Università Ca'Foscari Venezia

Master's Degree programme
Second Cycle (D.M. 270/2004)
in Economia - Economics

Final Thesis

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Behavioral risk factors and linguistic structure: does the language we speak affect our choices?

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Academic Year
2015 / 2016

Acknowledgements

I am grateful to my supervisor Professor Agar Brugiavini whose guidance and encouragement were essential for the completion of this thesis.

I would also like to offer my particular thanks to Cristina Orso, PhD, and Matija Kovacic, PhD, for their support and advise for the whole duration of the realization of this work.

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1. Introduction

The importance of language in affecting the way people think and act date back to the early twentieth century, when Ferdinand de Saussure[1] and Ludwing Wittgenstein[2] provided evidence of the language-cognition link. At the same time, Sapir-Whorf hypothesis of linguistic relativity arose, stating that the native language has a strong impact on the way people think and that certain thoughts of one individual in their mother tongue cannot be fully understood by individuals whose native language is not the same. Sapir-Whorf hypothesis of linguistic relativity takes its name from the fact that languages are relative in the sense that they vary in the expression of concepts, sometimes with remarkable effects. On the other hand, the semantic expression of concepts has an impact on the conceptualization in the cognitive domain, which does not require language mediation. The concept of relativity can be distinguished in strong and weak sense. Nowadays, the hypothesis is accepted by most of the researches only in the weak sense, according to the belief that language can have some effect on thought. Therefore, speakers of different languages with different grammatical characteristics and semantic use experience the world in different ways. This was demonstrated in many fields, such as spatial cognition and words for colors.

Given the difference in the dimension of color terms vocabulary, speakers of different languages have a different sensitivity to colors and select the categories across the continuum of the spectrum in different ways. Davies and Corbett (1997) maintained that languages with relatively few number of color terms, like Setswana (the language of Botswana), are expected to form fewer color categories than languages with a relatively high number of color terms, like English and Russian. Moreover, given the difference in the number of basic color terms in the blue-green region of the color spectrum, according to which Setswana presents one single term (*botala*) which include both green and blue, English shows two basic terms, *blue* and *green*, and Russian includes three basic terms, two terms for blue, distinguishing dark blue (*sinij*) and light blue (*goluboj*), and one term for green (*zelenyj*), Setswana speakers should be more likely to include blue and green colors in the same category than speakers of either of the other two languages. As a consequence of the distinction of two categories of blue, Russian speakers should be more likely to form groups distinguishing “dark blues” and “light blues” than either English or Setswana speakers. Even though the hypothesis that Setswana is more likely to form fewer color categories than English and Russian was not confirmed by evidence, in an empirical experiment based on color grouping tasks, blue and green colors were grouped together more often in Setswana than in English or Russian. On the other hand, the prediction that Russian, which distinguishes dark blues from light blues with two different terms, is more likely to group the first category of blues separately from the second category than the other languages is not confirmed. Overall, this research leads to the conclusion that the differences in color grouping might not be linguistic, but they might also be due to differences in

[1]Ferdinand de Saussure (1857-1913) was a Swiss linguist who stated that linguistic form is arbitrary because there is no relationship between the sign, the letters of the word, and the object which it refers to, the mental knowledge of the concept.

[2]Ludwing Wittgenstein (1889-1951) was an Austrian-born British philosopher who investigated language from a logical point of view, rejecting the idea that language is distinguished but corresponding to reality and maintaining that concepts need not to be defined to be meaningful, in fact “the speaking of a language is part of an activity, or of a form of life” (Tractatus Logico-Philosophicus, 1922).

cultural norms and habits, such as levels of education, the environment in which people involved in the experiment lived and climate. A more recent study reveals that previous failures in proving the effect of language on color perception may be due to the use of memory which may lead to difficulty and confusion between colors for languages that call those colors with the same name and to favor languages that associate different names to those colors. Winawer et al. (2007) overcome this problem by testing color discrimination with stimuli that can be viewed at the same time and matching one of the two options of colors to a reference color. Evidence showed that the performance in color distinction is different among Russian and English individuals as a consequence of the different perception habitually created by the language the individuals speak. The main point argued by the authors is not that English speakers are not able to distinguish dark blues and light blues, but that Russian speakers cannot avoid to do so in order to speak their language in a conventional manner. Therefore, it appears that language-specific distortions in perceiving different colors "arise as a function of lower-level perceptual processing and higher-level of knowledge system online, in the process of arriving at perceptual decisions".

The second field considered by the literature as a fundamental domain for the effects of language is spatial cognition. Languages vary in terms of their habitually used "reference frames", defined as "the psychological or linguistic representation of relationships between entities in space". According to Sapir-Whorf hypothesis of linguistic relativity, speakers of different languages show different results in the cognitive performance on spatial memory tasks (Pederson (2007)).

While spatial relationships and words for colors have been extensively analyzed for linguistic relativity effects, the consequences of different encoding of tenses, and in particular future, is a more recent research field which is still in development.

This thesis is organized as follows. Chapter 2 reviews the linguistic literature on future-time reference and linguistic structure on individuals' economic choices. In particular, providing an overview on the effect of risk aversion and time preference on Behavioral Risk Factors and the linguistic determinants on savings, analyzing the Life-Cycle Model and the amounts owned at the moment of retirement. Chapter 3 describes the data used in the empirical analysis, presenting the Survey of Health, Ageing and Retirement in Europe (SHARE) from which data are taken and delineating the steps for the construction of the dataset, taking descriptive statistics into account, both for the total sample and for the subsample including Linguistically Heterogeneous Countries. Chapter 4 explains the empirical strategy and shows the equations of the models used to take into account Strong FTR on Behavioral Risk Factors, both with the inclusion of controls for demographic and socio-economic characteristics and with the inclusion of a set of individual specific fixed-effects. An Instrumental Variables (IV) approach is adopted to analyze the effect of risk aversion on Behavioral Risk Factors, using the number of non-indicative moods used in *irrealis* contexts as an instrument. Chapter 5 presents the results from logistic regressions with Strong FTR linguistic marker, both for all countries and for Linguistically Heterogeneous Countries, from Fixed-effects logistic regressions in the total sample and within each single Linguistically Heterogeneous Country, and from IV estimation of the effects of risk aversion on the probability of smoking, drinking heavily, exercising and being obese. Chapter 6 presents the conclusions.

2. Literature review

The relationship between language and economic behavior was not widely considered in the past. To the best of my knowledge, only three research articles analyzed the effects of linguistic structure on individuals' economic choices.

The first study in this field in the one conducted by Chen (2013). Chen discovered that one of the main factors which affects our economic decisions about the future is language. He suggested that languages that grammatically separate the present and the future foster future-oriented behaviors. One of the main differences can be found between English and Mandarin grammatical features. The peculiarity of Mandarin is that verb tense is not expressed by any grammatical means, it is only stated by adding certain adverbs or understood through the context, therefore the tenses are vague. On the one hand, English speakers are forced to mentally separate time horizon distinguishing the present and the future, on the other hand Mandarin speakers, whose language does not have future markers, are not obliged to consider this difference between time frames. Chen gives the example of an individual who wants to explain the reason of their absence at a later meeting. In the Mandarin version of the sentence the speaker would omit any marker of future time and would use the present tense of the verb, as reported in the first sentence in Figure 1. On the other hand, English grammar does not allow to use the present tense when speaking about future events, and the correspondent English version of the sentence would be "I *will go/am going/have to go* to a seminar", as reported in the second sentence in Figure 1.

Fig. 1 – Chen's example of the difference between Mandarin and English

Wǒ *qù* *tīng* *jiǎngzuò*
I go.PRS listen seminar
'I am going to listen to a seminar'

Source: Chen (2013). The effect of Language on Economic Behavior: Evidence from Savings Rates, Health Behaviors, and Retirement Assets. *American Economic Review*, 103(2):690-731, page 3.

Chen tested the hypothesis according to which languages with a strong Future-Time Reference (FTR)[3], like English, are responsible for future-oriented behaviors which include less savings, less wealth during retirement age, a higher percentage of smokers and of individuals who suffer from obesity with respect to languages with a weak FTR, like Mandarin. This phenomenon can be explained by the fact that speakers of languages with strong FTR perceive the future as more distant than speakers of languages with weak FTR.

Chen's work focuses on three main relationships: the relationship between language and savings, the relationship between language and retirement assets and the one between language and health behaviors. His findings reveal that speakers of a language characterized by a strong Future Time

[3] See Appendix Table 1, Appendix A.

Reference save about 46% as much as speakers of languages characterized by a weak Future Time Preference. Similarly, when analyzing household retirement assets, evidence suggests that retired households who fall into the category of strong FTR languages own about 39% less at the moment of retirement. Finally, the relationship between language and health behaviors shows that languages which strongly distinguish present and future induce their speakers to be involved in unhealthy behaviors, such as smoking, low physical activity, and obesity, with a probability, respectively, 24%, 29% and 13% lower than people with same socio-demographic characteristics who speak a language included in the weak FTR category. All these results make Chen conclude that language's Future Time Reference is a fundamental predictor of people's economic choices and, therefore, the language we speak shapes our behavior.

The second empirical analysis regarding the connection between language and attitudes and habits is the study conducted by Kovacic, Costantini, and Bernhofer (2016). The main innovation of this research is the creation of a specific linguistic marker (IRR), "based on the number of non-indicative moods used in irrealis contexts, i.e., contexts that involve grammatical categories concerned with expression of uncertainty" (Kovacic et al. 2016). The six irrealis environments took into account are:

1. Complements of modal predicates (i.e., to be possible, to be likely, to be necessary);
2. Complements of desiderative and volitional predicates (i.e., to want, to wish, to desire);
3. Complements of epistemic (non-factive) predicates (i.e., to think, to believe, to doubt);
4. Complements of emotive-factive predicates (i.e., to regret, to be happy, to be sad);
5. Complements of declarative predicates (i.e., to say, to tell, to announce);
6. The protasis (the if-clause) and the apodosis (the main clause) in conditional sentences.

The higher the number of non-indicative forms used in a language in these six categories, in a range of integers between 1 and 6, the stronger is the linguistic marker (IRR)[4]. By running a Probit model of risk aversion on IRR, both discrete and categorized, and controlling for country, wave, cognitive ability and health conditions, Kovacic et al. (2016) report evidence that speakers of languages with a high number of non-indicative forms in *irrealis* context (high IRR) are 16% more risk averse than speakers of languages with a low value of the linguistic marker, on average. This finding is confirmed when restricting the framework only to linguistically heterogeneous countries, when controlling for linguistic families (Indo-European, Semitic, Uralic) and for linguistic sub-families (Slavic, Romance, Germanic) and when analyzing data of the World Value Survey, as a robustness check. In order to remark the effect of language on the level of risk aversion and to compare individuals who are identical in all characteristics apart from language, the authors run a Conditional Logistic model and introduce individual-specific fixed-effects in the regression, such as gender, age, income, education, marital status and the number of children as well as a country-wave fixed-effect. The results sustain the hypothesis of the importance of the number of "Irrealis" moods which characterizes the language the individual speaks in affecting the level of risk aversion, even when comparing individuals with identical demographic and socio-economic characteristics that only differ in the language usually spoken. The phenomenon could be explained by the fact that speakers of languages with strong IRR perceive the world as more mutable and uncertain than speakers of languages with weak IRR. This thinking, in turn, implies higher levels of risk aversion

[4] See Appendix Table 2, Appendix A.

and, as a consequence, the avoidance of risky behaviors. In order to test this hypothesis, a regression of the probability of holding risky assets on risk aversion using Instrumental Variables approach is built up. The first stage confirms the significance of the relationship between IRR and risk aversion and IRR represents a strong and valid instrument for risk aversion, given the high values of F-statistic and the results of the Endogeneity Test. The results of the second stage show that, on average, high risk aversion reduces the probability of holding risky assets by 11%. Moreover, the direct marginal effect of Future Time Reference marker, proposed by Chen (2013), on the probability of investing in risky assets is negative and significant. However, the effect of "Irrealis" linguistic marker on the level of risk aversion is three times larger than the effect of Future Time Reference on the same variable. As a conclusion, individuals speaking languages with an intensive use of non-indicative moods are more likely to be strongly averse to risk and they are less likely to be involved in risky behaviors, such as investing in risky assets. Furthermore, the linguistic marker which considers the intensity of use of non-indicative moods (IRR, Kovacic et al. (2016)) seems to explain these behaviors in a strongest way than the linguistic marker which considers Future Time Reference (FTR, Chen (2013)).

The third study which sheds light on this field, and in particular on the implication of linguistic differences on the relationship between risk aversion and individual's perception of immigration, is the one conducted by Kovacic and Orso (2016). They examine the hypothesis that more intensive users of non-indicative moods are more incline to be uncertain and to show higher levels of risk aversion than low intensive users of those moods. Moreover, the feeling of uncertainty created by the use of a higher number of non-indicative moods induces individuals to be more intolerant toward immigration. Considering individuals equal in all features apart from language, data suggests that speakers of languages with a high value of IRR have about 10% higher probability of feeling intolerant toward immigration than speakers of languages with a low value of IRR. The result is confirmed when considering Linguistically Heterogeneous Countries and reveals that intolerance toward immigration is particularly higher for men, low educated, married and poor individuals as well as unemployed. On the other hand, people who show high levels of trust in others seem to be less intolerant. The main conclusion in Kovacic and Orso (2016) is that people who speak different languages, characterized by different numbers of non-indicative moods in *irrealis* contexts, exhibit significantly different attitudes toward immigration. As a consequence, policymakers should apply specific measures according to the characteristics of each country, instead of a uniform integration framework.

In general, these researches prove the fundamental importance of language as a predictor of people's behavior, not only relatively to savings, retirement assets and health, but also other fields, such as immigration.

2.1 Behavioral risk factors

Unhealthy lifestyles, such as tobacco use, dietary and activity patterns, and alcohol consumption, are considered the main causes of death all over the world (McGinnis and Foege (1993), Mokdad et al. (2000)). These three factors may act independently, the risk being due to each single factor, or synergistically, as the effect of the interaction of the factors, but it is remarkable that lifestyles are related to high numbers of deaths. This is evident in the United States where about 20%, 16% and 4% of deaths is due to, respectively, smoking behavior, diet and physical activity, and heavy drinking, which are in turn associated to cancers, lung disease, cardiovascular diseases, and heart disease. Although with lower values, this phenomenon can be extended to the WHO European Region which shows one of the highest proportions of deaths attributable to tobacco use, given that 16% of all deaths in adults over 30 are due to tobacco.[5] Moreover, a very high proportion of heavy drinking problem is widespread across ages and all Europe. The burden related to alcohol consumption, which "increases the risk of liver cirrhosis, certain cancers, raised blood pressure, stroke and congenital malformations" was estimated to be about 9% in 2001 (Rehn et al. (2001)).

Even though the causal effect of language on behavioral risk factors is only a recent challenge, there is a wide literature of studies which found correlations between education, wealth, social class, race, and lifestyle choices.

According to Grossman(1972)'s "efficient producer" hypothesis, education raises an individual's knowledge about production and, therefore, increases his ability of choosing a healthy diet and avoiding unhealthy behaviors. Through this mechanism, schooling rises household's health production efficiency. On the one hand, smoking participation and alcohol consumption decrease thanks to the knowledge of the adverse consequences. On the other hand, the knowledge of good effects of exercise induces people to increase physical activity, even though the only remarkable response to a greater knowledge is the one on cigarette consumption (Kemna (1987), Kenkel (1991)). The relationship between education and life-styles is confirmed by Di Novi (2013) that, while trying to examine the impact of the quality of environment and pollution on health investment decisions, founds that being a college graduate or attending a college has a negative effect on cigarettes and alcohol consumption, on the risk of obesity and on stress[6]. By contrast, Lantz et al. (1998) argue that educational differences do affect lifestyle choices and can be considered as a prediction of morbidity, although the mechanism related to mortality can only be explained through the association between education and income.

