals)	3.29			
VPC Large Areas (%)	2.28	0.48	1.50	3.44
VPC Households (%)	38.16	1.52	35.24	41.18

Statistics of the model

Poor SPH	Log-LIkelihood	df	LR Test value	LR Test p_value	AIC
	-14,146	12	13,560	**0.00**	**28,316**

The effect of socio-demographic variables: age, gender and education is in the direction expected. Not surprisingly the objective health conditions are the main drivers of poor health status, with an odds ratio (probability of perceiving themselves as unhealthy rather than healthy) that is about 12 times higher for people with disability, and 6 times higher for people with multichronicity.

Having a disabled in the household increases the odds of perceiving poor health of 25%, denoting an important contribution of the burden of disease of a family member on an individual health status.

The overall variability between households decreases from 40 to 35 per cent, indicating that, once we correct for compositional bias, there is still a large proportion of differences that rely on household level.

Taking into account the results about proportion of variability at the Large Area level, we decided to not include specific Large Area covariates, since there was not a reasonable proportion of variability in need to be explained between Large Areas; rather we decided to focus on household variation, which seemed to be a non negligible dimension for the study of health. The only level-3 variable taken into consideration was the location of Large Area in the Italian *macro territorial partitions* (North, Centre, South, Islands).

4.3.3 The Contextual determinants: model with individual and group covariates

The large component of variability at the household level induced us to investigate what characteristics of the households could determine differences in health for the family components. We included in the models all the available structural characteristics of the households. These information were related to economic conditions (Adequacy of economic resources and housing conditions), household structure (size and typology) and municipality of residence (city size).

As anticipated we used also one attribute for Large Areas: their geographical location in the Italian macro territorial partitions (North, Centre, South, Islands).

Table 4.15 - Random intercept model with Individual and Group covariates - PCS

	PCS			MCS		
COVARIATES	COEFF	95% CI		COEFF	95% CI	
LEVEL 1 FIXED PARAMETERS						
Intercept	53.2	53.0	53.4	52.3	52.0	52.6
Age in classes						
< 50	2.4	2.3	2.5	0.9	0.8	1.1
50-64 (ref)				*0.0*		
65-74	-2.1	-2.2	-1.9	0.3	0.1	0.5
75+	-5.0	-5.2	-4.8	0.3	0.0	0.5
Gender						
Male (ref)	*0.0*			*0.0*		
Female	-0.9	-1.0	-0.8	-2.0	-2.1	-1.9
Education						
High (ref)	*0.0*			*0.0*		
Medium	-0.8	-1.0	-0.7	-0.1	-0.3	0.0
Low	-2.1	-2.2	-1.9	-0.7	-0.8	-0.5
Disability						
no (ref)	*0.0*			*0.0*		
yes	-12.9	-13.2	-12.7	-7.2	-7.5	-6.9
Multichronicity						
no (ref)	*0.0*			*0.0*		
yes	-7.7	-7.9	-7.6	-5.2	-5.4	-5.0
Living with disable						
no (ref)	*0.0*			*0.0*		
yes	0.0	-0.1	0.2	-1.7	-1.9	-1.4
LEVEL 2 FIXED PARAMETERS						
H_resources						
Good(ref)	*0.0*			*0.0*		
Insufficient	-0.9	-1.1	-0.8	-2.0	-2.2	-1.8
H_conditions						
Good(ref)	*0.0*			*0.0*		
Fair	-0.3	-0.4	-0.2	-0.4	-0.5	-0.2
Bad	-0.6	-0.8	-0.3	-1.2	-1.6	-0.8
H_size						
2/3 comp (ref)	*0.0*			*0.0*		
4 comp	0.2	0.1	0.3	-0.1	-0.3	0.1
> 4 comp	0.3	-0.1	0.6	1.2	0.7	1.7
H_structure						
Couple Headed (ref)	*0.0*			*0.0*		

Single Headed	0.1	-0.1	0.2	-0.7	-0.9	-0.5
City size						
>= 50.000 (ref)	*0.0*			*0.0*		
< 50.000	-0.4	-0.6	-0.3	0.1	-0.1	0.3
Geo_Area						
North (ref)	*0.0*			*0.0*		
Centre	-0.2	-0.4	0.1	-0.3	-0.8	0.1
South	-0.2	-0.4	0.0	0.0	-0.4	0.4
Islands	-0.5	-0.8	-0.2	0.6	0.1	1.2

	PCS			**MCS**		
	COEFF	**95% CI**		**COEFF**	**95% CI**	
RANDOM PARAMETERS						
Variance (Large Areas)	0.09	0.05	0.15	0.35	0.23	0.53
Variance (Households)	6.99	6.60	7.42	24.89	24.16	25.65
Variance (Individuals)	42.64	42.14	43.15	54.93	54.29	55.58
VPC Large Areas (%)	0.18	0.11	0.30	0.43	0.28	0.67
VPC Households (%)	14.25	13.48	15.06	31.48	30.72	32.26

Statistics of the model

PCS	**Log-LIkelihood**	**df**	**LR Test value**	**LR Test p_value**	**AIC**
	-307,207	24	384	**0.00**	**614,462**
MCS					
	-326341.1	24	1016	**0.00**	**652,730**

In this model the covariates representing relations among family members have a low, and often not significant, impact on health for PCS: cohabitation with disable, the size and the structure of the household, all exhibit small relevance in predicting physical components of health status.

The economic variables, on the other hand, take on a large weight in determining the individual physical status within households: families with good housing conditions and especially with good economic resources have a PCS which is 1.30/1.50 points higher than the score for people with inadequate economic conditions and respectively Medium/Low Housing conditions.

Characteristics of the place of living, city size and macro areas, influence health with an expected gradient: better health conditions are observed in the North and in larger cities. These two characteristics of place of living share a larger service availability and more opportunity of treatment and cure.

This full model presents a significant improvement in the goodness of fit compared to the individual model(LR test < 0.001 and AIC -full model is lower than AIC - model with individual covariates), confirming that, although contextual covariates explain a small part of contextual variance, if we remove them from the model this would significantly reduce the goodness of fit.

The Mental Component Summary has some peculiarities as health indicator: firstly, while gender and education exhibit the classical patterns, age show significant effects, but outside any clear pattern. The most disadvantaged age group is 50-64, in respect to which all the other age groups present a better mental health status. This result can be supported by some evidence: first of all, middle age is the period in the life course when individuals (especially women) have full time work, home engagement, children or teenagers to look after and often elderly relatives to be responsible of. Therefore they are exposed at the highest levels of responsibility, stress and external demands. Not surprisingly it is in these ages that the highest frequencies of mental health problems is reported. In the USA women aged 50-64 have the highest rate of “frequent mental distress”, which includes stress, depressions and emotional problems (Centers for Disease Control and Prevention 2008). The British NHS show similar figures: women in their 45-64 suffer from depression and anxiety more than any other social group and their proportion rose of about a forth from 1993 to 2007, passing from 20% to 25%. (NHS -Adult Psychiatric Morbidity Survey, 2009).

The age effect is not the only peculiarity of MCS. Another aspect that emerges from this model is the influence of relational networks on emotional health. All those social/relational aspects that were found to be not influential for PCS, come back to be very predictive for the mental component of health. The household size and structure shape the emotional well-being of its members: families with more than four components living together are more protected against poor mental health, similarly, couple-headed families experience better mental conditions than lonely parent households. Among these relational variables the highest impact is exerted by the burden of disability in the household: having a component affected by disability decreases the mental score of the cohabiting persons of 1.66 points on average.

Overall, living in situation of social disadvantage, such as: households with single-parent, burden of disability and inadequate economic conditions (both in terms of housing and current dispensable income) produce a cumulative decrease of the Mental Component Summary score that reaches 5.6 points. As already seen for PCS this model is better performing than the model with individual covariates only. Results from LR test and AIC justify the necessity of taking into consideration the contextual information, although they do not explain a major component of variance between Large Areas and households.

If we have a look to poor-SPH, we can also find some remarkable effects. First of all, the objective health conditions have an overwhelming effect on poor self-perceived health. As mentioned before, the coefficients can assume very extreme values as they are not meaningful in their absolute terms, rather with respect with the other coefficients in the same model. In this model, for instance, the disability has an effect that is 15 to 20 times stronger that the effect of any other covariate in the analysis.

A part from the objective health conditions, the economic component has a very strong effect both at individual and household level: education on level-1 and housing condition and economic resources on level-2 are the strongest predictors of poor health status, almost doubling the risk of poor health perception.

At level 2, the size of the family and the city are both related to health perception, but with an opposite direction: larger households are associated with better health status, as well as smaller cities. These two variables can in fact be seen as two complementary aspects of the social support and network: familiar and social ties are stronger in large families and little communities.

The geographical macro areas reproduce precisely the Italian health gradient as we knew it: poorer health conditions in the central area and in the islands.

Table 4.16 - Random intercept model with Individual and Group covariates for SPH

COVARIATES	OR	STD ERR	Z	Pr>Z	95% CI	
LEVEL 1 FIXED PARAMETERS						
Intercept	0.01	0.00	-51.08	0.00	0.00	0.01
Age in classes						
< 50	0.42	0.02	-14.68	0.00	0.38	0.47
50-64 (ref)	*1.00*					
65-74	1.22	0.07	3.56	0.00	1.09	1.36
75+	1.34	0.08	4.65	0.00	1.18	1.52
Gender						
Male (ref)	*1.00*					
Female	1.20	0.05	4.73	0.00	1.11	1.29
Education						
High (ref)	*1.00*					
Medium	1.40	0.08	5.62	0.00	1.24	1.57
Low	1.98	0.12	10.98	0.00	1.75	2.24
Disability						
no (ref)	*1.00*					
yes	22.48	1.55	45.17	0.00	19.64	25.73
Multichronicity						
no (ref)	*1.00*					
yes	8.65	0.43	43.61	0.00	7.85	9.53
Living with disabled						
no (ref)	*1.00*					
yes	1.29	0.08	4.16	0.00	1.14	1.45
LEVEL 2 FIXED PARAMETERS						
H_resources						
Good(ref)	*1.00*					
Insufficient	2.11	0.09	16.69	0.00	1.93	2.30
H_conditions						
Good(ref)	*1.00*					
Fair	1.20	0.06	3.82	0.00	1.09	1.32
Bad	1.81	0.17	6.17	0.00	1.50	2.19
H_size						
2/3 comp (ref)	*1.00*					
4 comp	0.75	0.04	-5.29	0.00	0.68	0.84
> 4 comp	0.65	0.09	-3.13	0.00	0.49	0.85
H_structure						
Couple Headed (ref)	*1.00*					
Single Headed	1.13	0.06	2.15	0.03	1.01	1.26

City size						
>= 50.000 (ref)	*1.00*					
< 50.000	0.89	0.04	-2.53	0.01	0.81	0.97
Geo_Area						
North (ref)	*1.00*					
Centre	1.59	0.13	5.65	0.00	1.36	1.88
South	1.31	0.10	3.70	0.00	1.14	1.52
Islands	1.79	0.18	5.90	0.00	1.47	2.17

	COEFF	STD ERR	95% CI	
RANDOM PARAMETERS				
Variance (Large Areas)	0.03	0.01	0.01	0.06
Variance (Households)	1.79	0.12	1.56	2.05
Variance (Individuals)	3.29			
VPC Large Areas (%)	0.56	0.20	0.28	1.12
VPC Households (%)	35.56	1.58	32.53	38.71

Statstics of the model

Poor SPH	Log-LIkelihood	df	LR Test value	LR Test p_value	AIC
	-13816.43	23	13,500	**0.00**	27,678

In order to provide a summarizing picture where all and only the significant determinants appear we produced specific figures that better highlight the profile of determinants for each health indicator.

Figure 4.10 - PCS profile of determinants in the full model: individual and group covariates

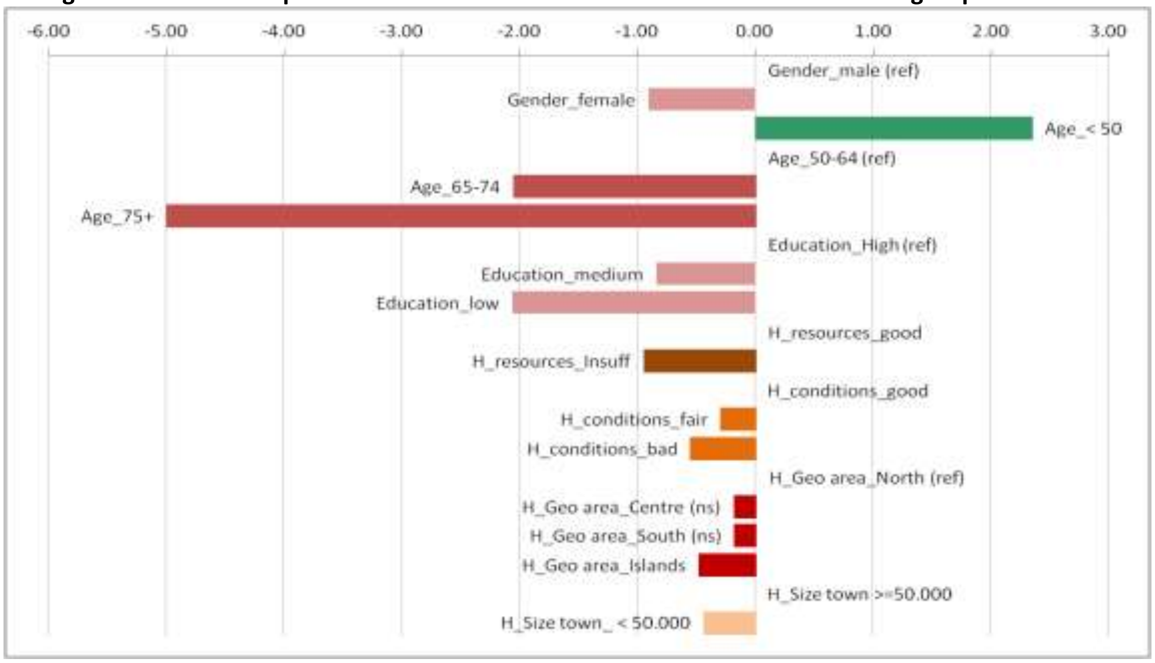
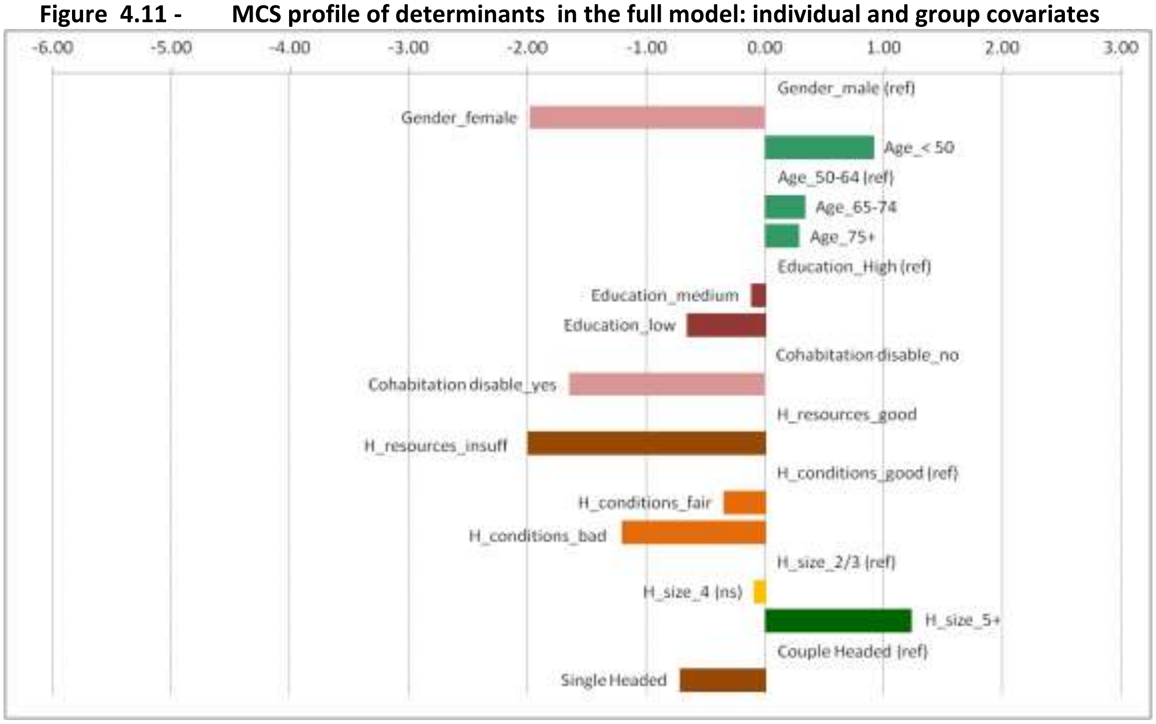


Figure 4.11 - MCS profile of determinants in the full model: individual and group covariates



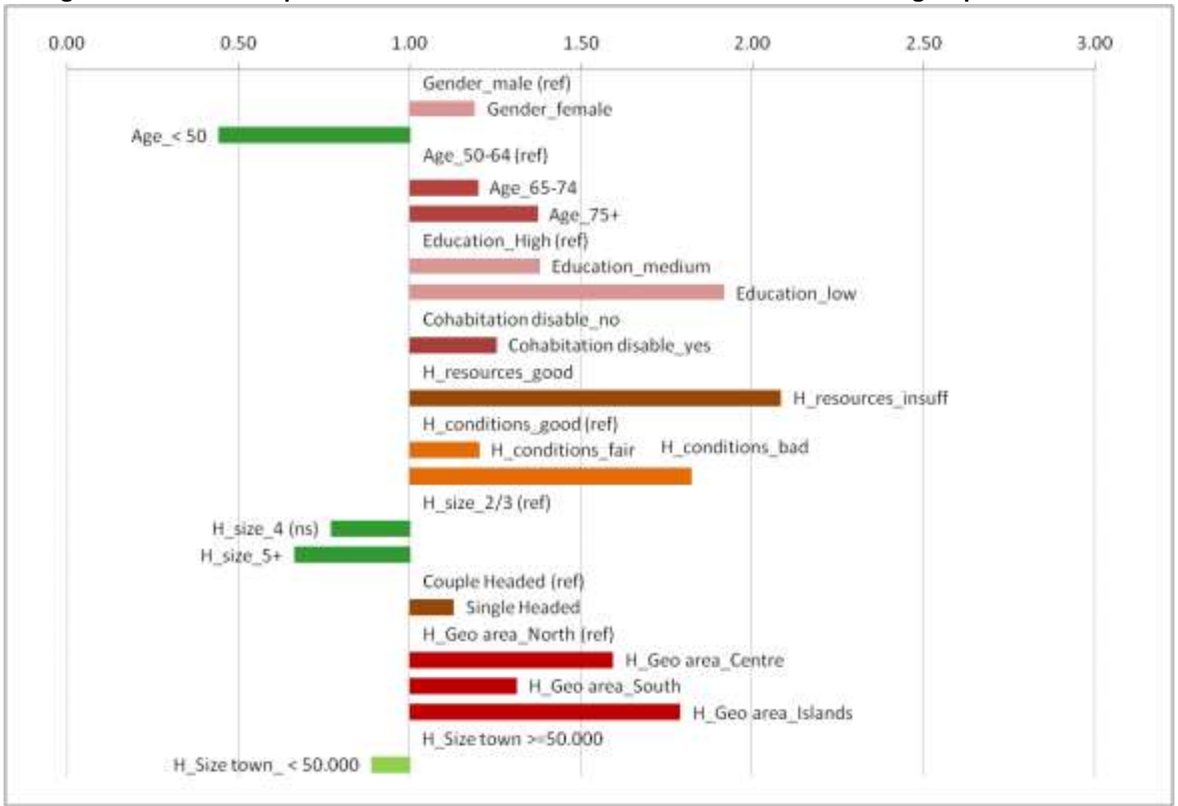
What is immediately evident from Figures 4.10 and 4.11 is that the determinants influencing physical and emotional health are remarkably different. The figures exhibits, in fact, almost opposite profiles: PCS has a predominance of factors in the upper part of the graph (individual factors) whereas MCS is more balanced and presents important contributions also in the bottom part (household factors).

Age and education mainly explain variations in physical health, while all the aspects of familial relationship play a role for mental health: cohabitation with disable, household size and structure. Particularly people in larger couple-headed households report better health conditions. Gender has influence on both the outcomes, but the women disadvantage is double for MCS than PCS.

Familial economic conditions also affect both the indicators, but with higher strength MCS, where the average condition decreases of 2 points when the economic resources are perceived as inadequate.

Finally, the geographical component appear as a factor influencing only physical health, favoring those living in the Northern Large Areas.

Figure 4.12 - SPH profile of determinants in the full model: individual and group covariates



What is interesting in the profile of determinants of poor self perceived health (Fig. 4.12) is the fact that they appear as a synthesis of PCS and MCS determinants.