Wealth is another variable which has been considered in literature in relation to lifestyles. In fact, the distribution of income within a society is related to mortality and life expectancy both within and between countries. A survey conducted in the United States revealed that belonging to the lowest income category as well as not being educated or having received a lower than high school education make people report fair or poor health and that living in a country with high levels of disparities in income show a higher probability to report fair or poor health than living in a country with the lowest

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[5] All data related to alcohol and tobacco use and physical activity in the European Region were taken from the World Health Organization (WHO), Regional Office for Europe, and belong to the "Disease Prevention" category. http://www.euro.who.int/en/health-topics/disease-prevention

[6] Di Novi (2013) founds that pollution appears to affect health-improving life-style choices and that "an intervention that reduces air pollution level may have not only a direct effect on individuals' heath status, but also an indirect health effect through a healthier life-style which seems to be one of the driving factors for good health. (…) According to our results while a higher concentration of $PM_{2.5}$ when fine particulate is in the satisfactory range would have a positive influence on healthy habits (in particular, a negative influence on smoking behavior, alcohol consumption, stress, and a positive effect on diet and flu vaccination) when $PM_{2.5}$ AQI values go above 100 an increasing level of fine particulate seems to lead individuals to invest less in health-improving activities with a positive effect on the probability of smoking, consuming heavy drinks and suffering from stress; in addition it decreases the probability of following a diet rich in fruits and having preventive care".

inequalities (Kennedy et al. (1998)). On the same track, a survey conducted in Denmark demonstrated a clear relationship between social class and smoking habit as well as between work environment factors and relative weight. Even though some limitations, like the long period of time took into account which might include changes in work environment, social class and health behaviors, and the lack of information on individual's life before the participation to the experiment or the duration of the exposure to lifestyle and to work environment, the results reveal higher indication of low self-rated health in the lower social classes (Borg and Kristensen (2000)).By contrast, some economists assert that social gradients in poor health are not only due to current economic, familiar, cultural and political environment, but also to factors from childhood and adolescence. Evidence was provided both in the study cases of United Kingdom and Finland. In the first case, Power et al (2008) use the results of personal interviews at ages 23 years and 33 years, in order to analyze the impact of the within period of transition in education and employment on health. Their evidence confirms the view that childhood context contributes to inequalities in wealth. In the second case, Lynch et al (1997), with the aim of trying to explain inequalities in health, looking at Behavioral Risk Factors and their different distribution by socioeconomic levels, analyzed three stages of life on Finnish individuals: childhood, measured by parents' socioeconomic status, adolescence, measured by education, and adulthood, measured by occupation. They found that people who started poor in life, who were less educated and belonged to the occupational category of blue-collar were more likely to show unhealthy behaviors, like smoking, heavy drinking, physical activity and being obese. This study provide evidence of a strong association between behavioral risk factors and all the stages of life course, suggesting that the impact of low wealth during childhood stage of life on adult health behavioral risk could be improved by an upward social mobility system. Moreover, Contoyannis and Jones (2004), using British panel data from the 1984 and 1991 *Health and Lifestyle Survey (HALS),* found evidence of a strong and significant gradient in the probability of sleeping well, exercising and being a non-smoker by social class, with those belonging to the highest socio-economic class being significantly more likely to sleep well, exercise and avoid smoking habit than those in the baseline category.

Race is another factor which seems to be correlated with health in the past literature. Hu and Wolfe (2002) suggest that being black is associated with poorer health and fewer doctor visits than being white, and that even if black women had the same characteristics as white individuals, in terms of education, marital status, wealth and insurance status, there would be little change in the utilization of health care. On the other hand, an important change in increasing the health status of black women is potentially attributable to insurance coverage. In fact, moving all women to insurance coverage would improve health of both races, and mainly of black women, but surprisingly, limiting the provision of insurance coverage only to women who currently did not have one would principally improve health of white women. Furthermore, race is an interesting variable also when associated to differences in risk aversion (Barsky et al. (1997)) and to education (Berger and Leigh (1989)). According to a 1992 survey conducted in the United States on individuals aged from 51 to 61, Asians and Hispanics are the most risk tolerant, Whites are the least risk tolerant, while Blacks and Native Americans are in the middle. Moreover, a survey conducted between 1971 and 1974 on U.S. individuals aged 1-74 reveals lower schooling levels for Blacks than Whites. However, this result seems not to be stable given that a survey conducted between 1966 and 1976 on males aged 14-24 indicates that Blacks and Non-Whites complete more years of schooling than Whites.

In addition to all these demographic and socio-economic characteristics, past literature found evidence of an impact of risk aversion and time preference on Behavioral Risk Factors.

2.2. Behavioral risk factors and risk aversion

Risk aversion is defined as the an individual's attitude to prefer a certain outcome over a gamble with an uncertain outcome, i.e. it is the reluctance of a person to accept to be involved in a choice with an uncertain payoff rather than another choice with a more certain, even though lower, expected payoff. Since attitudes toward risk are likely to affect the tendency of people to be involved in Behavioral Risk Factors, it is fundamental to analyze this relationship in order to establish policies aimed at prevention and improvement of health status.

There is no single proxy for risk preference. Past research studies have measured propensity toward risk through answers to hypothetical questions which involved a certain outcome against an uncertain one and classified respondents in a range of categories from the least risk tolerant to the highest risk tolerant. Alternatively, a cardinal measure based on the same categories was built up and was found to be statistically significant, with high values of the parameter of risk tolerance negatively associated to smoking, drinking and owning a health insurance (Barsky et al. (1997)). A third proxy for risk aversion was constructed as a dummy variable leading to the evidence that individuals showing higher values of risk aversion are more likely to exhibit alcohol consumption (Dave and Saffer (2008)). Other proxies based on binary variables built up on answers about self-reported attitudes extended the previous findings to the relationships between higher levels of risk tolerance and stock investment, self-employment and sports participation (Dohmen et al.(2005)). A further extension of these results considers a high magnitude in probability of being overweight or obese and not using seat belt use, as wells as heavy drinking, as being associated with risk aversion (Anderson and Mellor (2008)).

Furthermore, Conell-Price and Jamison (2012) maintain the existence of a connection between risk preference and perceived control over outcomes. They created two factors, the first one representing preventive health behavior, which included "habits" such as exercising, visiting the doctor or the dentist, eating fast food or eating healthy food, and the second factor representing active disinhibition, like smoking and drinking. Their results reveal a positive correlation between risk aversion and factor one and a negative correlation between risk aversion and factor two. First of all, preventive behaviors increase with perceived control given the individual's perception of their own behavior as being fundamental for future outcomes. Secondly, perceived control might induce individuals to over-estimate their ability to limit future negative consequences of their present attitudes, such as tobacco use and alcohol consumption.

Although the literature has found the association between risk aversion and a wide number of behavioral risks, it mainly focused on two of them: smoking and heavy drinking behaviors.

2.2.1Smoking

One of the recent research papers on the relationship between risk aversion and smoking behavior provides empirical evidence that the more risk taking individuals are more likely to be smokers and show a higher demand for cigarettes on a daily basis, using data from a panel survey conducted in Germany. Pfeifer (2012) built up a binary variable for smoking status and a proxy for attitude toward risk ranging from zero to one starting from respondents' values assigned to a general behavior in situations involving risk and to the willingness to take risks in areas which could be harmful in terms of health. To the extremes we find, on the one hand, when the proxy is equal one, extreme risk lovers who perceive no risks from smoking habit, neither in health terms or in income terms. On the other hand, at value zero, completely risk averse individuals perceive a very high risk from smoking, considering consequences of tobacco use, like cancer, to lead utility deriving from health status to zero and labor income to become null, in the absence of insurance or social assistances. Evidence suggests that being 0.1 more risk lover is associated to a 2.6 percentage point higher probability of smoking cigarettes and to smoke approximately 0.4 more cigarettes on a daily basis. Pfeifer (2012) argues that these finding are consistent with the view that risk takers underestimate the consequences from smoking and underlines the importance of improving information about the risks of tobacco use. The costs of the provision of additional knowledge could be offset by reducing information to high risk averse information who seem to be aware of the consequences of smoking.

2.2.2Heavy drinking

Analogously to smoking habit, higher values of risk tolerance are found to induce people to abuse of alcohol, causing detrimental effects on their health. The case study of the United States by Dave and Saffer (2008) reveals that, using a binary variable as a proxy for risk aversion, the increase of risk tolerance of individuals leads to a higher demand for alcohol and, in particular, to immoderate drinking, which is the cause of the increase of social costs. The research shows that risk taking individuals are 10% points more likely, on average, to over-consume alcoholic beverages than risk averse individuals. A remarkable point is that drinking prevalence is declining in age, meaning that more future oriented people give more importance to future events and think about a longer planning horizon, suggesting that time preference should somehow be included in the model. Moreover, results confirm previous evidence about the relationship between risk attitude and self-employment and insurance status. Finally, the authors conclude that raising alcohol excise taxes might be a good policy in order to discourage alcohol over-consumption.

2.3 Behavioral risk factors and time preferences

Time preference is the relative value associated to a good or a money amount at an earlier rate compared with its value at a future date. The most famous studies on time preference include the delay-of-gratification paradigm which indicates that being able to endure temptations is connected to future success. This hypothesis was tested through a behavioral experiment on four-year-old kids who were given a marshmallow and were in charge of deciding either to eat the marshmallow or to wait the experimenter to come back and to receive two marshmallows instead of one. Following studies showed that kids who were able to wait for a greater future reward became more successful in their future lives (Mischel (1972)).

As in the case of the "Marshmallow test", accumulated evidence has suggested the existence of a relationship between time preference, or a property to allocate resources over time, and lifestyle behaviors. One of the main studies in this field is attributed to Fuchs (1982) who states that individuals differ in their levels of time preference, defined as the amount of future utility that equals the current utility of consuming a good or a service, and it is evident that those with low rates of time discount invest in education as well as in healthy activities. Through a pilot survey based on questions on hypothetical situations involving different amounts of money offered at different point in time, a proxy for time preference was created analyzing respondents' choice between accepting lower amounts at present time and waiting for higher amounts in the future. The empirical results found that a greater level of the implicit interest rate, which measured time preference, did imply an increase in cigarette smoking, proving that there is a correlation between time preference and investments in health.

I will review the relationship between time preferences and four Behavioral Risk Factors, namely smoking and heavy drinking habits, obesity and physical activity.

2.3.1 Smoking

Many recent researches tried to replicate Fuchs (1982)'s study in order to confirm his findings and to extend his results to other health behaviors. Bradford et al. (2014) used both a proxy involving monetary domains, built up in a similar way to Fuchs (1982)'s, and five proxies of time preferences, including self-reported patience, willpower, ability to resist to junk food, hypothetical questions on the use of drugs for migraine headache relief and a cognitive reflection test. They confirmed the result that impatient and present-biased individuals are more incline to take up smoking behavior and extended it to heavy drinking. They also argued that a proxy based on questions directly related to health decisions is not found to have a better association to time preference than proxies based on questions related to monetary outcomes. Takagi et al. (2016) extended further evidence of the effect of time preference on behavioral risk factors, not only confirming previous literature on smoking and drinking, but also suggesting the existence of a relationship between time preference and being overweight or obese. These authors revealed that in the Japanese study there is strong evidence of a relationship between time discount rate and smoking habit as well as between time discount rate and alcohol consumption, both among men and among women, even though their small contribution in the mechanism which involve the connection between education and health behavior. The same findings were spread to overweight and obese individuals, showing the effect of time preference on overweight and obesity, analyzing a self-reported Body Mass Index (BMI), respectively, greater than 25 kg/m^2 and greater than 30 kg/m^2.

Innovative ways to measure time preference consider impulsivity and financial planning horizon. Since the decision to smoke consists of an inter-temporal tradeoff, measures of self-control seem to be a good predictor of the smoking status. Self-reporting information about the habit of making hasty decision, control of one's temper or acting on impulse as well as about the time period took into account by households when planning savings and spending lead to a fundamental knowledge on individuals' time preference. Evidence suggests that people who tend to act on impulse and are overwhelmed by emotion, instead of acting with rational manners, are more likely to have smoked in the past or to continue to smoke. Similarly, having shorter financial planning horizon is highly correlated with tobacco use. Therefore, self-control is an important proxy for time preference and a good predictor of smoking status. As a consequence, commitment devices may be an efficient solution in order to decrease the number of smokers and improve people's health (Khawaja et al. (2006)). Furthermore, less educated people, manual workers, unemployed and those with low financial resources are usually more present-oriented and more impulsive, proving the negative correlation between planning horizon and impulsivity. Therefore, tobacco policies should have present-time oriented smokers as a target and they should be aimed at strengthening future-oriented behaviors among smokers (Peretti-Watel et al. (2013)).

Past literature not only underlined the importance of the effect of time preference on people's choice of smoking, supported by the fact that impatient and present-biased individuals are more incline to take up unhealthy attitudes, but also emphasized the tendency of people to be less patient in immediate future choices, known as hyperbolic discounting, and the tendency to discount gains more intensively than losses, known as sign effect. People with a higher discount rate, which make them more patient, associate less importance to future consequences of nicotine dependence relative to the satisfaction from smoking and hence smoke more. A further distinction is made between hyperbolic discounters who are aware of being time inconsistent, named *sophisticated*, and hyperbolic discounters who misconceive their own behavior, named *naïve*. Some economists raised the hypothesis that a hyperbolic discounter's smoking status depends on whether (s)he is naïve or sophisticated. By analyzing responses to questions about one's preference about doing homework when (s)he was a child in school and one's preference about planning when to do homework, data on hyperbolic discounting and on the classification as a naïve or a sophisticated individual were created. Evidence showed that, even though present-biased individuals should be lead to smoke more than exponential individuals, given self-control problem which make them prefer immediate gratification to future advantages, naïve individuals are more likely to be involved in tobacco use than sophisticated hyperbolic discounters, since the latter update their preferences, being aware about their self-control problem (Kang and Ikeda (2014)).

2.3.2 Heavy drinking

An innovative approach for measuring time preference is considering the “Big Five” personality traits which consider five dimensions: Extraversion, Agreebleness, Consciousness, Emotional stability and Openness to experience.

Costa and McCrae (1992) defined Extraversion as characterized by warmth, gregariousness, assertiveness, activity, excitement seeking, positive emotions; Agreebleness as the sum of trust, straightforwardness, altruism, compliance, modestly, tender-mindedness; Consciousness as including competence, order, dutifulness, achievement striving, self-discipline and deliberation; Moreover, emotional stability (or Neuroticism) is identified by anxiety, angry hostility, depression, self-consciousness, impulsiveness and vulnerability and openness to experience is characterized by fantasy, aesthetics, feelings, actions, ideas and values. The “Big Five” personality traits, as a proxy of time preference, are found to be a better predictor of alcohol consumption than family background or wealth situation, and a strong and significant predictor in general.

On the basis of these dimensions as well as on information related to demographic information, such as age and gender, physical and psychological health, alcohol consumption patterns, provided from students of an Irish University through responses to a web-based survey, Delaney et al. (2007) built up a variable in order to measure the consumption of alcohol of each individual, defined as Alcohol Use Disorders Identification Test (AUDIT). The results of this variable showed that increasing the age at which the individual began to drink alcoholic beverages the level of AUDIT increased, meaning that the sooner an individual begins to consume alcohol the more (s)he will be involved in alcohol use disorders, and this relationship was found to be more likely for the male sample than the female’s one. Moreover, people with a high time preference, i.e. more impatient, were associated with higher levels of AUDIT. The study confirmed that having high rates of time preferences predicts a higher tendency for heavy drinking and a higher alcohol expenditure, and that this relationship is not related to personal income. Therefore, time preferences are strongly related to alcohol abuse and, personality traits, such as extraversion and consciousness, increase the probability of being involved in heavy drinking habits.

2.3.3 Obesity

Analogously to the psychological implication of time preference mechanism on tobacco use and alcohol consumption, a high time preference is associated to higher probability of suffering from overweight and obesity than a low time preference.

Some economists, trying to understand the causes of obesity, raised the hypothesis of food technological improvements, mass production of food, industrialization, and the consequent reduction of prices, as the main drivers of the problems of overconsumption and of the increased levels of obesity and overweight (Cutler et al. (2003)). Others suggested a causal relationship between genetics and situational influences and the recent rise in the figures related to obesity and overweight (Cutler and Glaeser (2005)). By contrast, other economists maintain that, even though technological change seems a plausible explanation for obesity and overweight rates, time preference appears to be a probable complementary cause. Both using saving rate and consumer debt (Komlos et al. (2004)) and a binary variable based on respondents' savings information(Smith et al. (2005)) as a proxy of the rate of time preference reveal that an increment in the marginal rate of time preference may be an important driver of the current rise of the obesity problem, that is mainly concentrated among black and Hispanic men and black women.