We can recognize the remarkable effects of age and education, distinctive of physical health, but also the risk associated with living with a disabled, with few people and in a lonely-parent household, typical of the mental component profile. The economic situation of the household mantains its significance: people with inadequate income and housing report an odds ratio of poor health 2 and 1.5 times higher than people in the reference category. Likewise PCS, people living in the North have an health advantage, while Cental Italy and Islands have 50% to 70% more risk of perceiving their health as poor. Peculiar of this indicator is the positive contribution of living in a relative small community (less than 50.000 inhabitans) already discussed in SPH full model.

4.4 SENSITIVITY ANALYSIS FOR WEIGHTED AND UNWEIGHTED MODELS

Since we dealt with survey data, specific sampling weights needed to be included in the analysis, in order to produce reliable population level estimates. However, we were also aware that estimations obtained from weighted data present some remarkable limitations, especially in terms of evaluation their performance: tests based on the likelihood function cannot be applied .

We decided then to run both a weighted and an unweighted full models[24] and to examine the relative differences in the estimation of parameters. We registered differences in the estimation of: coefficients (with standard errors), intercepts and random variances for PCS and MCS, and reported them as "percentage variation between unweight and weighted data":

$$\Delta\,(weight) = \frac{\hat{\theta}_{\,unweight} - \hat{\theta}_{\,weight}}{\hat{\theta}_{\,unweight}} * 100$$

These relative differences are lower than 5% for all the parameters with only two exceptions: Large Areas variance (for MCS) and the effect of small city size (for PCS). However, even in these cases looking at cross-model variation expressed by means of absolute values we saw that: Large Areas VPC changes from 0.43% (unweighted) to 0.37% (weighted); whereas the effect of small city size varied from -0.44 to -0.51 passing from unweighted to weighted model.

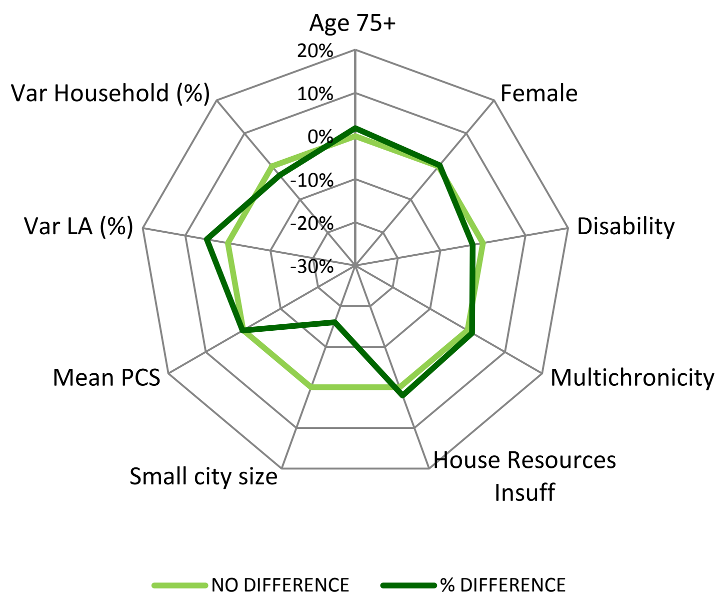
The consistency of the two models is therefore fairly evident: even for the parameters that exhibit the larger cross model percent variation, the meaning of the effects remain substantially unchanged.

In the radar graphs (Fig. 4.13 and Fig. 4.14) we plotted the cross model percent differences of some selected parameters. These parameters are: the main demographic parameters (age, gender, disability and multichronicity), the outcome mean (when all the covariates are set at zero, i.e. the overall intercept) and the variances attributable to Households and Large Areas. We included also the two specific covariates with the larger cross model variation respectively for PCS and MCS.

[24] Results of the weighted models are presented in Appendix B

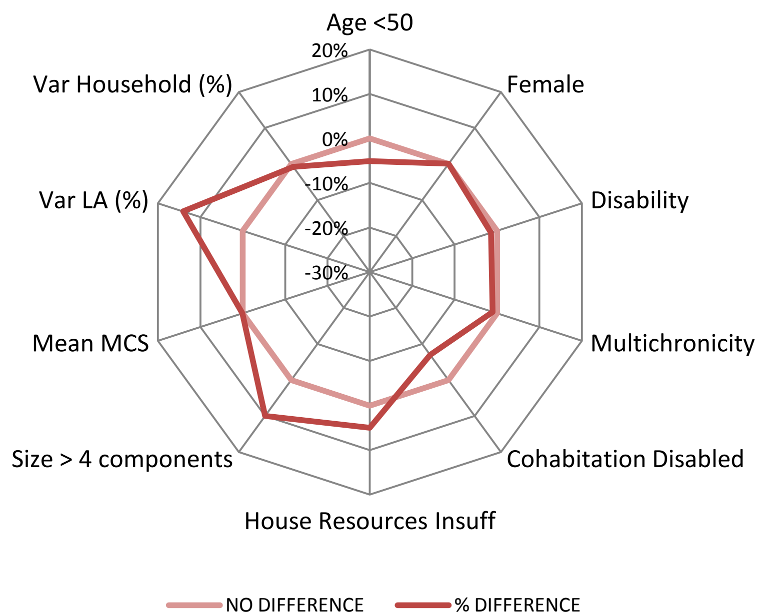
Age was represented only by the category with the highest difference with respect to the reference group (50-64).

Figure 4.13 - Percentual change of parameters from unweighted to weighted model - PCS



Light green line marks the value of zero (no cross model differences)

Figure 4.14 - Percentual change of parameters from unweighted to weighted model - MCS



Light red line marks the value of zero (no cross model differences)

Both the graph illustrate clearly how cross model differences are negligible for the main parameters of the model: age, gender, disability and multichronicity. The mean and the percentage variation at the household level also remain unchanged.

4.5 THE MAGNITUDE OF CONTEXTUAL EFFECTS

Up to this point we have investigated determinants of perceived health taking into account the hierarchical structure of the information and therefore we have produced estimations that are formally unbiased. Yet, we do not have a clear answer to the question: *what is the overall magnitude of effects of Large Areas and Households on perceived health?*

Explicit knowledge about magnitude of contextual influences, i.e. the intra-group correlation, is of substantive importance for demography and social epidemiology. In fact, the more the health of individuals within the same group is similar (which yields that the variability between groups is higher) the more likely it is that inequalities in individual health depends directly on contextual determinants (Merlo 2003).

In this section we deal with this issue, through an in depth examination of the magnitude of contextual effects, before and after controlling for individual characteristics and contextual factors.

In multilevel models the statistical idea of clustering is strictly linked to the epidemiological concept of contextual effects (Merlo *et al.* 2005): in fact they both provide information about the level of similarity of people pertaining to the same group/level.

The "crude" influence of a level is therefore expressed by means of the Intraclass Correlation Coefficient (ICC) in the empty model and it is considered as a benchmark. This crude impact can be refined by excluding compositional effects in the model with individual covariates. When we ultimately included contextual factors in the model, our goal was to explain the differences between groups by means of Large Areas and household characteristics. What remains as residual variance at group level in these models is the variation between groups not explained by all those macro structural factors already included in the analysis.

This residual variance can also be interpreted as the degree of homogeneity among units in the same specific group (net from the effect of homogeneity due to any higher level). This perspective consented us to advance a hypothesis for the explanation of household variability based on reciprocal influences of its members in terms of health and health related behavior.

As showed in the previous paragraphs, Large Areas do not have a strong influence on health perception, neither in the basic model nor after controlling for possible individual bias. The overall contribute goes from a maximum of 2.3% in the model with individual covariates for SPH to a minimum of 0.2% in full model for PCS. The impact of Households is, undoubtedly, more substantive: with proportions ranging from 23 to almost 40 per cent[25] the intraclass correlation indicates that if one randomly takes two individuals in one households knowing the health of one component one can to a fair extent predict the health of the other.

This result is consistent with findings from the few other studies that investigated jointly familial and geographical levels (Subramanian *et al.* 2003; Ferrer *et al.* 2005; Merlo *et al.* 2012). They documented a large disproportion of variability between the effects of familial and geographical levels, with VPC for the territorial level consistently lower than 1%. Conversely, the familial level showed a VPC that varies according to the health indicator, but it is consistently higher than 18 percent: the variability attributable to the family/household level is 18.6% for mortality (Merlo *et al.* 2012), around 20% for PCS and MCS (Ferrer *et al.* 2005) and it peaks at 47% for poor-SPH (Subramanian *et al.* 2003).

We start by commenting on PCS, which showed a significant variation in the magnitude of household effect (Table 4.17). The household contribution decreases of 39% with the introduction of individual covariates (from 23.4% to 14.7%), and it further decreases to 14.3 with household covariates. However a 14% of variability remained unexplained even after all the determinants are included.

Table 4.17 - Intraclass Correlation Coefficient (Household level) and goodness of fit in nested models for PCS

OUTCOME	**MODEL SPECIFICATION**	**VARIANCE PARTITION**			**GOODNESS OF FIT**
		Large Area	Household	Indiv	*Deviance*
PCS	Empty Model	0.5	23.4	76.1	*662,785*
	Individual Covariates	0.3	14.7	85.0	*614,765*
	Ind + Group Covariates	0.2	14.3	85.6	*614,562*

[25] In the empty model

Table 4.18 - Variance partition coefficient and goodness of fit for nested multilevel models for MCS

OUTCOME	MODEL SPECIFICATION	VARIANCE PARTITION			GOODNESS OF FIT
		Large Area	Household	Indiv	*Deviance*
MCS	Empty Model	0.7	33.1	66.2	*663,994*
	Individual Covariates	0.6	32.5	66.9	*653,572*
	Ind + Group Covariates	0.4	31.5	68.1	*653,286*

The 33% of the overall variability in MCS between units is due to household differences. Individual explicative variables do not reduce this remarkable result, which decreases only of about 1 percentage point. However, the deviance does not decrease substantially from the empty to the Individual model (Table 4.18), meaning that the covariates included are not explaining a large proportion of individual variability. This is not surprising as we know from literature and from a body of evidence that determinants of mental health are substantially different from those of self perceived poor health or physical health. Mental health is affected by determinants such as mood, life satisfaction, and a set of mental impairments, all variables extremely difficult to capture through surveys. Contextual covariates had significant effects, but they do not contribute much in explaining households' differences, whose proportion of variability decreases only of another percentage point.

Table 4.19 - Variance partition coefficient and goodness of fit for nested multilevel models for SPH

OUTCOME	MODEL SPECIFICATION	VARIANCE PARTITION			GOODNESS OF FIT
		Large Area	House	Indiv	*Deviance*
SPH	Empty Model	1.2	39.5	59.3	*42,038*
	Individual Covariates	2.3	38.0	59.7	*28,103*
	Ind + Group Covariates	0.6	33.6	65.9	*27,810*

Self perceived health has the strongest contribution (39.5%) of variability attributable to households. This variability observed in the empty model is partially due to a compositional effect, because it decreases at 38% after the adjustment for individual covariates. However, poor self perceived health in the households is predicted by some characteristics of the family, which globally explain a further 5% of the variability between households. The residual variability at the household level, after all the covariates have been included, is 33.6%.

The residual variability at Household level settles at 14% for PCS, 32% for MCS and 34% for SPH. It can be noticed that the value for SPH, that could be potentially overestimated due to the small cluster sizes, is perfectly in line with the value for MCS. Although we need to be cautious in interpreting the variance of SPH between households, the resemblance of this value with the correspondent value for MCS is a cross validation for the results of the binary outcome.

4.6 HEALTH HOMOGENEITY BY HOUSEHOLD STRUCTURE

4.6.1 The high variability at the household level: possible explanations

Multilevel results depict a substantial and persistent contribution of the household on individual health. This contribution is non explained by the structural characteristics of the household, such as resource availability, number of components and typology of internal relationships, or the size of municipality of residence. In fact, after all these predictors were considered, still a 15% -34% of the overall variability resulted from differences between households, rather than differences between individuals[26]. This result was quite revealing and we thought it deserved further investigation. We decided to deepen the issue of household contribution to health and started by examining potential explanations for the high proportions of variance relying at the household level.

One potential explanation was the absence of crucial macro variables that could explain the observed differences between households (*omitted covariate explanation*). Household variables in the Italian Health Survey are few and do not provide an exhaustive description of household characteristics . This allows us to suppose that some remarkable information are missing and that this causes the large unexplained variability at the household level. Obviously, if one important covariate is missing, then the differences determined by this variable, remain largely unexplained.

However, another possible explanation can be put forward. In multilevel settings, the high proportion of variability between groups has on the other side a high homogeneity within the groups. The more the groups are homogeneous, the more the variability between groups is emphasized. In our data, this means that people within the same household tend to report similar health conditions (household homogeneity), and therefore the high proportion of variability is found between households.

The resemblance of units within the same households in terms of health perception can have various origins: it can be due to an omitted covariate at the household level (as in the aforementioned hypothesis), but it can also originates from the network of relations within the

[26] The proportion of variability at the household level was 15% for PCS, 32% for MCS and 34% for SPH.

household (*mutual influence hypothesis*). Household members have been found alike according to many health related indicators: health seeking behavior, practitioner consultation and health perception itself (cit).

All these works conclude that the similarity within the households can be attributed to household reciprocal influences in terms of health and health related behavior. In other words, we find people living together more homogeneous in health because they have similar health related behavior, which produce similar health outcomes, or, even more straightforwardly, because the health characteristic of one member affects the same characteristic of the other members (Meyler et al, 2007). This can be true both for objective and subjective health conditions. Disability or illness impacts the health of other household members through the burden of care-giving, the physical fatigue and the emotional distress; the significance of the variable "cohabitation with a disabled", we included in the analyses, gives a specific indication of this kind of effects. However, poor self perceived health can also affect the mood, the well-being and in turn the health of other household members. One theory that has been applied to concordance of mental health between spouses is referred to as mood convergence or affective contagion. By living in an interdependent relationship with a partner, one's emotions are inextricably linked to the partner (Meyler et al, 2007; Goodman and Shippy, 2002; Joiner and Katz, 1999).

We generalized this theory with the hypothesis that the health resemblance between all the household members derives from their mutual influences. These mutual influences are expected to display a regular pattern: they will be more evident in groups where the ties are stronger and inter- relations more intense; furthermore, they will be higher for emotional health rather than physical conditions. We used this assumption to check whether the hypothesis of reciprocal influences has support from the data and it could be reasonably considered as an explanation for the high level of household effects.

4.6.2 Reciprocal influences on health: evidence from the homogeneity analysis

Within the household, reciprocal influence between members is expected to be sensitive to the typology of the relationship. The typology of the relationship is primarly determined by:

- The number of components: as they shape the strenght of the ties and determine the degree to which problems, burden and influences are shared by the cohabiting members of the household.

- The *family tie*: as understanding, affinity and empathy vary greatly according to the type of familial relationship. The husband-wife relationship is expected to have a larger extent of reciprocal influence than the brother-sister relationship.

- The *age*: as the emotional closeness between people is stronger according to th length of life span spent together. The age of individuals can operate in itself, but it can also be a proxy for the relationship duration: people in long-lasting relationships are expected to show tighter links, especially when they are in couple.

In the following passages we examine whether the relationships system is coherent with these expectations. We looked at the level of homogeneity according household structures that differ for one or more of the characteristics listed above. In this analyses only PCS and MCS are used as health measurements, because we needed robust estimation of the variability component.

The homogeneity levels are obtained as the intraclass correlation coefficients for the household level after the full model was run in specific subgroups of the sample (e.g. only 2-components households)[27]. In this way we have the level of residual homogeneity, adjusted for all the individual and group covariates. The number of household components is calculated considering both the total number of components and the numbers of component incuded in the research (i.e. older than 18).

[27] For further details about the relation between the residual variance (VPC) and the correlation between units (ICC) see Chapter 4.

An household with 2 components, for instance, is an household in which the total number of members is 2 and they are both older than 18. The same way, households classified as 3+ components are those where the total number of components was higher than 2 and at least 3 of them were higher than 18.

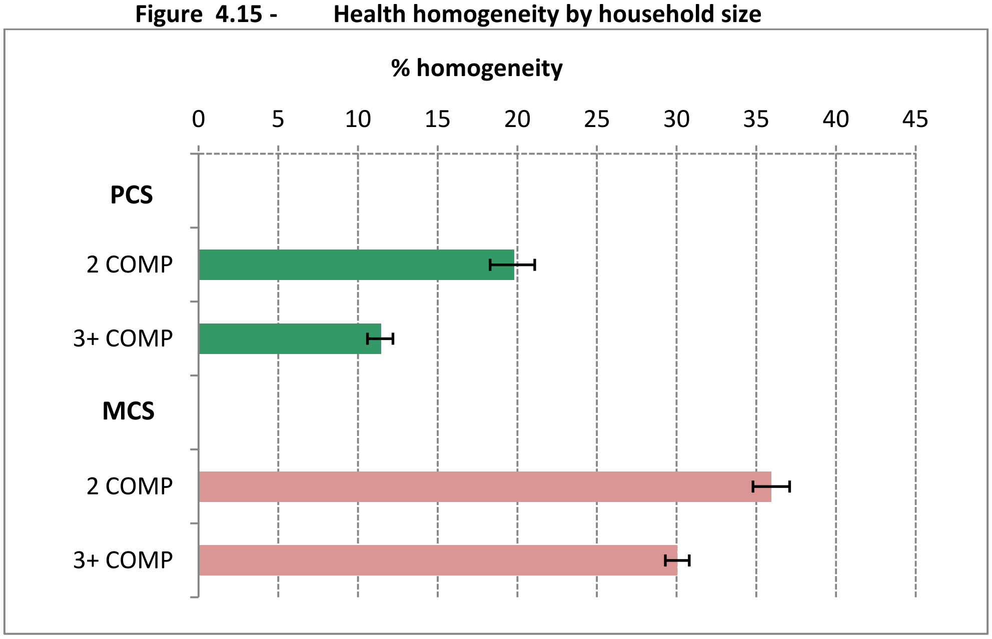
We present the results for the various household structures, specifying the hypothesis underlying each subgroup examined.

Household size

Hypothesis: in small households the homogeneity is higher because they are characterized by stronger ties and more exclusive relations.

Expected result: higher homogeneity in 2 component households than in 3+ component households.

Figure 4.15 - Health homogeneity by household size



For both the indicators the proportion of homogeneity is significantly higher in 2-components households than in families with 3 or more people cohabiting. The homogeneity is higher for MCS than for PCS, as expected (Fig 4.15)

Two component households: type of structures

Research hypothesis: among the 2 component households there could be different level of homogeneity according to different relationships between the household members. Particularly, the homogeneity is supposed to be the highest for couples in a long lasting relation.

Expected result: among people living in 2 component households those who are in couple and aged more than 50 (proxy of a long-lasting relation) exhibit more homogeneity than those having different forms of relationship (parent-child, brothers/sisters, …)[28].

Figure 4.16 - Health homogeneity in 2 component households: typology of relation

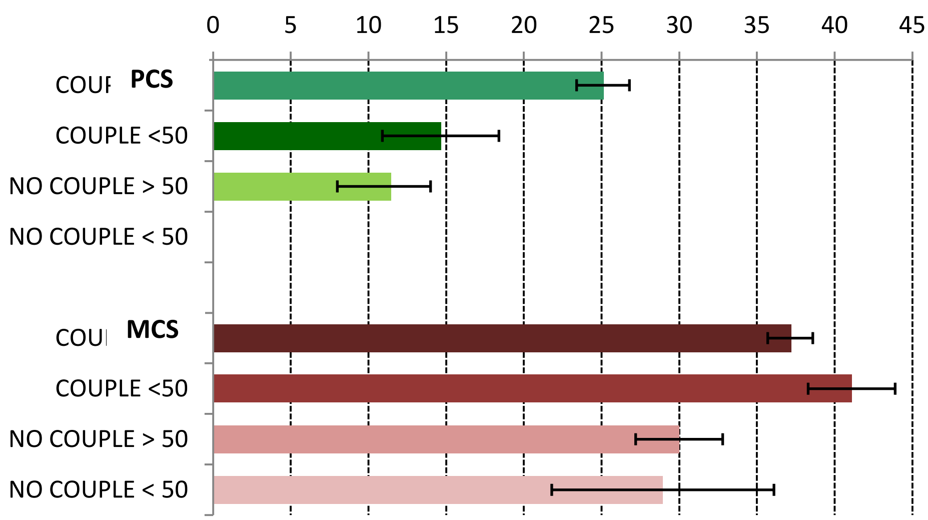


Figure 4.16 illustrates as our hypothesis is entirely confirmed for PCS, for which couples aged more than 50 show the highest level of homogeneity (25.1%). Their non coupled peers have significant lower homogeneity (11.4%) as well as young couples (14.6%). Few studies already pointed out that as the couples got older their concordance increased (Cheraskin *et al*, 1968; Johnson *et al*, 1965).