Among the more recent literature, Cavaliere et al. (2013) supports the argument that time preference can affect people's investment in health. By asking to individuals which is the prevailing factor in the choice between health and taste when deciding the diet to follow, they built up a binary variable as a proxy of time preference and they examined its relationship with Body Mass Index (BMI) data, constructed as the ratio between individuals' weight (in kilograms) and height (in meters squared). Evidence shows that low values of time preference, namely when taste is preferred to health in dietary patterns, are associated with high values of BMI. On the other hand, when health is an important driver of the decision concerning food behaviors, individuals are characterized by low levels of BMI. Therefore, when taste is preferred to health and in presence of high time preference, individuals are more likely to be overweight or obese. Those individuals are usually characterized also by less frequent weight checks and scarce interest in healthy food. Effective policies aimed at fostering healthy food consumption might include improving knowledge about the consequences of eating junk food on health, in particular about obesity risk, and organizing food-shelves in supermarket in a way that promote a healthy diet.

Another empirical research focused on the relationship between time preference and weight problems including food price effects. Courtemanche et al. (2011) argued that, on the one hand, food prices increase lead to the reduction of food consumption and consequently to a lower weight of population, on average, on the other hand, high discount factor coincides with high level of patience which makes people consume less food and, as a consequence, decreases their weight. Using National Longitudinal Survey of Youth (NLSY)'s data on the hypothetical respondents' request, in case of win of a prize, on the smallest amount required to accept the prize one month or one year from the present time instead of claiming it immediately. This responses allowed the authors to construct two time-preferences parameters, one associated with present-bias (β), the one related to one month from now, and the other associated with long run patience (δ), the one related to one year from now. Empirical evidence showed that individuals with a high level of patience were more likely to respond to changes in food prices than those who seemed to be more impatient. Moreover, the effect of food price on people's weight present the highest values among impatient individuals. Therefore, high level of impatience makes people consume more food and, as a consequence, increases their weight. This finding is in contrast to Bradford et al. (2014) who revealed that patient individuals are more likely to have unhealthy weights. Finally, present-bias and long-run impatience seemed both separately to affect people's Body Mass Index (BMI).

2.3.4 Physical activity

Overweight and obesity problems seem to be related also to the amount of people's physical activity. This idea is in line with the technological change hypothesis, which not only contributes to decrease relative food price but was also significant for a reduction of the amount of physical activity required at work as well as in everyday life (Smith et al (2005)), and with the time preference hypothesis, according to which exercise requires the expenditure of time and energy at present time with the purpose of improving future health (Komlos et al.(2004)).

In contrast to this idea, Adams et al. (2009)'s results reveal that physical activity is not associated with time perspective and if there is a significant relationship between these variables, it is not strong, and it depends on the marker of time preference used. In this study, time preference was measured through discount rate, the habit of "taking each day as it is rather than planning it out", the subjective probability of living to 75, the time period considered for financial planning and the "Five-factor personality inventory". Among these proxies of time preference, the only marker significantly associated with frequency of moderate intensity of exercise was the habit of "taking each day as it is rather than planning it out".

On the other hand, Hunter et al. (2011)'s study, based on gambles between monetary amounts involving smaller sums of money after short time delay and greater amounts after a longer time delay, shows that participants who have higher discount rates and are more risk averse tend to exercise less frequently. Moreover smokers practice physical activity for a significant longer period of time, measured by minutes of time, than their non-smokers or ex-smokers counterparts. This evidence is consistent with the idea that exercise is a health prevention behavior which characterize future-oriented individuals, confirming Fuchs (1982)'s view. By contrast, another research maintains that individuals with higher discount rates practice more physical activity, given that it provides immediate gratification, such as improved wellbeing and better mood (Connell-Price and Jamison (2012)). This recent findings might lead to development of health interventions targeted at individuals' with high discount rates, providing more information on delayed benefits deriving from healthy lifestyles.

2.4 Language and savings

The effect of language is not limited to the behavioral risk factors, but is extended to decisions about savings and the amounts owned at the moment of retirement. According to Chen's study, languages with a strong Future Time Reference induce their speakers to save about a half than their weak Future Time Reference counterparts. Analogously, the first category of languages is associated with almost 40% less retirement assets than retired households who fell into the second category of languages. This evidence reveals that strong FTR languages psychologically influence their speakers in a way that make them save less and, as a consequence, retire with less wealth. This findings are consistent with Modigliani (1986)'s Life-Cycle Hypothesis (LCH) which suggests that individuals plan their consumption and savings behavior over their life-cycle. People aim at smoothing out their consumption in the best manner over their lifetimes by accumulating their earnings in the first part of their life and dissaving when they are retired. The key assumption is that all individuals usually do not choose to save up a lot in one period and spend everything in the following period, but they tend to consume approximately the same amounts in every period of the entire life course, maintaining stable lifestyles. In order to understand how this mechanism works, I analyze the Modigliani and Brumberg(1954)'s model of consumption.

2.4.1 Life-Cycle Hypothesis (LCH)

Modigliani and Brumberg(1954)'s theory considers the following variables:

C_t consumption of the individual during the *t*-th year of their life, where *t* is measured at the beginning of the earning span;

y_t income in the *t*-th year;

s_t saving in the *t*-th year;

a_t assets at the beginning of age period *t*;

r rate of interest;

N earning span (retirement stage begins);

T life span (end of life period).

Simplifying the model, assuming that:

- Interest rate equals the rate of time preference (r = δ)
- Assets at time 0 are null ($a_0 = 0$)
- Assets at time T are null ($a_T = 0$), i.e. the individual does not bequeath the next generations

we can build up the following consumer's problem:

$$max_{Co,c1,\dots,cT-1} = \sum_{t=0}^{T-1} U(C_t)$$

$$\text{s. t. } \sum_{t=0}^{T-1} C_t = a_0 + \sum_{t=1}^{T-1} y_t = a_0 + h_0$$

Solving the Lagrangian:

$$\max_{C_0, C_1, \dots, C_{T-1}} L = U\left(C_0, C_1, \dots, C_{T-1}\right) + \lambda \left[a_0 + h_0 - \sum_{t=0}^{T-1} C_t\right]$$

we find that $\frac{U'(C_{t-1})}{U'(C_t)} = 1$, given the assumption that the interest rate equals the rate of time preference (r = δ). The only possible explanation is that for a well-behaved utility function (U'>0 and U''<0) the individuals tend to smooth marginal utility, and, as a consequence, to smooth consumption, no matter the level of income. The level of consumption, constant over time, is the result of the following formula:

$$\sum_{t=0}^{T-1} C^* = a_0 + h_0$$

which given the assumption that $a_0 = 0$ leads to the result:

$$C^* = \frac{h_0}{T} = \frac{Ny}{T}.$$

By taking the first difference, we can calculate the marginal propensity to consume: $\frac{\partial C_t}{\partial y_t} = \frac{\partial C}{\partial y} = \frac{N}{T}$, given that t is constant over time.

In contrast to the Keynesian theory of consumption, according to Modigliani and Brumberg(1954)'s theory, the marginal propensity to consume does not depend on income, but it is depending on the life cycle[7]. Dividing the life course in two main stages, the first one dedicated to work and aimed at receiving positive assets and the second one in which the individuals are retired, we can find the differences in income, savings and financial wealth.

INCOME y_t

$$y_t = \begin{cases} yt \le N-1 & (work) \\ 0 \quad t > N-1 & (retirement) \end{cases}$$

SAVINGS s_t

$$s_t = \begin{cases} y - C = y - \frac{N}{T}y = \left(1 - \frac{N}{T}\right)y & t \le N-1 \quad (saving) \\ 0 - C = 0 - \frac{N}{T}y = -\frac{N}{T}y & t > N-1 \quad (dissaving) \end{cases}$$

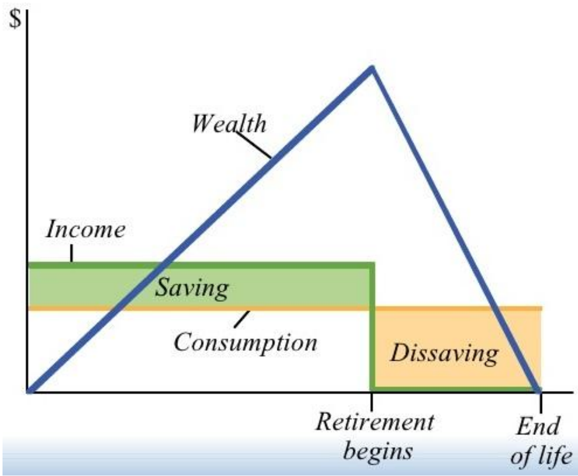
[7]Kenneth, K. K. (1955). "We depart from Keynes, however, on his contention of "a greater *proportion* of income being saved as real income increases(p. 97, italics his). We claim instead that the *proportion of income saved is essentially independent of income*".

ASSETS (or FINANCIAL WEALTH)a_t

$$a_t = \begin{cases} t\left(1-\frac{N}{T}\right)y & t \leq N-1 \\ N\left(1-\frac{t}{T}\right)y & t > N-1 \end{cases}$$

This model suggests that individuals tend to save during the working phase of their life in which they are paid for the job they do and tend to dissave when retirement begins, maintaining consumption constant for the entire life-cycle. Fig. 2 shows the hump-shaped wealth profile, which represents financial wealth, which is increasing in the working phase and starts to the decrease after reaching a peak when retirement begins. Moreover, the graph shows that, according to Life Cycle Hypothesis, saving varies systematically over a person's lifetime.

Fig. 2 – Life-Cycle Hypothesis



Source:N. Gregory Mankiw (2002*). Macroeconomics, 5th edition*. Harvard University. Worth Publishers.[8]

In reality, however, some of the assumptions need to be removed, and other variables need to be taken into account.

[8]The picture related to the Life Cycle Hypothesis is taken from: http://image.slidesharecdn.com/16-29945/95/macroeconomicsch16-32-728.jpg?cb=1168900361

2.4.2Certainty equivalence and “Precautionary saving”

Realistic inter-temporal choices are characterized by uncertainty about income, about the returns on risky assets and the duration of life.

“Certainty Equivalence” model allows to consider an environment which takes into consideration uncertainty in consumers’ inter-temporal choices, without losing the simplicity of models which ignore it. In fact, not only the best predictor of future consumption is current consumption, *ex-ante*, but also when considering variables after their occurrence (*ex-post*) future consumption varies only as a consequence of the forecasting error.

Furthermore, Campbell (1987)’s interpretation of the “Certainty Equivalence”, supposing infinite planning horizon, allows to construct the following saving function:

$$s_t = \sum_{\tau=1}^{\infty} (1+r)^{-\tau} E_t \Delta y_{t+\tau}$$

which indicates that saving(s_t) goes in the opposite direction with respect to the expected variations of labor income($E_t \Delta y_{t+\tau}$). In fact, if consumer predicts an increase in income($E_t \Delta y_{t+\tau} > 0$), savings will be negative since (s)he will prefer to increase present consumption through debt or the spending of assets. On the other hand, if, for instance, the probability of unemployment or tax hikes increase, the consumer will predict a decrease in income $E_t \Delta y_{t+\tau} < 0$, savings will be positive because (s)he needs to consume less in order to accumulate financial assets to cope with the future reduction in income.

According to “Certainty Equivalence” with r≠δ the reasons for saving are: an inter-temporal saving motivation (related to the interest rate) and a motivation associated with the Life-Cycle Model (related to the imbalance between present and future income). However, the model totally ignores a further explanation for saving, connected with the necessity of saving money in order to cope with unpredictable events, the so-called “Precautionary saving”. “Precautionary saving” reflects the desire of individual to accumulate assets through saving in order to overcome “possible emergencies, whose occurrence, nature and timing cannot be perfectly foreseen”, given that life span (T) and other risks are not predictable (Modigliani and Brumberg (1954)).

Blanchard and Mankiw (1998) approximate the following Euler equation:

$$u'(C_t) = \frac{1+r}{1+\delta} E_t u'(C_{t+1}) \qquad [1]$$

with a Taylor series expansion of the second order of $u'(C_{t+1})$ in the neighborhood of C_t:

$$u'(C_t) \cong \frac{1+r}{1+\delta} E_t \left[u'(C_t) + u''(C_t)(C_{t+1} - C_t) + \frac{1}{2} u''(C_t)(C_{t+1} - C_t)^2 \right]$$

Diving it by ${C_t}^2$ we find:

$$\frac{u'(C_t)}{{C_t}^2} + \frac{u''(C_t)}{{C_t}^2} E_t \left(\frac{C_{t+1} - C_t}{{C_t}^2} \right) + \frac{1}{2} u''(C_t) E_t \left(\frac{C_{t+1} - C_t}{C_t} \right)^2 \cong \left(\frac{1+r}{1+\delta} \right) \frac{u'(C_t)}{{C_t}^2}$$

Solving for the expected growth rate of consumption leads to:

$$E_t\left(\frac{C_{t+1}-C_t}{C_t}\right) \cong ESI\left(\frac{r-\delta}{1+r}\right)+\frac{1}{2}\,p(c)E_t\left(\frac{C_{t+1}-C_t}{C_t}\right)^2$$

where: p(c) = - $\frac{u'''(C_t)C_t}{u''(C_t)}$ is Kimball's coefficient of relative prudence

ESI = - $\frac{u'(C_t)}{u''(C_t)C_t}$ is the inter-temporal elasticity of substitution in consumption

$E_t\left(\frac{C_{t+1}-C_t}{C_t}\right)^2$ is a measure of the expected variability of consumption.

This formula is interesting since it underlines that the variability of future consumption leads to the reduction of present consumption. The consumption profile is steeper when taking uncertainty into consideration than in an hypothetical world without uncertainty. Moreover, the sensitivity of growth rate of consumption on uncertainty depends on the coefficient of relative prudence. However, given that it is widespread opinion that in practice the majority of risk averse individuals show a decreasing level of risk aversion, or at least constant, the use of quadratic utility function in problems implying uncertainty is controversial, as sustained by Guiso and Terlizzese (1994)[9].

2.4.3Habits and savings

The previous models supposed that utility function for each period depends exclusively on the consumption, and hence saving, of that period. However, in reality, each period is not separable from the others and utility of a good depends not only on present consumption, but also on past consumption or on the delayed level of aggregate consumption. Consumer's problem requires a dynamic analysis given that today consumption and saving's decisions depend also on those of other periods and they will affect future decisions. Literature distinguishes two types of behaviors involved in habit formation. First, consumers tend to get used to a certain level of consumption and they maintain those levels by "force of habit", trying to avoid modification over time (*internal habits*). The second consumers' behavior imply the tendency to imitate other consumers' behavior and to "follow the current fashion" (*external habits*)[10]. The importance of habits is not limited to consumption and saving's choices, in fact habits are fundamental in order to explain health problems, such as smoking and drinking addictions.

Jappelli and Pistaferri (2000) suggest the following model in order to take internal habits into account:

$$u(C_t, C_{t-1}) = \frac{(C_t+\alpha C_{t-1})^{1-\gamma}}{1-\gamma}$$

[9]Guiso, L., and Terlizzese, D. (1994). Economia dell'incertezza e dell'informazione. Scelte individuali, Mercati, Contratti. *Hoepli, Milano 1994*.
[10]Jappelli, T., and Pistaferri, L. (2000). Risparmio e scelte intertemporali. *Il Mulino, Bologna 2000*.

where α represents the internal habits. Depending on the sign of α, present and past consumption can be substitutes (α> 0) or complements (α< 0).