[28] Couples were classified "over 50" when at least one component of the couple is aged more than 50, "below 50" otherwise.

People younger than 50 not in couple were a too small group to produce reliable results

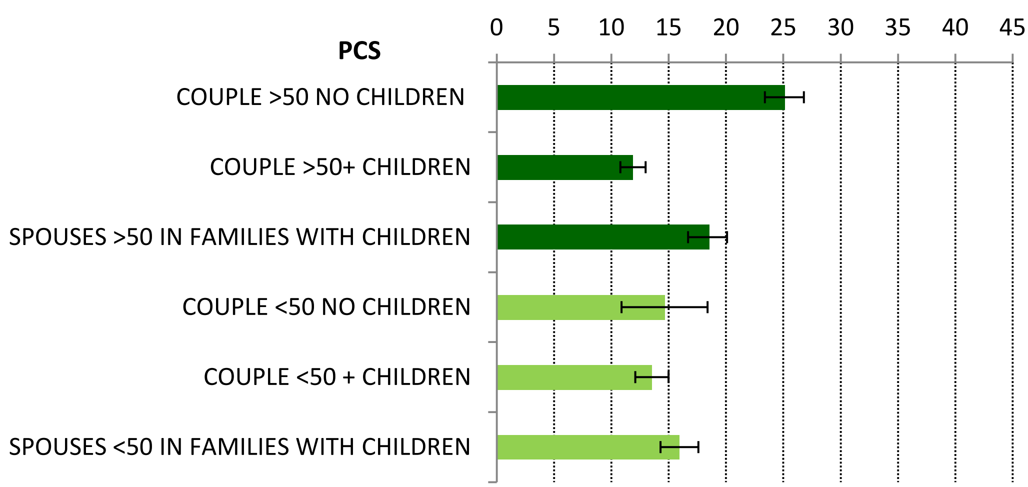
For MCS it appears clearly that homogeneity is not a matter of age/union duration, rather it depends on the quality of the relation between the two members: people in couple have an homogeneity over 36%, despite their age, while people not being in couple have always significantly lower levels of homogeneity (28.9% if younger than 50, 30% if older).

Couples with and without children

Research hypothesis: couples living alone have the highest level of homogeneity among 2 components households. The homogeneity is expected to be weaker for a couple living with children because the ties are less tight and the network of relations wider. The duration of the link (approximated by the age of the individuals) has the same effects hypothesized before.

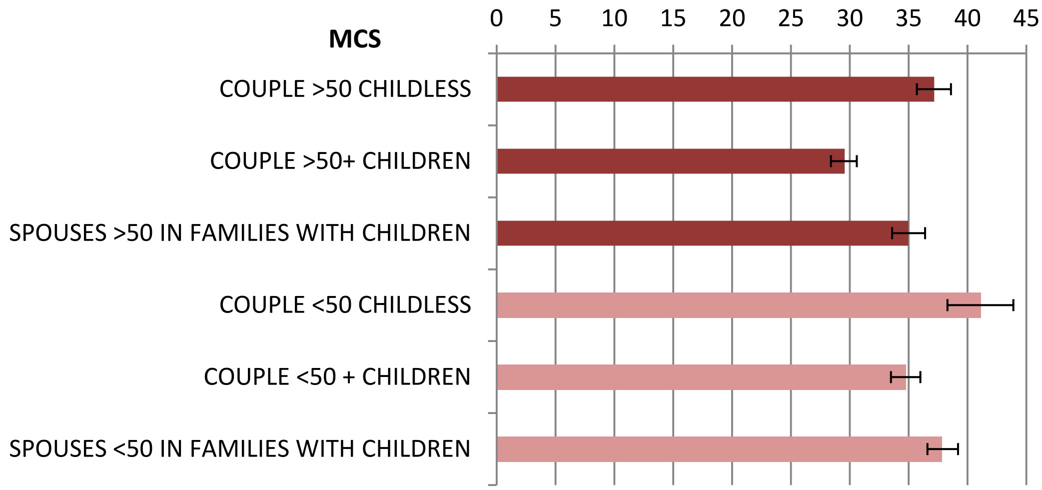
Expected result: comparing couples living alone with those living with children we expect couples living alone to exhibit the highest homogeneity. Couples with children will have lower homogeneity, both if we include children in the analysis and if we look only at the 2 spouses.

Figure 4.17 - Health homogeneity for couples with and without children - PCS



The hypothesis is once again verified for PCS in the group of people over 50, while no differences are detectable for people younger than 50 (Fig. 4.17). This is not surprising as in the young group the physical condition is generally good and exhibit very limited variation; this means that there is not enough variability to detect differences between household structures.

Figure 4.18 - Health homogeneity for couples with and without children - MCS



For MCS couples living alone have the highest homogeneity, and this is significantly different from the overall homogeneity of couples with children. This result is not dependent from the age of the spouses: the homogeneity differential between *couples alone* and *couples with children* is about 6/7 percentage points both for long lasting couples (37% versus 30%) and for younger couples (41% versus 35%). However, if we select only the 2 spouses from families with children, their level of resemblance is not statistically different from the level of couples alone, as the confidence intervals overlap (Fig.4.18). The presence of a shared experience as the parenthood probably compensate in terms of homogeneity the weakening of the ties due to the enlargment of the household.

Household with 3 or more components: different typologies

Research hypothesis: household with 3 or more components can assume very different structures. We classify them in four categories: (1) couple without children and with aggregated members (*Couple + aggregated*), (2) couple with adult children (*couple + children*),

(3) single parent with adult children (*single parent + children*) and (4) households with more than one family unit (*Multinuclear Households*).

Expected result: given the diversity of household structures, in this analysis is more difficult to formulate clear hypotheses about health homogeneity. As in the previous analyses, what we intend to test was that the degree to which health homogeneity is coherent with the reciprocal influence system, which depends, in turn, on number of components, familial ties and length of relationships within the household. Based on these characteristics we formulates the following expectations:

- Nuclear households exhibit more homogeneity than multi-nuclear ones (*hypotesis 1*).

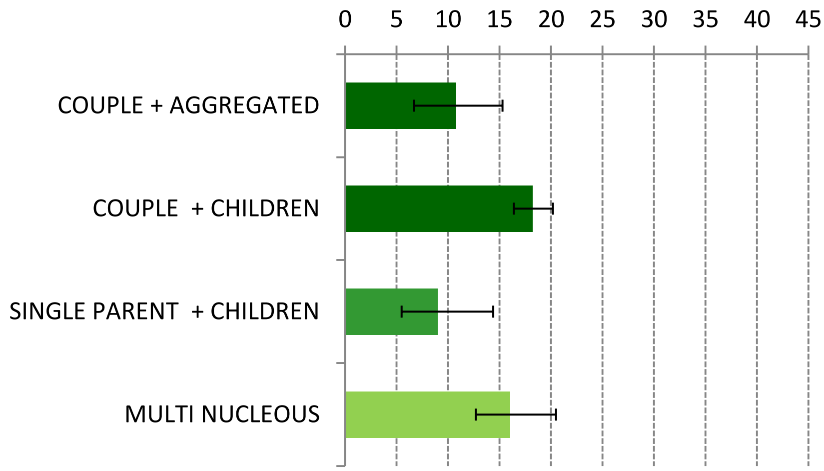
- Among nuclear households: we select couple-headed families and hypothesize that couples with children have higher homogeneity than couples with aggregated members, because the former household structure constitutes a more cohesive unit (*hypothesis 2*).

- Among households with children, those families headed by a couple could be characterized by higher homogeneity than mono-parental households, given the partner resemblance in health (*hypothesis 3*).

- Single parent families miss the contribution of the couple to household homogeneity; however a mechanism of compensation could take place: the link (and mutual influences) between the single-parent and the offspring could become stronger as a response to the the absence of a member of the couple. If this is the case, the homogeneity in single-parent household could not differ significantly from homogeneity in couples with children (*hypothesis 4*).

Hypothesis 3 and hypothesis 4 are antithetic. However, they are both supported by grounded theoretical arguments, therefore we keep both and test empirically which one prevail on the other.

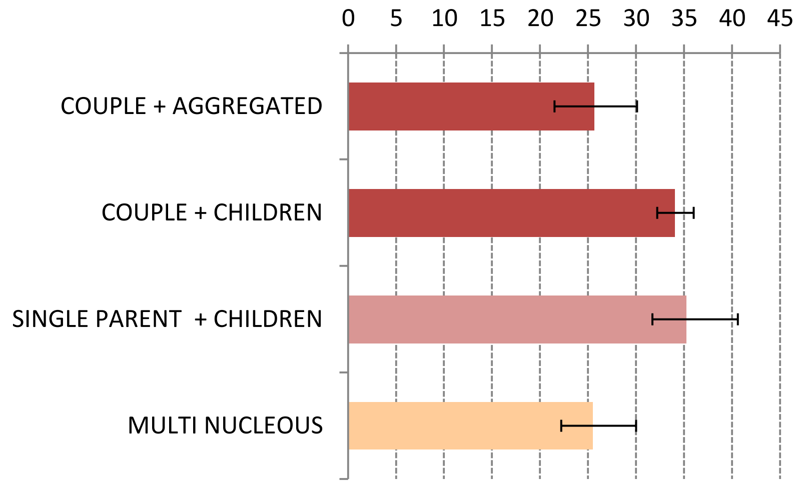
Figure 4.19 - Health homogeneity for 3+ households by structure – PCS



Hypothesis 2 and 3 are confirmed by PCS analysis of homogeneity (Fig. 6.16): couples with children have higher resemblance than couples with aggregated members and much higher similarity than one parent households. Non nuclear households do not exhibit a level of homogeneity significantly different form the other groups according to physical health.

The picture given by MCS in Figure 6.17 is entirely different: the homogeneity of emotional status is the highest for households with children, despite the number of parents (*hypothesis 4*). When the household is constituted by a couple (without children) living with relatives, the household members exhibit very different emotional status, with a significant less resemblance than parents and children (hypothesis 3). People living in multinuclear households are more heterogeneous than people living in a more traditional form of family (Hypothesis 1).

Figure 4.20 - Health homogeneity for 3+ households by structure - MCS



The results of the homogeneity by household structure have a very clear pattern for 2-components households, while they appear more articulated when the household size increases.

Overall this section of analyses seem to support the hypothesis of *mutual influences* versus the hypothesis of *omitted covariates* in explaining the role of households on health.