Supposing the presence of uncertainty about income and infinite planning horizon, the consumer's problem becomes:

$$\max E_t \sum_{\tau=0}^{\infty}(1+\delta)^{-\tau}u(C_{t+\tau}, C_{t+\tau-1})$$

$$\text{s.t. } a_{t+1} = (1+r)(a_t + y_t - C_t)$$

It is evident that consumer's problem considers two variables of interest: assets (a_t) and past consumption levels (C_{t-1}) on which consumers' habits depend. Therefore the Value Function becomes:

$$V_t(a_t, C_{t-1}) = \max_{a_{t+1}, C_t} u(C_t, C_{t-1}) + \frac{1}{1+\delta}E_t V_{t+1}(a_{t+1}, C_t)$$

And the first order condition is:

$$\frac{\partial u}{\partial C_t} - \frac{1}{1+\delta}(1+r)E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} + \frac{1}{1+\delta}\frac{\partial V_{t+1}}{\partial C_t} = 0 \qquad [2]$$

Supposing $C_t^*(a_t, C_{t-1})$ is the optimal solution of the consumer's problem, the Value Function becomes:

$$V_t(a_t, C_{t-1}) =$$
$$= u\,[C_t^*(a_t, C_{t-1}), C_{t-1}] + \frac{1}{1+\delta}E_t V_{t+1}\{(1+r)[a_t + y_t - C_t^*(a_t, C_{t-1})], [C_t^*(a_t, C_{t-1})]\} \qquad [3]$$

Deriving [3] with respect to a_t and to C_{t-1}, and using [2] leads to the following expressions:

$$\frac{\partial V_t}{\partial a_t} = \frac{1+r}{1+\delta}E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} \qquad [4]$$

$$\frac{\partial V_t}{\partial C_{t-1}} = \frac{\partial u_t}{\partial C_{t-1}} \qquad [5]$$

Reorganizing the first order condition expression, taking into account of [4] and [5][11] leads to the following Euler Equation, which considers consumption habits:

$$\frac{\partial u_t}{\partial C_t} - \frac{1}{1+\delta}E_t\frac{\partial u_{t+1}}{\partial C_t} = \frac{1+r}{1+\delta}\left[E_t\left(\frac{\partial u_{t+1}}{\partial C_{t+1}} + \frac{1}{1+\delta}\frac{\partial u_{t+2}}{\partial C_{t+1}}\right)\right] \qquad [6]$$

It is remarkable that this Euler equation is not limited to the relationship between present consumption and future consumption, independently on delayed variables, as in equation [1] presented in paragraph 2.4.2. Equation [6] includes the consideration of the effect of present consumption (C_t) on future utility (u_{t+1}), in the second component of the left side, and the

[11]Details about the derivation of Euler equation [6] are given in Appendix C.

consideration of future consumption (C_{t+1}) on utility of the following period of time (u_{t+2}), in the second component of right side.

Supposing that $\alpha< 0$ means that present and past consumption are complements and, according to the Euler equation above, utility increases if consumption at time t increases, but it decreases if consumption at time t-1 increases. Therefore, consuming at time t-1 reduces utility at time t and the only way in order to increase utility at time t is to further increase present consumption at time t. Habits induce individuals to maintain the same levels of consumption they kept in the past and tend to smooth consumption over time, and hence, they smooth savings over time. Every time individuals need to choose the amount of consumption and saving they look both at future and past decisions. As a consequence, present savings depend on past savings and will affect future choices about savings.

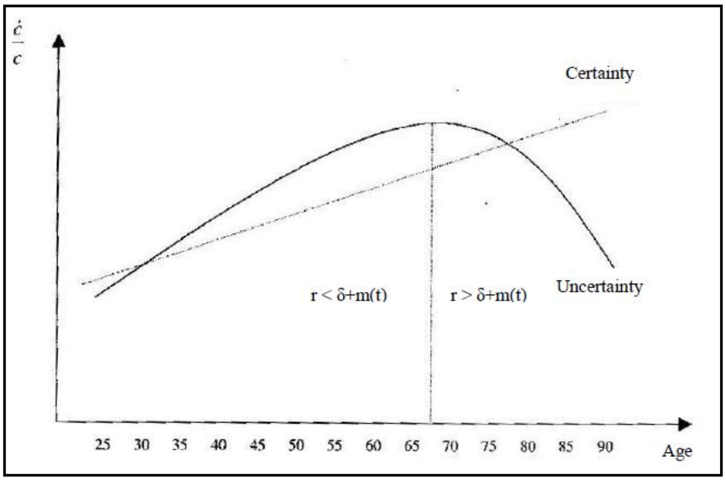
2.4.4Other reasons for savings

Jappelli and Pistaferri (2000) consider other reasons for saving which include the uncertainty about the duration of life, bequests and the institutional set up, such as pension funds and tax incentives.

First, the Life-Cycle Hypothesis does not take into account the uncertainty about the duration of life (T), even though the risk to survive for a longer period of time than predicted and to exhaust all financial resources in the retiring period is of wide importance for individuals. Theoretically, this problem could be solved through insurance contracts which provide a certain income in exchange for an insurance premium. However, this solution is not common in practice, because of problems of moral hazard and averse selection. The introduction of the uncertainty about the life span presents several consequences. First, consumer will discount future utility at a higher rate because of the inclusion of the probability of surviving, and therefore, (s)he is induced to anticipate consumption at current time. Second, given the validity of the hypothesis of non-negative assets at time T and that the consumer does not know if (s)he will survive to the following period, a liquidity constraint needs to be introduced. Finally, considering uncertainty about life duration, the destocking of assets is slower for aged individuals than predicted by Life-Cycle Model. In fact, old people choose to keep a certain amount of assets in order to protect themselves from the eventuality of living longer and not to have enough money to allocate in consumption.

Mortality function during the life-cycle suggests that the inclusion of uncertainty of life duration in the model makes consumption vary over time. In particular, when the interest rate is greater than inter-temporal preference rate plus the mortality rate ($r>\delta+m(t)$), consumption increases with age. This is characteristic of young individuals, whose mortality rate is very low, and are incentivized to save money given the high value of the interest rate. On the other hand, when the interest rate is greater than inter-temporal preference rate plus the mortality rate ($r<\delta+m(t)$), consumption decreases with age. After a peak at which the interest rate is equal to inter-temporal preference rate plus the mortality rate and consumption arrives to its maximum value, when people reach old age, they are characterized by high mortality rate and, therefore, start to anticipate consumption to present time, as a consequence of the uncertainty of their remaining time to live (Fig. 2). Therefore, uncertainty strengthen the Life-Cycle Model conclusion of consumption being a concave function of age.

Fig. 2– Comparison between consumption patterns under certainty and Uncertainty about the duration of life

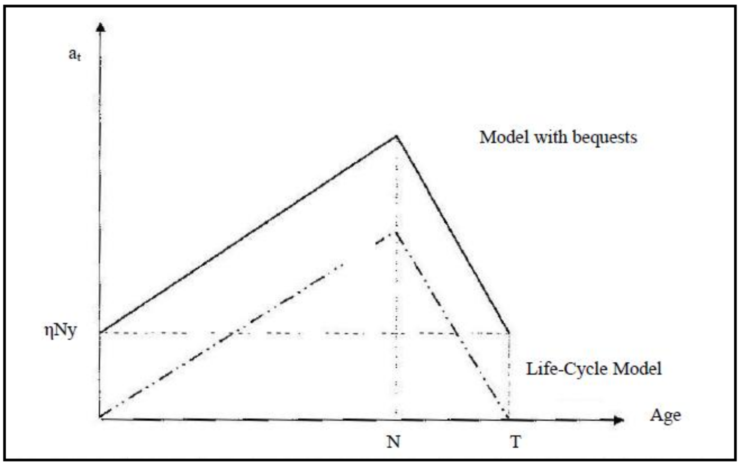


Source: Jappelli, T., and Pistaferri, L. (2000). Risparmio e scelte temporali. Il Mulino, page 210.

A further consideration is that Life Cycle Model does not take bequests into consideration, and their introduction could make evidence partially deviate from the model's prediction. According to some economists, bequests should be divided into two categories: *joy of giving*, which considers bequests as a constraint hypothesizing that parents have a certain predetermined objective in terms of bequests, and *bequests as consumption*, which considers bequests as any other consumption good.

The model with *joy of giving* explains why the final assets of aged people does not become null in reality, however, it is not able to account for the slower rate of the destocking of assets for aged individuals seen in reality than the one predicted by Life-Cycle Model. Therefore, an individual characterized by $a_0 = a_T = \eta Ny$, who would like to leave an amount η of their assets to the future generation, present a pattern of hump-shaped assets and smoothed consumption, as in the model without bequests, but with a higher level of assets of time 0 and time T than in the other case (Fig. 3).

Fig. 3 – Assets in the Life-Cycle Model with bequests



Source: Jappelli, T., and Pistaferri, L. (2000). Risparmio e scelte temporali. Il Mulino, page 228.

Moreover, the introduction in the model of *bequests as consumption* provides an explanation for the evidence which shows that old individuals do not destock their assets completely at the end of their life, and that the destocking of assets is slower for aged individuals than predicted by Life-Cycle Model without bequests. In fact, bequests increase utility at future time thanks to the non-negative assets constraint and reduces present consumption in favor of future consumption. This mechanism induces individuals to postpone consumption to the future and creates a pattern of consumption less steep than before.

Finally, other causes of variation in saving's behavior may be due to institutional set up, such as pension funds and tax incentives[12].

Considering a welfare system based on the compulsory deposit of contributions by law in order to give a provision to individuals at the end of working period affects significantly saving and assets composition. Welfare systems are divided into two categories: *funded pension plans* and *unfunded pension plans*. Compulsory social security transforms part of the individuals' assets into annuities, which can be perceived from a pension fund which works following a funded pension scheme, or Social Security Administration which works following an unfunded pension scheme.

In funded pension schemes, pensions of each generation are financed through contributions previously deposited from the same generation. Therefore, young workers deposit a contribution d_t at time t and they receive the contribution capitalized at the market interest rate $(1 + r_{t+1})d_t$ at time t+1. With this mechanism, the annuity accumulated from t to t+1 and distributed from the pension fund is only depending on the market interest rate. Supposing the fund pension interest rate equals the interest rate received from the individual, this system induces individuals to reduce private savings as contribution (d_t) increases, but, given that the contribution represents a compulsory saving through the pension fund, the contribution perfectly substitutes private saving. This effect, known as *wealth replacement effect*, is such that inter-temporal choices are not modified in funded pension schemes, unless the fund interest rate differs from the interest rate on individual saving.

On the other hand, in unfunded pension schemes, also known as *pay-as-you-go* pension plans, social contributions d_t collected at a certain period of time t are used to finance pension provisions distributed at the same period of time t. Therefore, the Social Security Administration, at time t, receives the contributions d_t from young workers and proceeds to transfer the amount $(1 + n)(1 + g)d_t$ to old people of the previous generation, where n is the growth rate of labor force and g is the growth rate of productivity. In the following period of time t+1, the annuity will be distributed to the old generation (which coincides with the generation of young workers at time t) from the contributions of the new generation of young workers. Given that the right to receive a pension depends on having financed pensions of previous generation, through social contributions, this system is founded on an intergenerational pact, which marks the difference from the funded pension plans. As for funded pension schemes, funded pension plans induce individuals to reduce private savings given that workers are aware of the fact that from the moment of retirement there will be

[12]Examples of tax incentives boosting retirement savings can be seen in Individual Retirement Accounts (IRA) and 401(k) Funds in the United States, penalties in anticipated reimbursement for complementary funds in Canada, Tax-Exempt Special Saving Account (TESSA) in the United Kingdom, and fiscal deductibility on life insurance and complementary social security in Italy.

new workers who will transfer assets to them. Therefore, trust in the intergenerational pact is essential for the funded pension provision to be bearable.

3. Data

All data I consider in this thesis are taken from the Survey of Health, Ageing and Retirement in Europe (SHARE) and analyzed through Stata 13 statistical software package.

3.1 The Survey of Health, Ageing and Retirement in Europe (SHARE)

The Survey of Health, Ageing and Retirement in Europe (SHARE) is a multidisciplinary and cross-national panel database of micro-data on health, socio-economic status and family networks of approximately 123,000 individuals from 20 European countries (plus Israel, non-European country) aged 50 or older. The country considered in SHARE are: Austria, Germany, Sweden, Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, Czech Republic, Poland, Ireland, Luxembourg, Hungary, Portugal, Slovenia, Estonia.

Nowadays, SHARE counts more than 293,000 of interviews which include four panel waves based on current living information and one wave which provides information on individuals' retrospective life history ranging from childhood conditions, the respondents' partners and children, housing, financial and employment history to detailed questions on health and health care (Wave 3, SHARELIFE). The first wave was collected in 2004/2005, the second in 2006/2007, SHARELIFE in 2008/2009, the fourth wave in 2011 and the fifth wave in 2013. Not all countries participated in each wave and the timing of interviews slightly differs between countries. Table 1 provides information about the participation of countries and the timing of data collection from Wave 1 to Wave 5.

Table 1. Countries, Languages and Fieldwork Times in SHARE Waves 1-5

Country ID	Language ID	Country (Language)	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
11	11	Austria (German)	2004	2006/07	2008/09	2011	2013
12	12	Germany (German)	2004	2006/07	2008/09	2011/12	2013
13	13	Sweden (Swedish)	2004	2006/07	2008/09	2011	2013
14	14	Netherlands (Dutch)	2004	2007	2008/09	2011	2013
15	15	Spain (Castilian)	2004	2006/07	2008/09	2011	2013
	39	Spain – Girona (Catalan)	-	-	-	-	2013
	40	Spain – Girona (Castilian)	-	-	-	-	2013
16	16	Italy (Italian)	2004	2006/07	2008/09	2011	2013
17	17	France (French)	2004/05	2006/07	2009	2011	2013

18	18	Denmark (Danish)	2004	2006/07	2008/09	2011	2013
19	19	Greece (Greek)	2004/05	2007	2008/09	-	-
20	20	Switzerland (German)	2004	2006/07	2008/09	2011	2013
	21	Switzerland (French)	2004	2006/07	2008/09	2011	2013
	22	Switzerland (Italian)	2004	2006/07	2008/09	2011	2013
23	23	Belgium (French)	2004/05	2006/07	2008/09	2011	2013
	24	Belgium (Flemish)	2004/05	2006/07	2008/09	2011	2013
25	25	Israel (Hebrew)	2005/06	2009/10	-	-	2013
	26	Israel (Arabic)	2005/06	2009/10	-	-	2013
	27	Israel (Russian)	2005/06	2009/10	-	-	2013
28	28	Czech Republic (Czech)	-	2006/07	2008/09	2011	2013
29	29	Poland (Polish)	-	2006/07	2008/09	2011/12	-
30	30	Ireland (English)	-	2007	2009/10/11	-	-
31	41	Luxembourg (French)	-	-	-	-	2013
	42	Luxembourg (German)	-	-	-	-	2013
32	32	Hungary (Hungarian)	-	-	-	2011	-
33	33	Portugal (Portuguese)	-	-	-	2011	-
34	34	Slovenia (Slovenian)	-	-	-	2011	2013
35	35	Estonia (Estonia or Russian)	-	-	-	2010/2011	2013 (XT only)
	36	Estonia (Estonian)	-	-	-	-	2013
	37	Estonia (Russian)	-	-	-	-	2013

Source: SHARE Release Guide 5.0.0

SHARE introduces some form of uniformity among the interviews in different languages thanks to a common generic questionnaire which is translated in the national languages employing an internet based translation tool and processed in a Computer-Assisted Personal Interviewing (CAPI) instrument. Nonetheless, some variables require a further country-specific measurement, such as variables related to education (ISCED).

For each wave, the questionnaire is divided into coverscreen questionnaire, main questionnaire and some special questionnaire modules. The coverscreen part is the first module of the interview and includes demographic information about the respondent and other components of the household, such as gender, month and year of birth of both the respondent and the partner, month and year of the interview, the household size, and the identity of the family respondent (*fam_resp*), financial respondent (*fin_resp*) and household respondent (*hou_resp*). In fact, not every eligible household member is asked every questionnaire module, family respondents answer questions on children and social support, household respondents answer questions on housing, financial respondents answer financial transfer and asset questions, on behalf of the couple, and household income and consumption, representative for all household members, on behalf of the couple. The main questionnaire is divided into 24 modules: Demographics and Networks (DN), Social Networks (SN, only Wave 4), Children (CH), Physical Health (PH), Behavioral Risks (BR), Cognitive Function (CF), Mental Health (MH), Health Care (HC), Employment and Pensions (EP), Computer Use (IT, only Wave 5), Mini Childhood (MC, only Wave 5), Grip Strength (GS), Walking Speed (WS, only Wave 1 and 2), Chair Stand (CS, only Wave 2 and 5), Peak Flow (PF, only Wave 2 and 4), Social Support (SP), Financial Transfers (FT), Housing (HO), Household income (HH), Consumption (CO), Assets (AS), Activities (AC), Expectations (EX), and Interviewer observations (IV).Finally, the questionnaire usually ends with the self-completion questionnaire which can include a paper and pencil questionnaire, the so-called *drop-off*, which is partly country-specific, it differs across waves, and, although available for all waves, was conducted only in three countries in Wave 5 (Austria, the Czech Republic and Israel), *vignettes* which aim at improving cross-national comparability and are available only for Wave 1 and Wave 2, and the *end-of-life questionnaire*, in case the respondent deceased between two waves, which includes information on life circumstances in the year before the death and at the moment of death provided by a proxy-respondent who can be a family member, a household member, a neighbor or any other person of the closer social network of the deceased respondent.

The methodology applied in the data collection of the main questionnaire is based on computer-assisted personal interviewing (CAPI) which allows the interviewers to conduct face-to-face interviews using a laptop computer on which the CAPI instrument is installed. The drop-off and the vignettes questionnaires are conducted via paper and pencil in the same way as the end-of-life interviews that can be conducted also via Computer-Assisted Telephone Interview (CATI).

The target of SHARE interviews includes all individuals aged 50 years and over at the time of the interview and have their domicile in the respective SHARE country, however in all waves additional information is provided about current partners living in the same household regardless of their age. All people that are “incarcerated, hospitalized or out of the country during the entire survey period, unable to speak the country’s language(s) or has moved to an unknown address” are excluded from the survey.

SHARE provides a certain number of generated variables for each wave in order to assure fast and easy comparison across national data. Some of these variables includes internationally standardized variables, such as the International Classification of Education (ISCED), others are generated variables which enhance the handling of SHARE data. The generated variable modules are divided into: health, ISCED, ISCO (only in Wave 1), housing, networks and SSW (only in Wave 4), deprivation (only in Wave 5), weights, and imputations.

Health module of the generated variables (*gv_health*) contains variables related to respondents' physical status, like self-perceived health (*sphus*), the Body Mass Index (BMI), the number of chronic diseases (*chronic*), an index on mobility (*mobility*) and limitations with instrumental activities of daily living (*iadl*), and mental health status, like the EURO-D depression scale (*eurod*).

Education module of the generated variables (*gv_isced*) includes the 1997 International Standard Classification of Education (ISCED-97) for respondents as well as for respondents' children and respondents' parents (only for Wave 5). Wave 5 provides two versions of ISCED. The first version is the same of the previous waves and considers the 1997 classification. The second version takes into account significant changes in education systems worldwide after the ISCED revision adopted by UNESCO Member States in 2011 (ISCED-11).

ISCO module of the generated variables (*gv_isco*)classifies respondents' occupation as well as former partners' and their parents occupation, according to the International Standard Classification of Occupations (ISCO-88) provided by the International Labour Organization (ILO). The corresponding industries version of this module is coded on the basis of the Statistical Classification of Economic Activities in the European Community (NACE, version 4 rev. 1 1993).

The housing module of the generated variables (*gv_housing*) considers a hierarchical classification system for dividing up the economic territory of the EU, known as "Nomenclature of Territorial Units for Statistics" (NUTS). This system is fundamental in order to locate SHARE households respondents in terms of territorial unit. The Nomenclature of Territorial Units for Statistics is available at three different levels: major socio-economic regions (NUTS 1), basic regions for the application of regional policies (NUTS 2) and small regions for specific diagnoses (NUTS 3)[13].

The weights module of the generated variables (*gv_weights*) takes into account cross-sectional sampling design weights and calibrated weights. On the other hand, the imputations module of the generated variables (*gv_imputations*) involves the Fully Conditional Specification (FCS) method, for each wave and country, only for the monetary variables which satisfy specific requirements. SHARE provides five multiple independent imputations of the missing values on each variable indexed by the variable *implicat*. Since they are five independent imputations, it is possible to choose one single imputation methods selecting one of the five available *implicats* and there is no specific reason to prefer one particular *implicat* to the others.

Some generated variables modules are available only for one specific wave. This is the case of networks module of the generated variables (*gv_networks*) which contains information about respondents' personal social networks and is available only for Wave 4, given its dependence on the Social Network (SN) module of the main questionnaire. Similarly, the deprivation module of the generated variables (*gv_deprivation*) contains indices for material and social deprivation and is available only for Wave 5.

The last generated variables module includes two measures of individual accrued Social Security Wealth (SSW) (*gv_ssw*) and is "the first attempt of computing and deliver to the scientific community a set of internationally comparable measures of pension wealth computed for a large

[13]Due to privacy legislation reasons not every NUTS level is available for every country.

number of countries"[14]. These variables were created with the aim of understanding the role played by institutions and set of laws in pension policies, inequalities and allocation, or re-allocation, of resources over the life cycle and across countries. The main innovation proposed by these new variables is their availability both for retirees and for workers. In fact, Social Security Wealth measures present data for individuals who participated to SHARE Wave 4 and declared to be either a retiree or a worker. The SSW of retirees has been computed through self-reported information about pension amounts received and provides knowledge on Social Security Wealth for all countries which took part to Wave 4. The SSW of workers is based on retrospective information on individuals' working career and residence, acquired from Job Episode Panel, and is available only for those individuals who participated to both Wave 3 (SHARELIFE) and Wave 4. Furthermore, one more distinction is necessary, given that Job Episode Panel gives information on net of taxes earning but pension rules are often computed considering amounts gross of taxes. Taking account of the complexity of grossing up wages, two versions of Social Security Wealth measures are available, one measure based on net wages (SSW_nv) and one based on approximate measure of grossed-up wages and of minimum pension benefits (SSW_gw).

Social Security Wealth measures are computed through the following formulas for retirees and workers, respectively:

$$SSW_i = \sum_{j=a}^{\Omega} P_{i,j}\,\pi(j|a)(1+r)^{a-j} \quad \text{(for retirees)}$$

where: i is the individual, a is age at the time of the interview, Ω is the maximum attainable age, $\pi(.)$ are conditional survival probabilities, according to current life tables, r is financial discount rate, P is the self-reported public old age pension benefit, and,

$$SSW_i = \sum_{j=R}^{\Omega} \widehat{P_{i,j}}(R)\,\pi(j|a)(1+r)^{a-j} \quad \text{(for workers)}$$

where $\widehat{P_{i,j}}(R)$ is the public old age pension benefit computed assuming that the individual will retire at current age a from the labor market and will start receiving pension income from the old age (retirement age) R.

Given the difficulty of integrating current data and micro-data on the whole life period of each individual, some assumptions were necessary and Social Security Wealth measures are reliable more from an ordinal point of view than a cardinal point of view. The main assumptions are that:

- "individuals will continue to reside in the country they currently reside until they reach the old age (retirement age) to evaluate eligibility whenever this information is relevant";
- "the individual has received payments for the whole years", without considering "shorter payments periods if the individual retired during the interview year";
- Not considering lump sum payments, including thirteenth month;
- "individuals working less than 35 hours per week are part-time workers";
- "wages are considered constant in real terms within each working spell, while nominal wages change with inflation within each spell";

[14]Information on SSW available in: Belloni, M., Carrino, L., Orso, C. E., Buia, R. E., Cavapozzi, D., Pasini, G., and Brugiavini, A. (2016): "Internationally comparable measures of individual Social Security Wealth in SHARE Wave 4". SHARE Working Paper Series: 24-2016

- If first wage amount is not available, “wages of that employment spell are excluded from the computation of pensionable wages” even though it counts “for the computation of insurance and contribution years”;
- “pension credits accrued during periods of child caring, university education and military service” are ignored;
- “upper-bound limit of earning taken into consideration in the calculation of pension contributions” are ignored;
- Spouse is considered as independent from the partner for all married individuals;
- There is no premium for late retirement;
- “respondents will reach eligibility for old-age pension in the country in which they reside at the time of the interview in Wave 4 (2010)”.

3.2 The construction of the dataset

In my empirical study, I combine data from SHARE Wave 2 (release 5.0.0), which includes data from 2006/2007, apart from Israel whose data are from 2009/2010, and SHARE Wave 5 (release 5.0.0), which includes data from 2013, in order to include the highest possible number of individuals and countries. The respondents in my sample come from 17 European countries and Israel, speaking 17 different languages, sometimes different even within the same country (Linguistically Heterogeneous Countries). The countries considered in my study are: Austria, Germany, Sweden, Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Israel, Czech Republic, Poland, Ireland, Luxembourg, Slovenia, and Estonia. Moreover, I use data from SHARE Wave 4 (release 5.0.0) in order to take into account two measures of individual accrued Social Security Wealth (SSW),which are not available for linguistically heterogeneous region of Spain, Greece, Israel, Luxembourg and Estonia, since these measures require the participation to the survey in both Wave 3 (SHARELIFE) and Wave 4.

I started my study by merging all the necessary modules through the “merge” command in Stata 13 and creating a single data file which included all the variables I needed. Each respondent to the survey is associated with a unique code, defined “mergeid”, which is the same through all waves. I preferred this key variable to “hhidW”, where “W” stands for the specific Wave number, given that I need data on individual level rather than on household level. Moreover, those who do not participated in an individual interview are associated with the code “no int. w. x”, where x is the number of the wave took into consideration.

The first module I took into account was the Coverscreen on individual level (*cv_r*) since it provides basic information about the individuals and it was the first module submitted chronologically. Through this module I received information about the identity of the family respondent, the financial respondent and the household respondent as well as about the country where the individual lives, the household size, information on the date of the interview (month and year) and on whether the partner, if any, lives with the respondent, only for Wave 5.

Then I considered the Demographics and Network module (DN) from which I took information about month and year of birth, country of birth, gender, marital status, the highest degree obtained and whether the parents live in the household, separately for mother and father. From the Social Support (SP) module I gained knowledge on whether the individual receives any help, meaning someone living in the household who helps with personal care.

Furthermore, I considered one of the most important modules for the purpose of my thesis, the Behavioral Risks (BR) module in which respondents are inquired about smoking and drinking alcoholic beverages habits. Individuals are asked whether they have ever smoked daily (br001_), whether they are current smokers (br002_), whether they stopped smoking since the last interview (br022_) and to provide the number of years they have been smoking (br003_). Moreover, they are required to say if they have ever drunk alcoholic beverages (br021_) and, in case of positive answer, to give the number of drinks they usually drink in a day (br019_), the frequency of alcohol consumption in the last three months (br010_), the frequency of consumption of four or more drinks in the last three months (br020_, in Wave 2) or the frequency of consumption of six or more drinks in the last three months (br023_, in Wave 5). Finally, respondents are requested about the type and amount of physical activity in their daily life, both vigorous exercise (br015_) and activities which require a moderate level of energy (br016_). Wave 5 contains also data on how often the respondents' consume fruit and vegetables (br029_), as a an index of the dietary pattern[15].

Afterwards, I took data on risk aversion from the Assets (AS) module and on current job situation from the Employment and Pensions (EP) module. Information on dwelling occupancy status (ho002_), which says if the individual is an owner, a tenant or if the household is occupying this dwelling rent free, are taken from the Housing (HO) module, the amounts in the savings account (cf015_) are taken from the Cognitive Function (CF) module, while information about the number of children (ch001_) is taken from the Children (CH) module.

Finally, I considered some generated variables created in order to make comparison across waves and countries easier and faster.

I took into account the Body Mass Index (BMI), a measure given by the ratio between the weight (kg) and the height (m^2), as well as the Body Mass Index categories (BMI2), which divides the BMI into four levels: underweight (BMI below 18.5), normal weight (BMI 18.5-24.9), overweight (BMI 25-29.9) and obese (BMI 30 and above). Closely connected to the previous indexes, another measure of interest on health is Physical Inactivity (*phactiv*). Further generated variables which could be related to our study are number of limitations with activities of daily living (*ADL*) and the related variable for the presence or absence of limitations with activities of daily living (*ADL2*), the number of limitations with instrumental activities of daily living (*IADL*) and the respective variable which only considers the presence or absence of these limitations (*IADL2*), the number of chronic diseases (chronic) and the related variable which counts at least two chronic diseases (*chronic2*), specific for Wave 2 and Wave 5, the depression scale EURO-D (*eurod*) and the EURO-D categories (*eurodcat*). Finally, in order to propose again part of the study in Chen (2013), I took into account the maximum grip of strength measure (*maxgrip*), even though the generated variables on current

[15]Specific expressions of the questions on Behavioral Risk Factors are reported in Appendix B.

smoking (*cusmoke*), on walking speed (*wpeed*, *wspeed2*) and on drinking more than two glasses of alcohol almost every day are not available for Wave 2 and Wave 5[16].

Moreover, I considered the 1997International Classification of Education (*ISCED*) in order to look at the level of education of respondents and their parents, for participants to Wave 5. I decided not to take the 2011 classification of education into account for a motivation of harmonization of variables between waves. I selected the nomenclature of territorial units for statistics (NUTS) from the housing generated variable module for the three levels available (*NUTS1*, *NUTS2*, *NUTS3*), in order to locate the SHARE households respondents more precisely in terms of territorial unit.

Finally, I took the imputation module into account which includes five imputations (or implicates) of the missing values on each variable indexed by the variable *implicat*, for each wave. These multiple imputations are constructed using five independent replications of imputation Fully Conditional Specification (FCS) method. This procedure is repeated several times until the iterative algorithm gives a set of stationary distributions and convergence is assessed[17]. Given that SHARE provides five independent imputations, it is possible to choose one single imputation methods selecting one of the five available *implicats* and without a motivation which lead to prefer one particular *implicat* to the others. Therefore, I chose to keep only data for which *implicat* was equal to 1 and to keep only observations for which the interview in the respective wave was conducted (if *mergeid* differs from “no int w.2” and “no int w.5”, respectively), in order to analyze data on two measures of household income, one obtained by aggregating at the household level all individual income components (*thinc*) and the other obtained from the one-shot question on monthly household income (hh017_) (*thinc2*), and household net worth (*hnetw*).

Before moving to generate variables required for the analysis of individuals, I generated a variable “wave_” which refers to the questionnaire version used. This variables takes on value 2 if the interview took place in 2006 or 2007, plus the case of Israel which took place in 2009 and 2010, and it takes on value 5 if the interview took place in 2013. I created “wave_” variable in order to distinguish if data refer to Wave 2 or Wave5.

For each Wave, I generated some discrete and categorized variables for demographic and socio-economic variables, such as age, gender, education, marital and occupational status, trust and life expectancy in ten years. First of all I generated a variable “Age” which represents the age of the respondent at the moment of the interview by subtracting respondent’s birth year from the year in which the interview took place if the year in which the interview took place was greater or equal than respondent’s birth month, and by subtracting a further year in the opposite case.[18] I considered only individuals older than 40 and I built up a categorized variable for individuals’ age, in order to consider people who were born in the same decade.

[16]The generated variable on current smoking (cusmoke) is not available for Wave 5, the generated variables on walking speed (wspeed, speed2) are available only for Wave 1 and Wave 2 and the generated variable which considers the habit of drinking more than two glasses of alcohol almost every day is available for Wave 1 only.

[17]As stated in SHARE Release Guide 5.0.0, convergence is assessed by the Gelman-Rubin criterion (Gelman and Rubin 1992; Gelman et al. 2004) applied to the mean, the median and the 90th percentile of the distributions of the imputed variables.

[18] Age = interview year –birth year if interview month ≥ birth month and Age = (interview year – birth year)- 1 if interview month <birth month, in order to have a greater precision in data regarding age.

Moreover, I generated dummy demographic variables, such as gender which is equal one if the individual is male and 0 if the individual is female.