5. DISCUSSION AND CONCLUSIONS

The international research about self perceived health is oriented into two wide dimensions: the analysis of the predictive power of perceived health on mortality, especially for poor-SPH, and the study of what determines health perception.

This work belongs to this second line of studies, with a specific interest in understanding the contextual determinants of perceived health.

It is well-established that health is affected by influences exerted at different levels (Kawachi and Subramanian 2005), but analyses about contextual factors and the magnitude of these effects on health are still sparse. Our research gives a contribution in this direction, by producing further evidence of determinants of self-perceived health for the Italian adult population in a comprehensive approach that includes individuals and social and territorial contextual levels.

The main findings can be classified into three groups:

i) illustration of a picture as much detailed as possible of perceived health determinants , by means of three health indicators and multiple levels covariates;

ii) estimation of the magnitude of territorial and household effects of perceived health

iii) investigation of circumstances under which contextual effects (familial) are especially pronounced, supporting the hypothesis of mutual influences within the households.

On the one hand, findings about determinants of perceived health were generally in line with our expectations. Nevertheless, they outline some specificities that were not previously detected by the existing literature, such as the very sharp effect of cohabiting with a disabled on mental health of relatives (but not on their physical health) and the much more pronounced effects that territorial and urban variables have of physical perception rather than emotional well-being.

On the other hand, results about magnitude and circumstances of contextual effects were largely unexpected and constitute an enrichment of our knowledge about context and health.

5.1 DETERMINANTS OF PERCEIVED HEALTH

The choice of using three different indicators of health perception gives as a result a profile of covariates that is quite different according to the health indicator under consideration. Although all of the three measurements, Physical Component Summary (PCS), Mental Component Summary (MCS) and Self Perceived Health (SPH), refer to a perceived dimension of health, nevertheless they capture aspects that are not completely overlapped, therefore they appeared sensitive to different factors. PCS responds particularly to very concrete agents such as age, education, economic conditions, whereas MCS is particularly linked to socio-relational dimensions at the individual and household level. This result is coherent with the knowledge about determinants of mental health, i.e. social support, perceived stress and self esteem (Bovier *et al.* 2004). Furthermore, physical health is affected by the geographical component, with Northern areas and bigger cities exhibiting, on average, higher levels of PCS. Northern Large Areas are notably favored by a more efficient health care system, more wealth, and more public health expenditure, therefore an health advantage is generally foreseeable. Differently, we can speculate on the relation between health and city size. A cogent viewpoint is the conflicting role than living in urban context has on health. Social and health services are frequently more available in larger cities (Galea *et al.* 2005) which contributes to improvements in health of residents, at the same time a number of studies have documented higher rates of mental illness in urban compared to non-urban context (van Niekerk *et al.* 1979; Farbos *et al.* 2000; Telfair *et al.* 2003). This is partially reflected in our findings, which report a positive effect of living in cities with more than 50 thousands inhabitants for PCS but no effect for MCS. For the latter this can be due to a counterbalance of the two opposite causal mechanism described above.

Poor self-perceived health appears as synthesis of physical and mental dimensions and, in fact, it is affected by a larger number of factors than the other two dimensions.

As far as we are concerned, a systematic comparative analysis of determinants of the three indicators of perceived health (PCS, MCS and SPH) on population-based data was not available at date, and it constitutes a first contribution of this work to the body of existing literature. However, more original results came up from the analysis of the magnitude of contextual effects.

5.2 MAGNITUDE OF CONTEXTUAL EFFECTS

The very limited role of Large Areas in determining perceived health of Italian adults was largely unexpected. Previous works have illustrated clearly a health gradient for objective and subjective health measures (Costa *et al.* 2003; Mazzuco 2009).

However, researches that adopted a multilevel approach to investigate the Italian Regional/Large Area heterogeneity in perceived health came to our same conclusion, recognizing a proportion of variability at Large Area level of 2.9%, for poor self-perceived health among the elderly (Pirani and Salvini 2012b). The slightly higher impact of Large Areas reported by Pirani and Salvini compared to our result (1.2%) can be ascribed to the absence of the household intermediate-level. In fact, when we run the analysis excluding the household level (i.e. a 2-level random model with individuals and Large Areas) we found an ICC of 2.7%[29]. The interpretation of this difference can be linked to an uneven geographical distribution of households across the Large Areas: if households with poorer health are concentrated in some geographical areas, not taking into account the household level will produce an (apparent) increase in the proportion of variability at the geographical level. This proportion dramatically reduces when the household level is introduced. Moreover, population aged over 65 is more homogeneous in terms of health and for many other explicative covariates. Thus, inter individual differences are reduced and this facilitates the observation of contextual differences, when they occur.

Although unexpected the small territorial variability in health is not entirely surprising for at least two reasons. The first reason is linked to the discussed concept of ecological fallacy. Ecological analyses can produce the impression that geographical factors have an influence on health, however, only through multilevel analysis this influence can be clearly ascribed to the context (Merlo *et al.* 2012). The degree of territorial heterogeneity as summarized by measures such as the Index of Dissimilarity and Population Attributable fraction can give a misleading picture of the territorial impact on health: they can emphasize differences that are actually due to unequal distribution of individuals among areas.

The second reason refers to the appropriateness of selected geographical boundaries.

[29] This is a result from preliminary analyses, in which we tested the intensity of random effects also for the different combinations of 2-level models: Household-Individual and Large Area-Individual models (complete results not shown).

Large Areas have been selected as representative of local health care system. A more efficient system of health services generally intervenes mostly on tertiary prevention (activities of care and rehabilitation) rather than primary and secondary prevention (i.e. reducing exposure to risk factors, and diagnose precociously the illness). It mans that the majority of the effects are not on the onset of the diseases, rather on physical consequences of a chronic condition, such as functional limitations and disabilities. The effects of a heterogeneity in health care provision, thus, is best captured by objective indicators of functional health, such as disability, whereas it is weakly reflected by health perception. The effects of health care system on perceived health are, in fact, indirect: living in a place with a more efficient system of care can produce a general feeling of safety and protection, which results in improved self-perceived health. In this perspective the health care system can also be seen as a mediator of the effect of objective conditions on perceived health: in places where the services are more efficient when the illness occurs it is cured promptly and appropriately, therefore it is less disabling and in turn it has a lower impact on the perception of health.

Large Areas were selected as geographical units on the base of a health care perspective. They are the dimensions that better represent potential differences in health care provision, as they were built up from aggregation local health care providers (ASL), autonomously responsible for health facilities management. However this dimension is apparently not the most effective in capturing the Italian geographical variability of perceived health. The definition of geographical boundaries we adopted could be not the most appropriate. We made use of geographical areas based on administrative boundaries, which is the most common procedure, but the pertinence of *a-priori defined* areas needs to be ultimately tested by quantifying the observed clustering of the health outcomes within these areas (Merlo *et al.* 2009). When the level of clustering (i.e. the proportion of variability) between selected areas is small, it means that the geographical boundaries selected are not appropriated for the phenomenon. In such a case, if we hypothesize contextual influences, they operate on a different scale (neighborhoods, municipalities, Regions) which needs to be identified through the same procedure. This is the case for self-perceived health in Italy, where diversities are more pronounced in terms of macro zones (North, Center, South and Islands) than between Large Areas. This suggests that territorial differences in health can derive from factors other than Health Care services, and more linked to cultural, macro economic, social differences traditionally characterizing the four large macro areas of the country.

The other aspect of analysis whose results exceeded expectations was *the role of family on health*. We defined family based on cohabitation and according to this definition we documented an influence ranging from 15 to 38 per cent, after adjustment for all the individual covariates.

A handful of studies have looked at households influences on health, and across these studies health outcome, the target population and the countries characteristics vary largely. Thus it is not easy to compare our results with international findings. Merlo *et al.* In a very recent study (2012) reported a 18.6% of variability at the household level for all-cause mortality. Subramanian et al. in 2003 found a very large effect of households on poor self perceived health in a Chile (VPC of 47%), however they made use solely of the binary indicator (SPH), therefore they results are affected by potential distortions for the e random parameters (the variance at different levels). Minh et al. (2010) reported, for over 50 Vietnamese people, a 15% of influence of households on *perceived good health,* which however, is a different outcome and cannot simply be seen as the other side of the coin of our outcome. Good perceived health, in fact, is known to be less predictable by means of classical determinants, such as SES, gender, objective health conditions. It is then not surprising that also the effect of contextual levels is reshaped when the focus is on good rather than poor health. The only study concerning developed country is settled in the USA and revealed a maximum influence of family of 22 percent for PCS and 26 percent for MCS[30]. The authors used census families, which include all the persons related to the head of the household by blood or marriage, disregarding the co-residence requisite. This can partially explain the lower effect of family on health with respect to our findings. A latest work that is worth mentioning is that by Merlo *et al.* (2013), which makes use of a different approach (quasi-experimental family design), but yields epidemiological results that deserve further thinking. The authors compared the effect of neighbourhood and family on the onset of Ischemic heart Disease in Sweden. More particularly they selected full-brothers living in two different neighbourhoods (therefore the family is

[30] The authors evaluated the VPC for different familial typologies: those reported are the highest effects observed.

defined by blood and it does not correspond to household in any case). They found a VPC of about 1% for the geographical component and about 20% for the familial level.

With our work we provided additional strength to the household influence on perceived health, and, more generally, we revealed the public health importance of family for health in a European context, where it has never been investigated.

The relevance of household on health is 15-40 times larger than Large Area importance. However, scientific interest and major political efforts of the last decades have concentrated in the direction of geographical determinants of health, whereas very few actions have been directed to family. One reason for this preference is certainly the fact that public interventions on geographical areas are easier to define and immediate to apply. On the contrary, a policy targeted to households can be much more difficult to project and it relies on household members compliance to be effective. Nevertheless, it seems that the level with more room for improvements for self perceived health is precisely the family rather than the Health Care providers.

The reasons that cause households variability in health are largely unclear. The covariates we controlled for, i.e. household's economic resources, housing conditions, size and typology of household structure together with the size of the municipality of residence, did not provide a convincing explanation of why some households have a better health status than others[31].

We advanced the hypothesis that a role can be played by *mutual influences* within households. Concretely, people living in the same households can have similar individual health determinants, such as nutritional choices, prevention attitude , health-seeking behaviour or health care utilization, derived from shared familial behaviour. However, there is another interpretation of mutual influences we found more stimulating and persuasive: perceived health of one person can be directly affected by perceived health status of people living in the same household, especially in case of poor health. In this situation we observe mutual influence not related to similar determinants but related to the outcome itself.