Afterward, I created a categorized variable for respondent's education on the basis of the 1997 ISCED classification and divided the levels of education into three categories: "Low Education" if the respondent has no degree and their highest level of education is the lower secondary education at most, "Average Education" if the respondent has a degree and include (upper) secondary education and post-secondary non tertiary education, and "High Education" if the respondent has a first stage of tertiary education, including bachelor's degree or master's degree, or a second stage of tertiary education leading to an advanced research qualification, PhD.

In order to have knowledge about the composition of the household, I generated dummy variables to know if respondent's mother or father is living in the household, if any children is living in the household, in case the respondents has children, if the respondent levels with the spouse, and if (s)he helps someone in the household, meaning "someone living in the household whom the respondent has helped regularly during the last twelve months with personal care, such as washing, getting out of bed, or dressing" or if (s)he receives help in the household by "someone living in the household who has helped him/her regularly during the last twelve months with personal care, such as washing, getting out of bed, or dressing".

I generated some dummy variables related to the individual's marital status, considering if the individual is married, separated or single (including never married, divorced or widowed), and to occupational status, considering if the individual is retired, employed or self-employed, unemployed, disabled or homemaker.

I generated a categorized variable for the level of trust in other people and for life expectancy in 10 years, ranging from 0 to 100.

Most importantly, I generated binary variables for behavioral risk factors, namely tobacco use and alcohol consumption, exercise and obesity from questions of the Behavioral Risk module of SHARE Survey.

I considered four questions related to respondent's smoking habit. First of all, I generated a binary variable providing information on whether the respondent has ever smoked in their life, on the basis of the question: "Have you ever smoked cigarettes, cigars, cigarillos or a pipe daily for a period of at least one year?" (*br001_*). If the answer was positive, respondent was asked further questions related to the fact of smoking currently (*br002_*), the number of years (*br003_*) and if (s)he quitted smoking after the previous interview (*br022_*). All the dummy variables are equal 1 in case of positive answer (having smoked, smoking at present time, stopped smoking after the last interview) and equal zero in case of negative answer (having never smoked, not being a smoker currently, not smoking by the last interview or still being a smoker). Only for the number of years of smoking a categorized variable was created considering a decade as a scale.

Analogously, I took into account four variables pertaining to alcohol consumption. Firstly, I generated a dummy variable in order to state if the respondent consumes alcohol though the answer to the simple question: "Have you ever drunk alcoholic beverages?" (*br021_*). Afterward, I analyzed questions related to the quantity and the frequency of alcohol consumption. In the first case, I considered the respondent as characterized by heavy drinking if (s)he drank more than two drinks in the last three months (*br019_*), and as drinking frequently if (s)he drank at least three or four days a week in the last three months (*br010_*). As a last question, the individual was asked to report the frequency of heavy drinking. The question slightly differed between Wave 2 and Wave 5. In the first case the question was expressed as: "In the last three months, on how many days have you had four or more drinks on one occasion?" (*br020_*), while Wave 5 asked: "In the last three months, how often did you have six or more drinks on one occasion?" (*br023_*). I found two main differences in the formulation, the first regarding the number of drinks, which is four in Wave 2 and six in Wave 5, and the second related to the scale of analysis which ranged from 0 to 90 days in Wave 2 and as the frequency in a week or a month in Wave 5. This last formulation of the question provided a multiple choice of seven possible answers to respondents between: 1) Daily or almost daily; 2) Five or six days a week; 3) Three or four days a week; 4) Once or twice a week; 5) Once or twice a month; 6) Less than once a month; 7) Not at all in the last 3 months. In order to make the comparison between the two scales available, I converted the number of days of Wave 2 into the same categories presented in Wave 5 and considered the respondent a frequent consumer of alcoholic beverages frequently if (s)he drank at least three or four days a week in the last three months. Unfortunately, the questions need a separated analysis for Wave 2 and Wave 5 given the difference regarding the reference number of drinks.

Moving to Survey part related to the type and amount of physical activity the respondent does in their daily life, I noted that SHARE distinguishes two types of exercise: vigorous exercise and moderate exercise. Vigorous exercise includes activities such as "sports, heavy housework , or a job that involves physical labor" (*br015_*), while moderate exercise deals with actions which require a moderate "level of energy such as gardening, cleaning the car, or doing a walk" (*br016_*). In both cases, I considered the individual as doing physical activity if (s)he exercise at least one to three times a month and as not doing physical activity if the respondent answered to do it "hardly ever or never".

Finally, I considered variables related to weight, and in particular, the categorized version of Body Mass Index (BMI) variable, which considers the ratio between weight (kg) and height (m^2). I generated a variable for obesity if the BMI was greater or equal than 30 kg/m^2 and a variable for overweight if the BMI was greater or equal than 25 kg/m^2. Furthermore, I generated a variable related to dietary pattern from the question on the frequency of consumption of fruit and vegetables in a regular week and I assigned value one if the respondent consumes them every day and value zero if the respondent consumes them three to six times a week or less. I also considered the consumption of fruit and vegetables at least three to six times a week. This variable is available only for a low number of individuals since the question was asked only in Wave 5 (*br029_*).

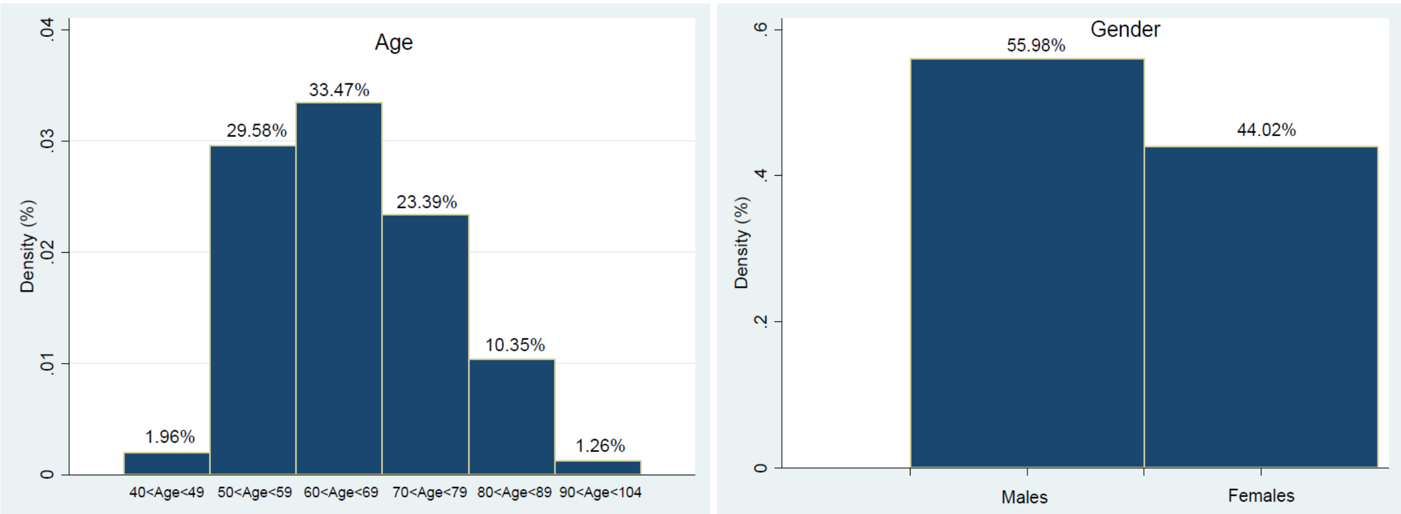
At this point I joined Wave 2 and Wave 5 through the command "append" in Stata 13 and constructed the panel dataset.

3.3 Descriptive statistics

The panel dataset I take into consideration is composed of a total of 98 057 observation, of which 35 218 observations from Wave 2 (release 5.0.0) and 62 839 observations from Wave 5 (release 5.0.0). It includes individuals for which we have demographic and socio-economic information, as well as knowledge about family, cognitive and health conditions, behavioral risk factors, life expectancy, trust in other people. I decide not to consider individuals who were not born in the country, in order to avoid imprecision that could be due to confusion between primary language and other language for immigrants with respect to natives, on the example of Kovacic et al (2016).

My sample is composed of people with an average age of 65 years, the majority of individuals are aged between 60 and 70 (33.47%), between 50 and 60 (29.58%), and between 70 and 80 (23.39%). Only 1919 individuals are younger than 50, which correspond to the respondents' partners given that SHARE interviews individuals aged 50 or older, and only 30 individuals are aged 100 or older. There is a prevalence of female respondents who represent 55.98% of the sample while the remaining 44.02% are males (Fig. 5).

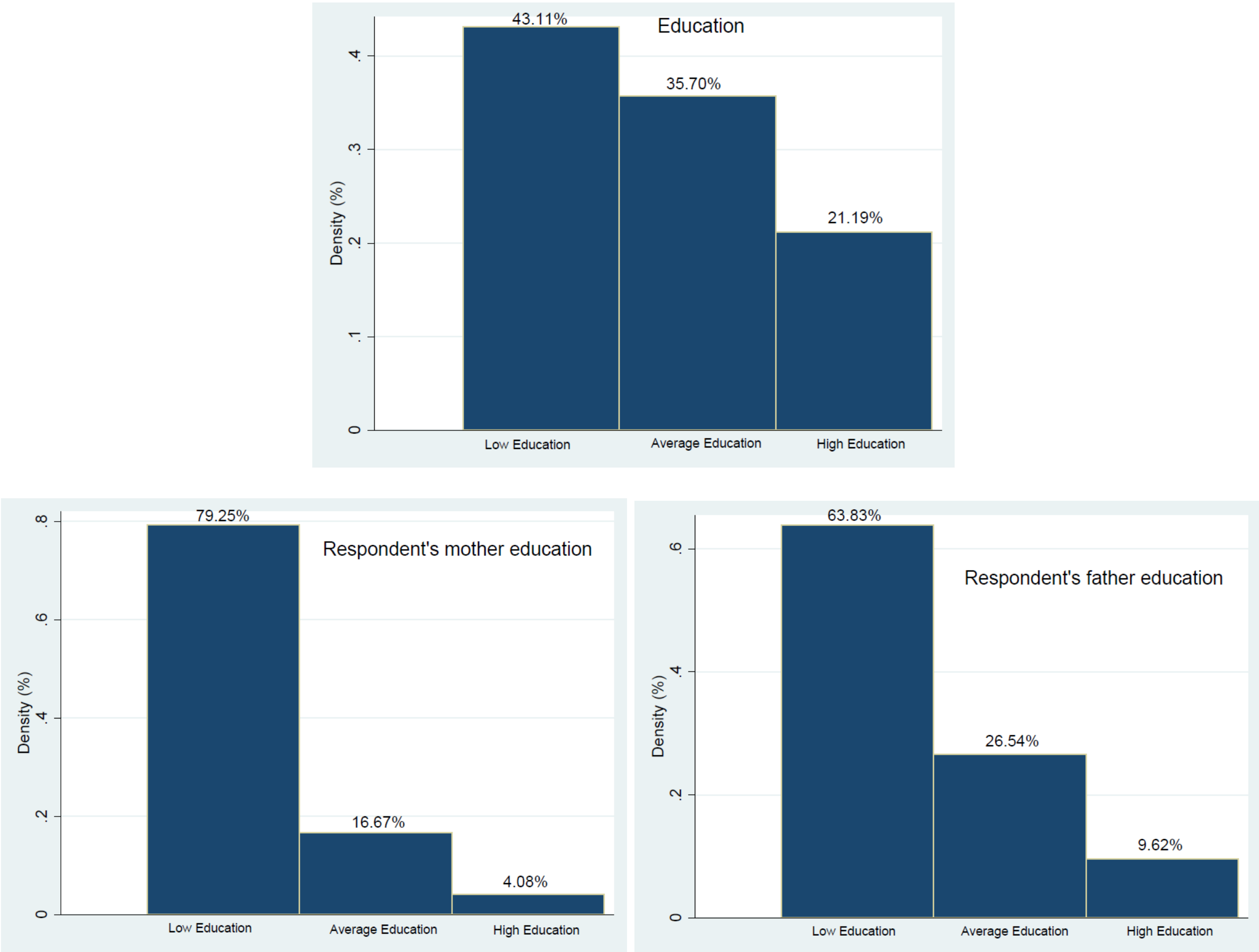
Fig. 5 – Percentage of individuals by age and gender



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

As regards education, the majority of individuals are characterized by a low or average education. In fact, 43.11% of the interviewees are classified as low educated, meaning that they have no degree and their highest level of instruction is the lower secondary education or even lower, 35.70% of the individuals are characterized by an average education, namely a secondary education degree or post-secondary non tertiary education degree, and only 21.19 % of the sample is well-educated and owns a bachelor's degree or master's degree or even a PhD. Information about parents' level of education is available only for Wave 5, but shows that respondents' parents level of education is even lower with 79.25% of respondents' mothers and 63.83% of respondents' fathers belonging to the low education category, 16.67% of mothers' respondents and 26.54% of fathers' respondent belonging to the average education category and only 4.08% of mothers' respondents and 9.62% of fathers' respondents showing a high level degree of education (Fig. 6).

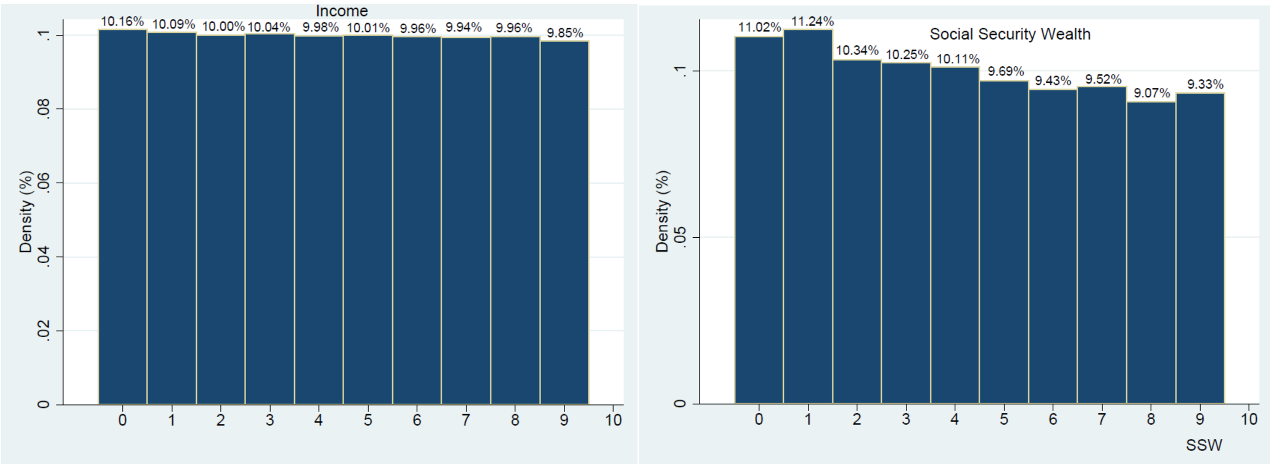
Fig. 6 – Percentage of individuals by respondent's level of education, mother's level of education and father's level of education



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Moving to socio-economical variables, the mean total income of individuals divided in deciles (in a range between 0 and 9) is 4.48 and individuals seem to be well distributed across the levels of wealth. On the other hand, the mean Social Security Wealth (SSW) in the same range 4.31 and individuals seem well-distributed also in this case, even though more concentrated in the first deciles than in the last ones (Fig. 7).

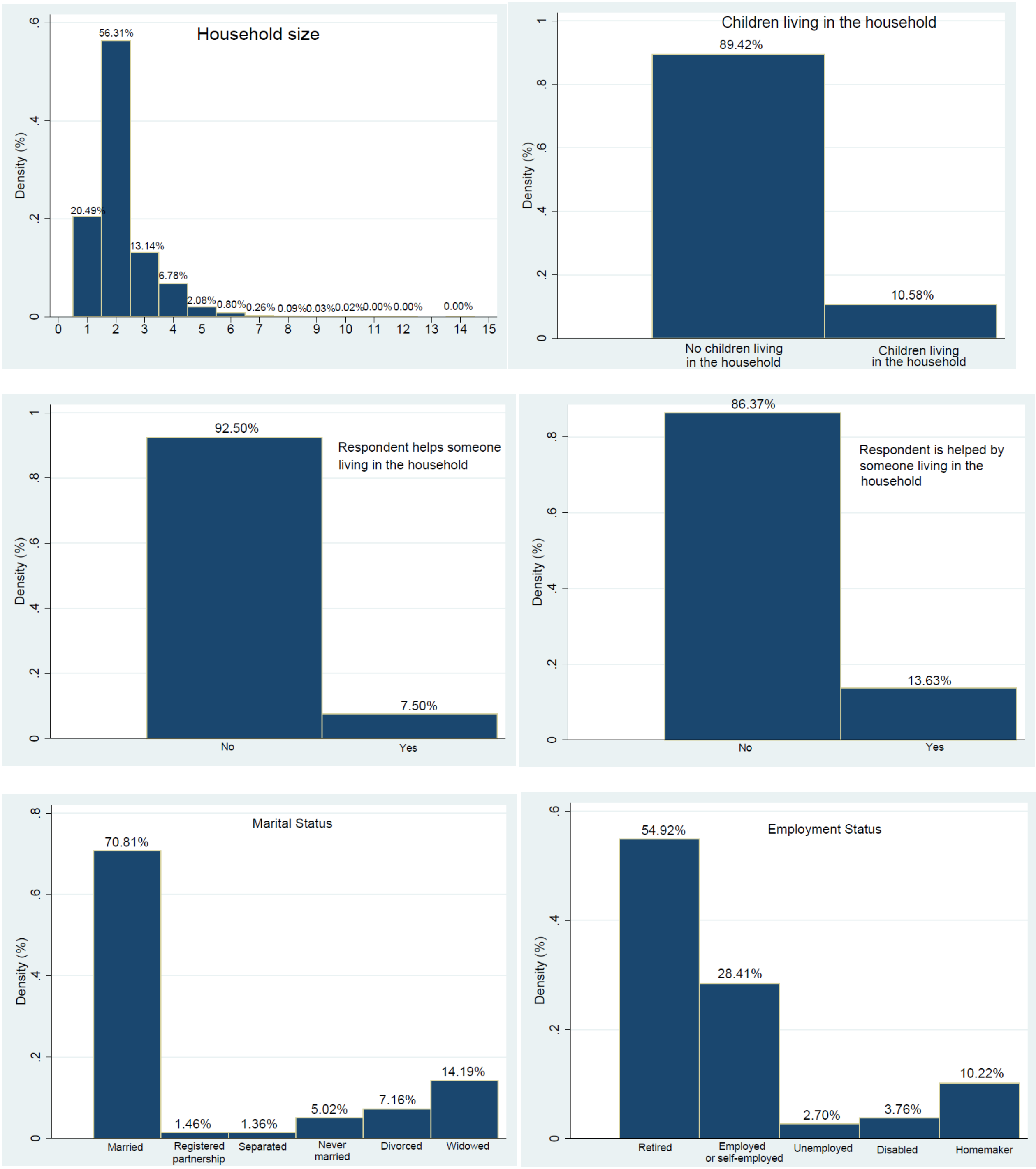
Fig. 7 – Percentage of individuals by Income and Social Security Wealth (SSW)



Source: These figures use data from SHARE release 5.0.0 (Wave 4, for individuals present also in Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Moreover, about 73% of interviewees declare to own the house where they live, without paying any rent. The household is composed, on average, of two individuals, and the sample is mainly characterized by households of up to five individuals, ranging from a minimum of one individual (the respondent) to fourteen individuals. About 14% of those who answered questions related to help in the household, who are about 36% of the total sample, affirmed to have received some help with personal care regularly in the last year by someone living in the household, on the other hand, only 8% of those who answered questions related to help in the household, who are about 30% of the total sample, claimed to have helped someone in the household in the last year. About 11% of those who answered questions related to where respondents' children live, who are about 22% of the total sample, declared to have one or more children living in the household. Information on marital status provides knowledge about household composition given that 70% of the total sample claimed to be married and to live together with the partner, therefore the spouse is a component of the household. Moreover, 1% of the total sample affirmed to be married but living separated from the partner and the remaining 26% includes those who never get married, widowed or divorced. Concerning occupational status, we own information for about 98% of the sample, 54% of which are retired, 28% are employed or self-employed, 3% are unemployed, 4% are disabled or permanently sick, and 10% are homemaker (Fig. 8).

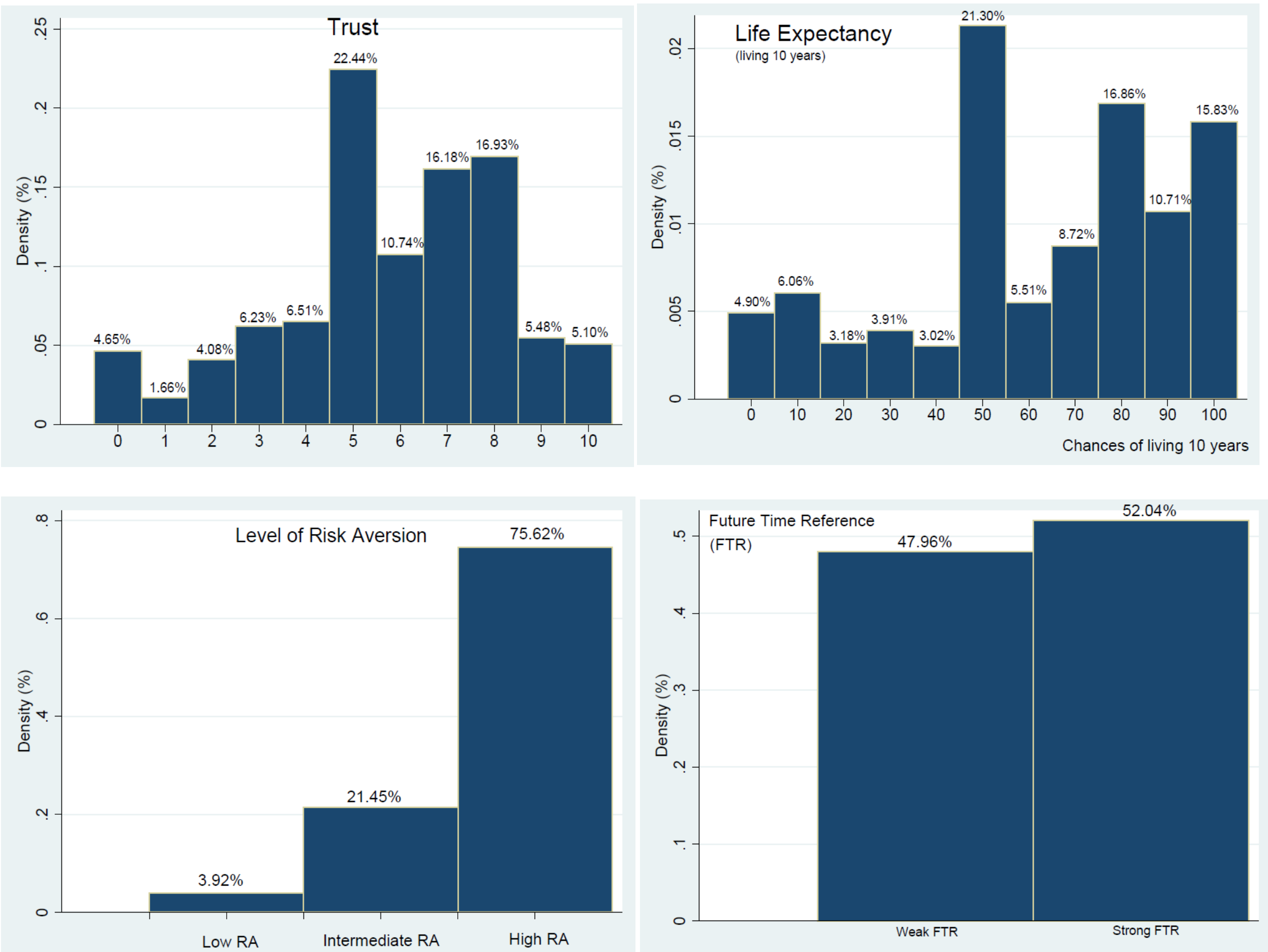
Fig. 8 – Percentage of individuals by household size, children living in the household, respondents helping or being helped by someone living in the household, marital status and employment status.



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

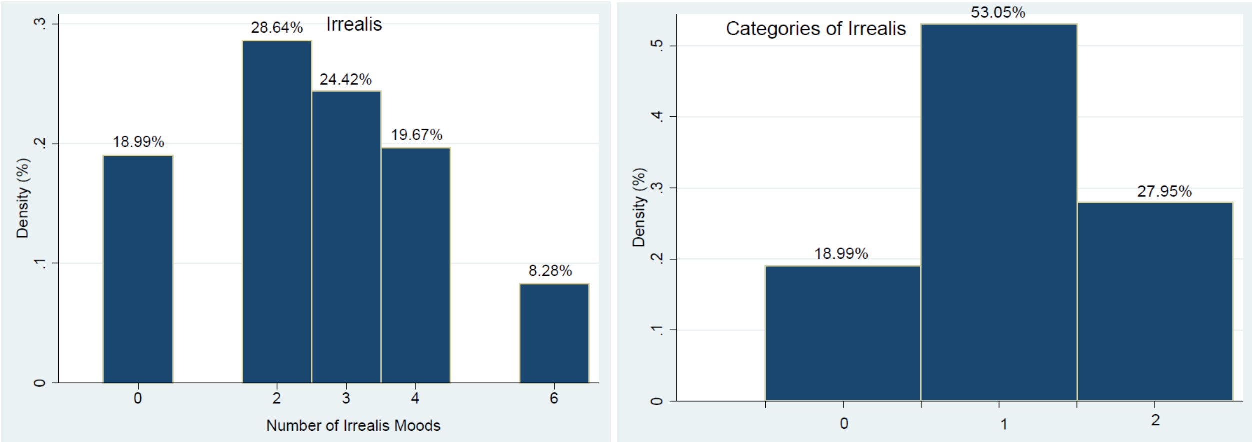
As regards information about people's expectation, the level of uncertainty they feel about the future and linguistic marker, the level of trust in other people is 5.80 in a range between 0 and 10. Moreover, 70% of the total sample provides information about life expectancy and their self-assessed probability of living ten years from the moment of the interview is 63%, on average. These variables suggest that individuals in the sample I consider do not trust other people but neither are totally suspicious, they tend to maintain an average position on both trust and life expectancy. Unfortunately, information about risk aversion is available only for Wave 5, since no question about it was present in Wave 2, and we own data only for 60% of the total sample. The subsample is characterized by a high level of risk aversion, in fact the mean risk aversion is 3.70 in a scale ranging from 1 to 4 and about 75% of the individuals are highly risk averse. Individuals seem to be well distributed between speakers of languages characterized by strong Future Time Reference (53%) and languages characterized by weak Future Time Reference (47%), even though a slight prevalence of speakers of languages with strong FTR (Chen 2013) (Fig. 9). On the other hand, concerning the "Irrealis" linguistic marker (Kovacic et al. 2016), 18.99% of the sample is characterized by the absence of any non-indicative mood, 28.64% presents two non-indicative moods, 24.42% shows three non-indicative moods, 19.67% presents four non-indicative moods and 8.28% are characterized by six non-indicative moods. Moreover, the categorized version of the "Irrealis" linguistic marker sees 18.99% of individuals speaking languages with no indicative moods, 53.05% speaking languages with two or three non-indicative moods and 27.95% speaking languages with four or six non-indicative moods (Fig. 10).

Fig. 9 – Percentage of individuals by trust, life expectancy of living in 10 years, risk aversion and Future Time Reference.



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); Risk aversion available only for Wave 5. Computations by the author.

Fig. 10 – Percentage of individuals by discrete version of "Irrealis" and categorized version of "Irrealis".



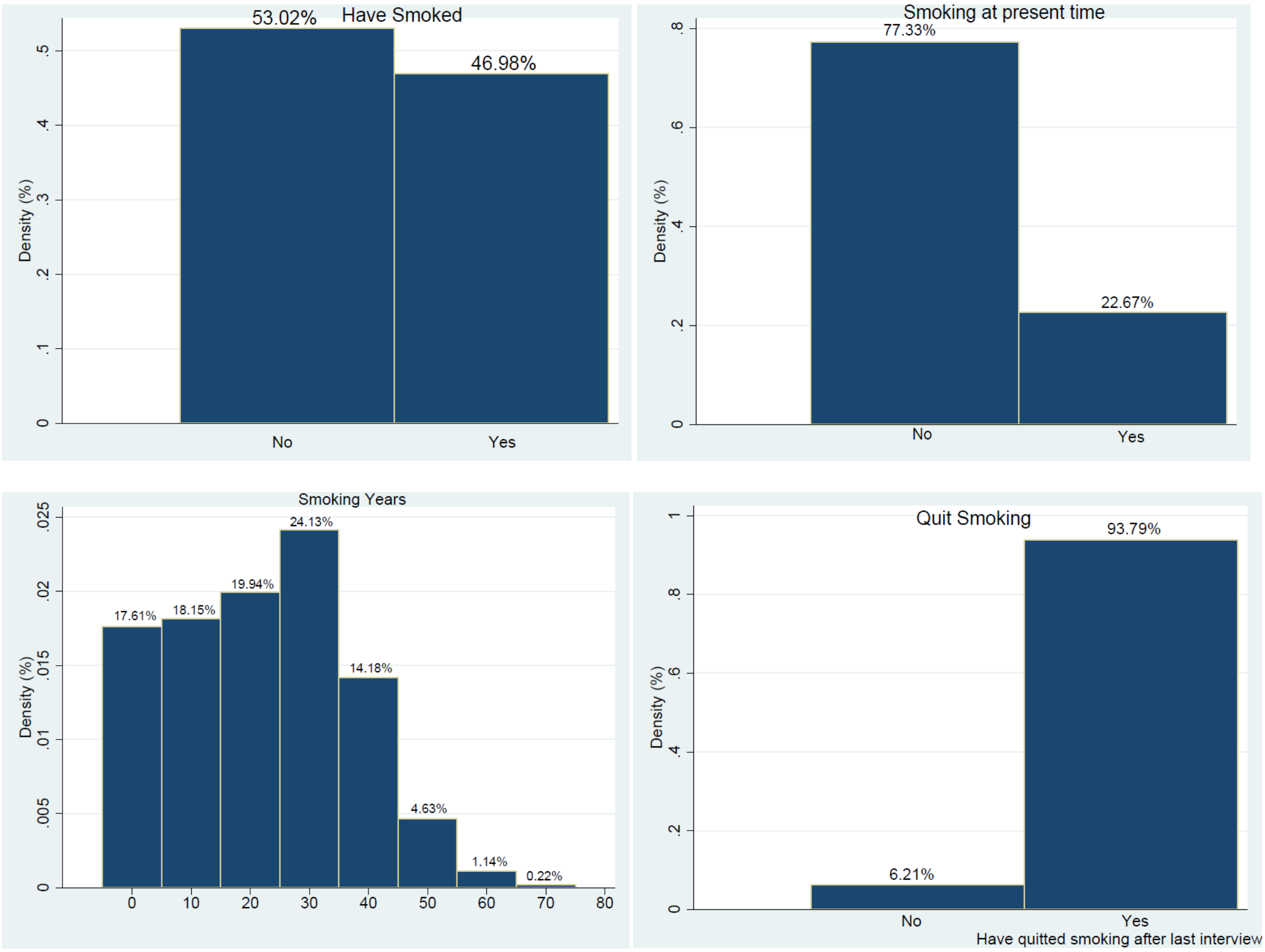
Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

At this point I analyzed the distribution of Behavioral Risk Factors of individuals in the sample I considered.