[31] They all have a significant effect in explaining health diversities, but the residual variance between households did not decrease substantially.

It was not possible to test this hypothesis conclusively from our data, however the analysis of homogeneity according to household structure produced some insights in this direction. The effects of households were especially pronounced for small family and between age peers.

Moreover, households where the family ties were stronger exhibited consistently higher homogeneity (and in turn more relevance of the household level). This evidence seems to support the hypothesis of mutual influences, even if it was not possible to further detect whether it is linked to similar behaviours or health perception itself.

Mutual influences on health, especially for couples, have already been documented in other disciplines, especially in psychology (Meyler et al. 2007; Monden 2007) were studies exploring concordance about spouses in mental illness, depressive symptom and distress, or they elaborated on the relationship between partners interactions and well-being, happiness and life satisfaction (White 1983). Clinical medicine also devoted studies to couple concordance for specific diseases (mainly cardiovascular), while sociology explored primarily health related behaviors. Nearly all studies find evidence of couples' resemblance especially for depressive symptoms.

Furthermore, the family constellation has already been taken into consideration in relation to life satisfaction and well-being, notions profoundly connected with health. A variety of social science disciplines suggest that family structure is one of the most important determinants of life satisfaction (Evans and Kelly 2006; Vignoli *et al.* 2012).). Interpersonal relationships and social supports heavily shape individual's well-being and most detailed investigation revealed that the effects of social support on well-being vary depending on family structure and the person providing support

Abundant prior research supports the hypothesis of mutual influences on health. We corroborated this hypothesis through our findings. In fact, we illustrated as homogeneity of PCS and MCS consistently higher in smaller families (2 components), and when the people are in a marriage-like relationship. We also documented that as the couples got older their concordance increased, which was already noticed in studies of clinical medicine (Cheraskin *et al*, 1968; Johnson *et al*, 1965).

5.3 STRENGHTS AND LIMITATIONS

This research is not without limitations. A first limitation is methodological: the multilevel approach applied to our hierarchical system is fully-functional for quantitative variables, as the physical and mental component summaries, but it is questionable for the analysis of self perceived health. Some evidence (Raudenbush 2008), mainly based on simulation studies (Austin 2010), shows potential distortion in the estimation of random parameters when the cluster size is small (as in the household case) and the outcome is binary (as SPH). We are aware that the estimations of variance attributed to the different levels are not robust for poor self perceived health, however the results for this indicator are always consistent with the estimations for MCS. At each step of analysis the two outcome exhibit very similar values, and we made use of the indicator of mental health as a cross validation for results of self perceived health.

A second limitation concerns the family, which is defined on the base of co-residence[32]. This is a very strict definition of family, especially in the recent decades when the traditional family has declined and household arrangements has become more diverse. Other possible definition of family can be adopted, for instance those based on frequency of contacts (number of visits or number of telephonic contacts) or spatial proximity (e.g. living within 1 kilometre of distance (Castiglioni 2013).

Although other definitions would enrich the knowledge about the issue of family and health, the one based on co-residence is the most precisely specified, and it is also the condition where we expect the most of the influences between members. So we believe it was sensible to have this analysis as a benchmark and eventually test the same results on other concepts of family.

Finally, some considerations are needed about the issue of causality. Data are cross-sectional, thus a remarkable limitation is that they hinder the interpretation of the effects as causal. The problem at the base is that of reverse causality: we can not be sure that a factor influenced health or health influenced the factor of interest. However, we selected the covariates intentionally to limit this problem: the most of the covariates are very stable conditions which do not depend on health. Variables of this kind are: cohabitation with

[32] More precisely it is based on co-residence and affective links (cf. Chapter 2)

disabled, housing conditions or family size, which would be difficult to imagine as a consequence of health status. Some remarkable exception are education and economic resources, for which a risk of reverse causality is likely to be. We generally commented results in the light of a causal link, but we are aware that further research, hopefully with longitudinal studies, is needed to corroborate this interpretation.

This research has some merits in different directions: first of all it brings back the attention of health researchers on the role of the family. Already in 1977 Engel proposed the so-called biopsychosocial model, which claims that health is affected by the interplay of biological, psychological and social factors and underlined the importance of framing health and illness in a multilevel context. Research on the influences of family on health mostly date from the 1970 and 1980. Later on, with the advent of individualization theory, risk-factor epidemiology and patient-centred approach, family medicine showed a declining trend. More recent studies have looked at couples concordance for a wide range of health outcomes, such as mental distress (Du Fort *et al.* 1994; Teichman *et al.* 2003) and specific disease occurrence, among which cancer (Friedman and Quesenberry 1999) and cardiovascular diseases (Hippisley-Cox and Pringle 1998). However they rarely take the whole family into consideration and hardly ever the family is seen as the target for health interventions.

What has gained attention in the last years, as a consequence of aging and of increasing number of oldest-old, is the role of care-givers and the way it impacts on health. In this perspective the family has been recovered as the unit in which the informal care are provided and researchers have come back to consider the potential effects of illness on people co-living with the sick person. Studies of this kind are mostly concerning with chronic progressively disabling diseases, with a large prevalence in the elderly population, such as dementia (Ory *et al.* 2000; Betts Adams and Sanders 2004; Egidi *et al.* 2013).

Our research enlarges this kind of studies looking at familial effects with an ample perspective and points out that who you live with matters for health as much as who you are.

This study also attempts to initiate a line of research about mutual influences on health which is not widespread in demography. Mutual influences have been extensively documented in other disciplines, such as psychology, sociology, medicine and epidemiology but they are mainly focused on couple relations.

Couples have consistently shown concordance in mental health, physical health, especially cardiovascular diseases, well being and health behaviours, however, Mayden et al. (2007) in their review of studies about couples' health concordance underlined the paucity of attention paid to theory. They lament the scarcity of studies that explicitly test a theory and invoke new researches devoted to proposing or testing theories rather than simply observing the phenomenon. With our study we aimed at developing possible pathways for explaining household homogeneity. The demographic contribution in this direction could precisely be to gain a better understanding of causes and circumstances that determine household health resemblance and this evidence is needed in order to elaborate a consistent theory of the role of family on health.

5.4 FURTHER DEVELOPMENTS

Future developments of the study can follow many promising directions. The most interesting for public health is the study contextual effects for objective health conditions (disability). As previously stated the territorial effects on objective health conditions are expected to be much stronger, as the impact of health care services affects disability and physical limitations more straightforwardly than for perceived health. On the contrary, the household impact should be consistently downsized for objective health.

Household is not a unique criterion to define the family. Insights can derive from the adoption of different definitions of family too. Spatial proximity influences significantly relations and exchanges between relatives (Bengtson 2001; Bian *et al.* 2005), and in this perspective the "walking distance" can be more informative than the co-residence alone in representing kinship proximity (Castiglioni, 2013). New promising areas of demographic research are looking at support and social networks (Amati *et al.* 2013) and according to this perspective more articulated definitions of family can be considered. The classification of relatives as part of the same family on the base of frequency of contacts or residential proximity are remarkable examples; but more generally researchers are given preliminary attention to all those classifications that are able to encompass the modern forms of families and to better capture information about familial support.

A final area of interest would be the deepening of health contagion hypothesis. With specific ad hoc surveys it would be valuable to understand the pathways of health influences within families, for instance the role of interactions between members on the level of health resemblance.

The analysis of mutual influences can also be refined with the available data through a more detailed investigation of familial ties that exhibit the highest similarity. In case of mono-parental households, for example, it would be important to understand if the parent-child gender concordance has a role. Is the mother-daughter/ father-son resemblance higher than when the parent-child genders are discordant. An alternative hypothesis could be that households where the single-parent is the mother have higher internal resemblance than those headed by a single-father, because of the women greater attitude to express and share their emotional status.

5.5 CONCLUSIONS

With this research we provided evidence of the existence and the complexity of contextual factors influencing perceived health. The better knowledge of these factors is fundamental for contemporary societies in order to reach two primary goals they explicitly set as priorities: the need to promote a healthy aging and the goal of achieving equity in health.

Concerning the benefits of healthy aging it has been pointed out how the increase in life expectancy has produced a shift in all the stages of an individual life, including the entrance in the "old age". As a consequence, people can be considered as having two different ages: *nominal age* and *real age* (Fauchs 1984). Being an economist, Fauchs borrowed the idea from the well-known economic distinction between values measured at current prices (nominal values) and those adjusted for inflation (real values). He proposed the very same distinction for demographic age: the nominal age is the chronological one, whereas the real age is the that adjusted for life expectancy changes, (also called prospective age). Stated differently the chronological age can also be seen as the distance from birth whereas the prospective age measures the distance from death. A person aged 60 today has dramatically different health conditions and remaining life perspectives than an age peer in 1950. The adoption of a fixed age threshold to define the elderly population (generally age 65) has become to be perceived as inadequate. The “elderly population” is more sensibly defined whether on the base of prospective age (Sanders and Scherbov 2008) or according to deterioration of health conditions.

From this perspective it appears clearly that societies that will succeed in promoting a healthy aging will observe a *counter-aging* process for their populations (Giarini 2000; Cagiano de Azevedo and Ambrosetti 2003; Sanders and Scherbov 2005). In presence of such a process, the average age of the population will still be increasing, but the overall population will be younger in terms of prospective age and overall health conditions. Moreover, the “dependency ratio” of the elderly population will remain stable (or even decrease) because people aged more than 65 tend to remain longer in the active population.

This perspective is receiving preliminary attention, in particular concerning the labour-market reforms. Many proposals have been developed that take advantage from the extension of life in good health. An example is the *recovery of adult people* (Castagnaro and Cagiano de Azevedo 2008), which suggests a gradual exit from the labour-market through part-time work at ages 65-79, paralleled by a part-time entrance in the age group 18-29. From an economic perspective, this would increase the years of contribution of the population, improving the economic balance of the public retirement system; from the social point of views this enables a segment of population that is still capable and productive to extend their working life and to be formally recognized as still active part of the society.

The extension of working age has been advocated also by other studies (Marshall *et al.* 2003; Vaupel and Loichinger 2006; Christensen *et al.* 2009*).* All these authors discuss a redistribution of work over the life course, extending the active ages. Vaupel and Loichinger (2006) propose an increase in part-time work, especially for ages of child-bearing, when the free time is more desirable. This loss of working hours can be compensated by increasing the age at retirement with part-time employment after the age 65. Christensen at al. (2009) highlight that shorten working weeks over extended working lives not only alleviates the economic burden of elderly on the welfare system, but can also further contribute to increases in life expectancies and health.

The target of improving health conditions among the elderly is of primary importance, whatever the perspective and the proposal for policy intervention.

Scientific knowledge about all those factors (individual and contextual) that have an effect on health can be further expanded both in the Italian and international settings. However, contextual determinants are more responsive than individual ones to political and social interventions. Hence, a deeper understanding of contextual elements is necessary in order to address public policies to effective interventions, targeted to the most appropriate level and designed to improve the health of specific segments of population, particularly at risk of poor health.

Territorial inequalities have deserved a long and wide concern among demographers, epidemiologists, medical geographers and researchers in the field of social science. However, very often in these studies the "place" has been regarded as a black box that mysteriously affect health, without a clear conceptualization of the pathways by which area may influence health (Macintyre *et al.* 2002). The same authors suggested that further researchers on place and health should develop specific hypothesis by which the area affects health and define the territorial boundaries coherently with the conceptualization of the place effect.

The research presented in this thesis satisfies these requirements, by developing specific hypotheses for territorial inequalities, stemming from the Italian health administrative organization. We hypothesized that the variation in the amount and quality of public health care facilities can have an effect on perceived health, and tested this assumption by defining the territorial units as proximate Local Health Care Providers constituting a unit for health planning (Large Areas).

Furthermore, since we documented that family deserves as much attention as individual in the determination of perceived health, we do believe the time has come to systematically include the familial perspective in the study of health. Only by doing so it will be possible to effectively remove the obstacles to the achievement of substantial equality in health.

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Appendix A1:
Large Areas and correspondent population size

CODE	NAME	Pop Size	CODE	NAME	Pop Size
1	Piemonte 1	861444	35	Toscana 4	1285320
2	Piemonte 2	1310582	36	Umbria	834210
3	Piemonte 3	561729	37	Marche 1	349293
4	Piemonte 4	627319	38	Marche 2	1135308
5	Piemonte 5	870060	39	Lazio 1	946965
6	Valle d'Aosta	120909	40	Lazio 2	1645710
7	Lombardia 1	1247052	41	Lazio 3	871763
8	Lombardia 2	2474376	42	Lazio 4	698911
9	Lombardia 3	1362486	43	Lazio 5	982546
10	Lombardia 4	492751	44	Abruzzo 1	587243
11	Lombardia 5	986924	45	Abruzzo 2	686041
12	Lombardia 6	1126249	46	Molise	321047
13	Lombardia 7	698787	47	Campania 1	1008419
14	Lombardia 8	720020	48	Campania 2	895811
15	Prov. aut. Bolzano	467338	49	Campania 3	1171430
16	Prov. aut. Trento	483157	50	Campania 4	854956
17	Veneto 1	813294	51	Campania 5	286611
18	Veneto 2	838221	52	Campania 6	432115
19	Veneto 3	807046	53	Campania 7	1075756
20	Veneto 4	1100268	54	Puglia 1	1039919
21	Veneto 5	1018579	55	Puglia 2	524203
22	Friuli Venezia Giulia 1	379101	56	Puglia 3	688902
23	Friuli Venezia Giulia 2	812487	57	Puglia 4	980361
24	Liguria 1	729506	58	Puglia 5	790572
25	Liguria 2	842691	59	Basilicata	596821
26	Emilia Romagna 1	373018	60	Calabria 1	1274733
27	Emilia Romagna 2	553619	61	Calabria 2	732659
28	Emilia Romagna 3	664056	62	Sicilia 1	1662491
29	Emilia Romagna 4	1105680	63	Sicilia 2	659513
30	Emilia Romagna 5	989822	64	Sicilia 3	898697
31	Emilia Romagna 6	344025	65	Sicilia 4	1751423
32	Toscana 1	352940	66	Sardegna 1	457871
33	Toscana 2	1085593	67	Sardegna 2	416923
34	Toscana 3	792443	68	Sardegna 3	762845

Appendix A2: Values of the three health outcomes per Large Area

CODE	NAME	% SPH	MEAN PCS	MEAN MCS
1	Piemonte 1	0.069	50.70	48.45
2	Piemonte 2	0.051	50.68	49.14
3	Piemonte 3	0.055	50.63	50.62
4	Piemonte 4	0.040	51.74	50.75
5	Piemonte 5	0.042	51.76	50.64
6	Valle d'Aosta	0.048	51.18	50.98
7	Lombardia 1	0.051	51.68	50.56
8	Lombardia 2	0.039	51.86	50.31
9	Lombardia 3	0.046	50.73	49.81
10	Lombardia 4	0.028	50.97	51.52
11	Lombardia 5	0.038	51.38	50.72
12	Lombardia 6	0.064	50.24	50.59
13	Lombardia 7	0.031	51.37	50.90
14	Lombardia 8	0.046	50.50	50.10
15	Prov. aut. Bolzano	0.036	51.19	52.43
16	Prov. aut. Trento	0.036	51.04	50.09
17	Veneto 1	0.045	50.90	49.91
18	Veneto 2	0.043	50.49	50.26
19	Veneto 3	0.047	50.36	48.98
20	Veneto 4	0.051	50.26	49.17
21	Veneto 5	0.046	50.12	49.77
22	Friuli Venezia Giulia 1	0.038	52.33	51.96
23	Friuli Venezia Giulia 2	0.041	50.88	50.76
24	Liguria 1	0.061	50.62	49.12
25	Liguria 2	0.061	51.04	50.49
26	Emilia Romagna 1	0.049	51.10	49.52
27	Emilia Romagna 2	0.052	50.88	49.99
28	Emilia Romagna 3	0.055	50.30	49.20
29	Emilia Romagna 4	0.044	50.89	49.83
30	Emilia Romagna 5	0.050	50.77	49.49
31	Emilia Romagna 6	0.072	50.10	49.13
32	Toscana 1	0.065	51.27	49.58

33	Toscana 2	0.078	50.03	49.69
34	Toscana 3	0.073	50.62	49.15
35	Toscana 4	0.071	50.31	50.11
36	Umbria	0.072	50.30	48.91
37	Marche 1	0.073	49.98	49.25
38	Marche 2	0.075	50.13	48.81
39	Lazio 1	0.081	51.50	49.48
40	Lazio 2	0.082	50.85	49.47
41	Lazio 3	0.061	49.93	49.26
42	Lazio 4	0.075	50.30	50.81
43	Lazio 5	0.057	50.83	50.68
44	Abruzzo 1	0.067	50.89	50.96
45	Abruzzo 2	0.054	50.62	49.91
46	Molise	0.058	49.83	50.19
47	Campania 1	0.099	50.72	48.22
48	Campania 2	0.075	50.50	48.51
49	Campania 3	0.084	50.66	49.73
50	Campania 4	0.041	51.02	51.48
51	Campania 5	0.055	50.32	49.84
52	Campania 6	0.088	49.47	48.45
53	Campania 7	0.057	49.89	49.93
54	Puglia 1	0.055	51.09	49.44
55	Puglia 2	0.055	50.24	49.54
56	Puglia 3	0.057	51.10	50.60
57	Puglia 4	0.080	49.86	49.92
58	Puglia 5	0.074	49.24	48.22
59	Basilicata	0.078	49.64	49.85
60	Calabria 1	0.082	49.97	49.29
61	Calabria 2	0.098	48.65	49.14
62	Sicilia 1	0.093	49.82	49.52
63	Sicilia 2	0.102	49.78	50.54
64	Sicilia 3	0.085	49.99	49.57
65	Sicilia 4	0.072	50.59	50.07
66	Sardegna 1	0.079	49.66	50.23
67	Sardegna 2	0.090	49.05	50.58
68	Sardegna 3	0.088	49.50	49.86
Min		0.0278	48.65	48.22
Max		0.1018	52.33	52.43
Mean		0.06	48.65	48.22
Std Dev		0.02	0.70	0.84
Coeff Var		0.30	0.01	0.02

Appendix B:
Multilevel full model with weighted data

	PCS			MCS		
COVARIATES	**COEFF**	**95% CI**		**COEFF**	**95% CI**	
LEVEL 1 FIXED PARAMETERS						
Intercept	53.1	53.0	53.4	52.3	52.0	52.6
Age in classes						
< 50	2.5	2.3	2.5	1.0	0.8	1.1
50-64 (ref)						
65-74	-2.1	-2.2	-1.9	0.2	0.1	0.5
75+	-4.9	-5.2	-4.8	0.2	0.0	0.5
Gender						
Male (ref)						
Female	-0.9	-1.0	-0.8	-2.0	-2.1	-1.9
Education						
High (ref)						
Medium	-0.9	-1.0	-0.7	-0.1	-0.3	0.0
Low	-2.1	-2.2	-1.9	-0.6	-0.8	-0.5
Disability						
no (ref)						
yes	-13.2	-13.2	-12.7	-7.3	-7.5	-6.9
Multichronicity						
no (ref)						
yes	-7.6	-7.9	-7.6	-5.2	-5.4	-5.0
Living with disable						
no (ref)						
yes	0.0	-0.1	0.2	-1.8	-1.9	-1.4
LEVEL 2 FIXED PARAMETERS						
H_resources						
Good(ref)						
Insufficient	-0.9	-1.1	-0.8	-1.9	-2.2	-1.8
H_conditions						
Good(ref)						
Fair	-0.3	-0.4	-0.2	-0.3	-0.5	-0.2
Bad	-0.4	-0.8	-0.3	-1.2	-1.6	-0.8

H_size						
2/3 comp (ref)						
4 comp	0.2	0.1	0.3	-0.1	-0.3	0.1
> 4 comp	0.1	-0.1	0.6	1.3	0.7	1.7
H_structure						
Couple Headed (ref)						
Single Headed	0.0	-0.1	0.2	-0.7	-0.9	-0.5
City size						
>= 50.000 (ref)						
< 50.000	-0.5	-0.6	-0.3	0.0	-0.1	0.3
Geo_Area						
North (ref)						
Centre	-0.2	-0.4	0.1	-0.3	-0.8	0.1
South	-0.2	-0.4	0.0	0.0	-0.4	0.4
Islands	-0.5	-0.8	-0.2	0.6	0.1	1.2

		95% CI			**95% CI**	
RANDOM PARAMETERS						
Variance (Large Areas)	0.08	0.05	0.15	0.30	0.23	0.53
Var iance (Households)	7.08	6.60	7.42	25.45	24.16	25.65
Var iance (Individuals)	41.23	42.14	43.15	54.46	54.29	55.58
VPC Large Areas (%)	0.15	0.11	0.30	0.43	0.28	0.67
VPC Households (%)	14.25	13.48	15.06	31.48	30.72	32.26