As regards smoking habit, even though the low number of respondents (36%) to the question about having ever smoked in one's life, the characteristic of having smoked cigarettes, cigars, cigarillos or a pipe daily for at least one year seems to be well distributed in the sample. In fact, 53.02% of those who answer to the question declare to have smoked and 46.98% declared to have never smoked in their life. The number of current smokers is low, given that 77.33% of those who answered to the question about smoking at the time of the interview (about 80%) affirmed not to smoke currently and only 22.67% state the opposite. These percentages are consistent with the high number of people who claimed to have quitted smoking since after the last interview (93.79%), despite this information is based on less than 2% of the respondents. Focusing on the number of smoking years, those who smoke tend to smoke for long periods of time, 22 years on average, and among those who declared to have smoked, the majority affirmed to have smoked for 30 years. (Fig. 11)

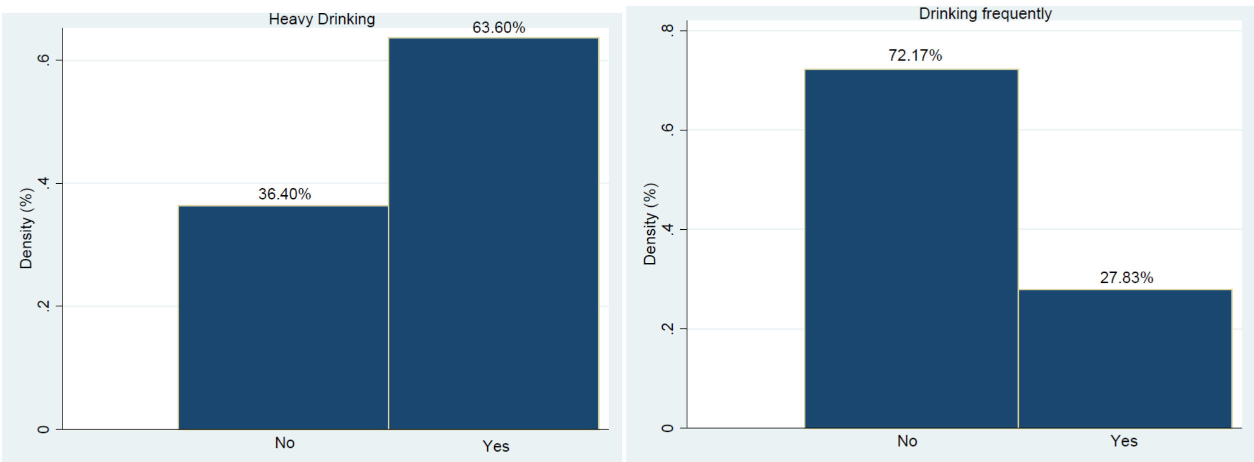
Moving to alcohol consumption variables, the information about having ever consumed alcoholic beverages is available only for 18% of the individuals in the sample, but individuals are well-distributed between those who have drunk alcohol and those who have not. As regards the probability of heavy drinking, there is a higher number of individuals who declared to have drunk more than two drinks in a day in the three months leading up to the interview (63.60%) with respect to those who did not drink heavily in the period before the interview (36.40%). On the other hand, the majority of people claimed not to have drunk more than once or twice a week (72.17%). Moreover, only 3.88% and 2.22% affirmed to have drunk, respectively, six (or more) drinks or four (or more) drinks in the three months before the interview.

Fig. 11 – Percentage of individuals for smoking habit



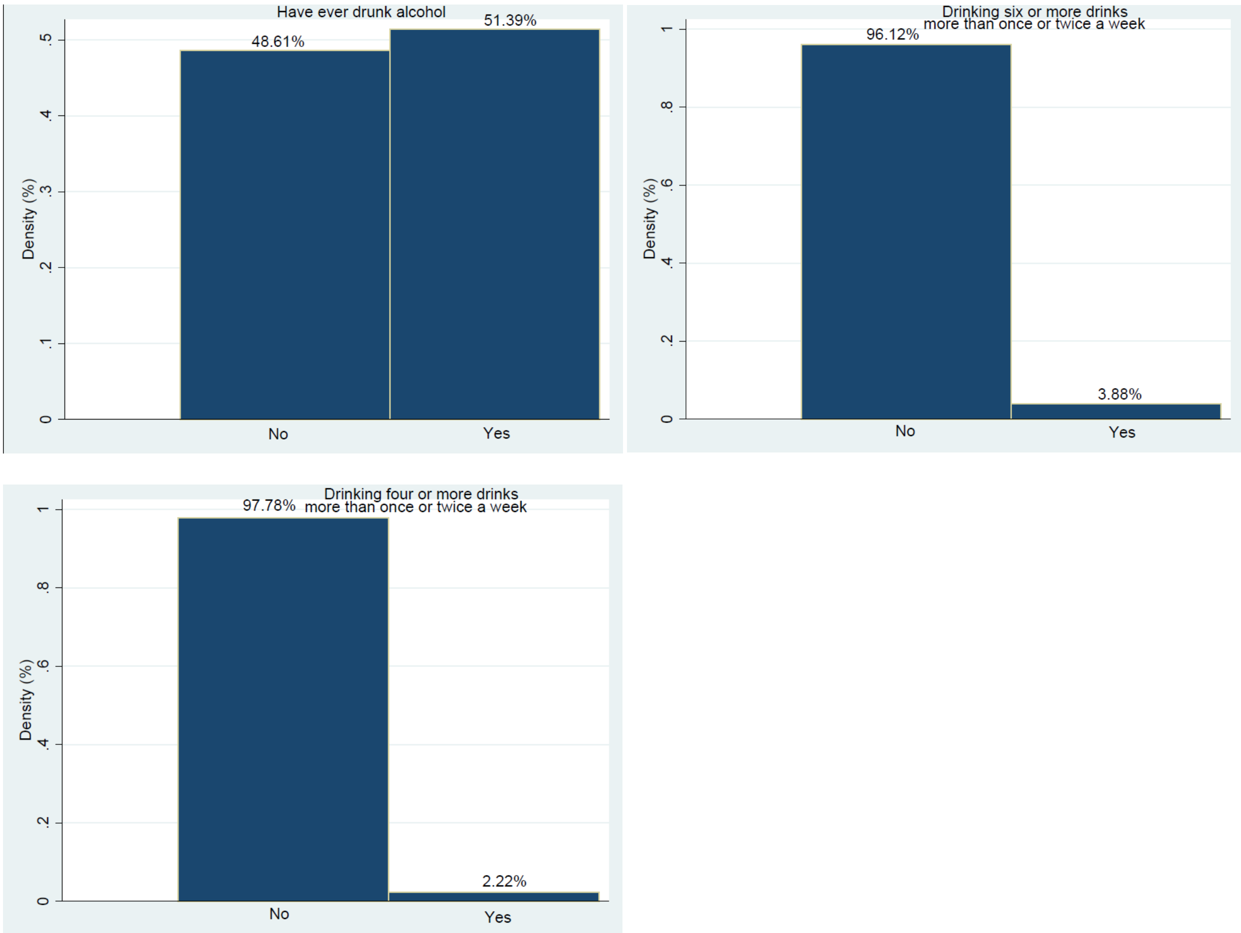
Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Fig. 12 – Percentage of individuals for drinking habit



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Fig. 12 – Percentage of individuals for drinking habit (continue)



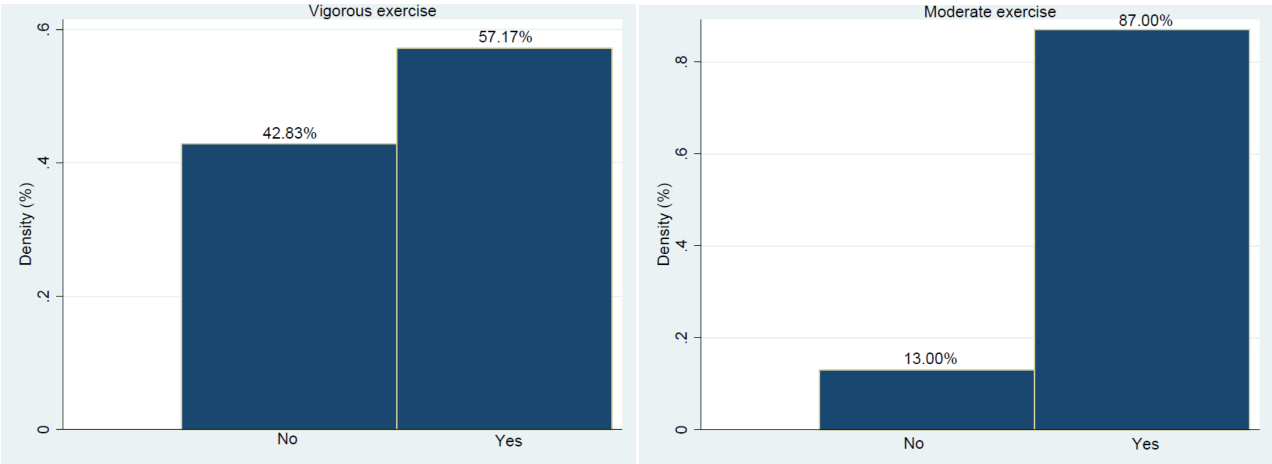
Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Concerning physical activity, according to *phactive* variable almost all individuals in the sample do physical activity regularly. Looking at the distinction between vigorous exercise and moderate exercise, 57.17% of the sample claimed to be involved in vigorous activities, such as sports, heavy housework or a job that needs physical labor, while 87% of the sample self-declared to be involved in activities which require a moderate level of energy, such as gardening, cleaning the car or doing a walk (Fig. 13).

Finally, focusing on individuals' weight and dietary habits, data show that 20.15% of the sample is obese, 41.43% is overweight, 37.07% has a normal weight and 1.35% in underweight and that the majority of individuals maintain a healthy dietary pattern, at least related to the consumption of fruit and vegetables, given that 78.57% claimed to consume fruit and vegetables every day and 98.96% affirmed to consume them at least three to six times a week (Fig. 14).

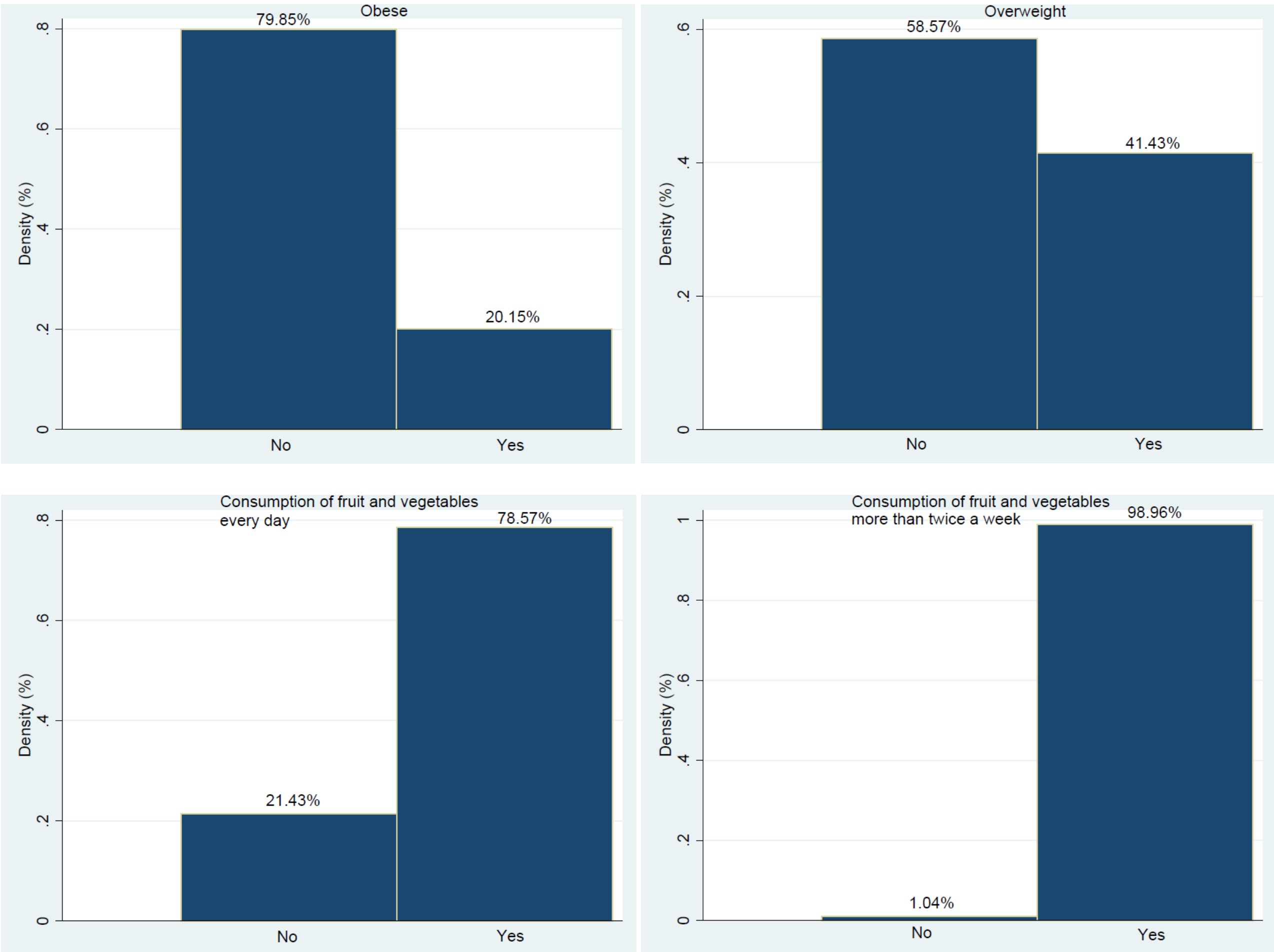
Table 2 reports descriptive statistics for all variables, including mean, standard deviation, minimum, maximum, and the number of observations.

Fig. 13 – Percentage of individuals for exercise



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Fig. 14 – Percentage of individuals for obesity and overweight and dietary pattern



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

Table 2. – Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	N. observations
Have Smoked	0.470	0.499	0	1	34890
Current Smoker	0.227	0.419	0	1	79055
Smoking Years	21.867	15.211	0	70	16211
Quit Smoking	0.938	0.241	0	1	1433
Heavy Drinking	0.636	0.481	0	1	76942
Frequency Drinking	0.278	0.448	0	1	97512
Ever Drunk Alcohol	0.514	0.500	0	1	17650
Frequency Heavy Drinking 4	0.022	0.147	0	1	22887
Frequency Heavy Drinking 6	0.039	0.193	0	1	42443
Vigorous Exercise	0.572	0.495	0	1	97512
Moderate Exercise	0.870	0.336	0	1	97520
phactive	0.999	0.025	0	1	98057
Obese	0.202	0.401	0	1	95084
Overweight	0.414	0.493	0	1	95084
Normal weight	0.371	0.483	0	1	95084
Underweight	0.013	0.115	0	1	95084
Fruit and Vegetables every day	0.786	0.410	0	1	62839
Fruit and vegetables 3-4 times a week	0.990	0.101	0	1	62642
Strong FTR	0.520	0.500	0	1	98057
IRR0	0.190	0.392	0	1	93382
IRR2	0.286	0.452	0	1	93382
IRR3	0.244	0.430	0	1	93382
IRR4	0.197	0.398	0	1	93382
IRR6	0.083	0.276	0	1	93382
CatIRR0	0.190	0.392	0	1	93382
CatIRR1	0.530	0.500	0	1	93382
CatIRR2	0.280	0.449	0	1	93382
Risk Aversion	3.697	0.574	1	4	60409
HighRA	0.746	0.435	0	1	60409
Income	4.479	2.873	0	9	98057
SSW	4.313	2.882	0	9	56556
Owner	0.728	0.444	0	1	65174
EduCat	0.781	0.771	0	2	96294
EduCatMother	0.248	0.518	0	2	61488
EduCatFather	0.458	0.664	0	2	60112
hhsize	2.179	1.010	1	14	98057
AgeCat	61.437	10.557	40	90	98048
Sex	0.440	0.496	0	1	98057
Retired	0.543	0.498	0	1	96750
Employed	0.281	0.449	0	1	96750
Unemployed	0.027	0.161	0	1	96750
Disabled	0.037	0.189	0	1	96750
Homemaker	0.101	0.301	0	1	96750
helpinhh	0.075	0.263	0	1	28200
helpedinhh	0.136	0.343	0	1	35273
childreninhh	0.106	0.308	0	1	21201
Married	0.808	0.394	0	1	57877
Separated	0.570	0.495	0	1	35218
Single	0.675	0.469	0	1	35218
LifeExpectancy10	62.632	29.435	0	100	86836

Source: Data are from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

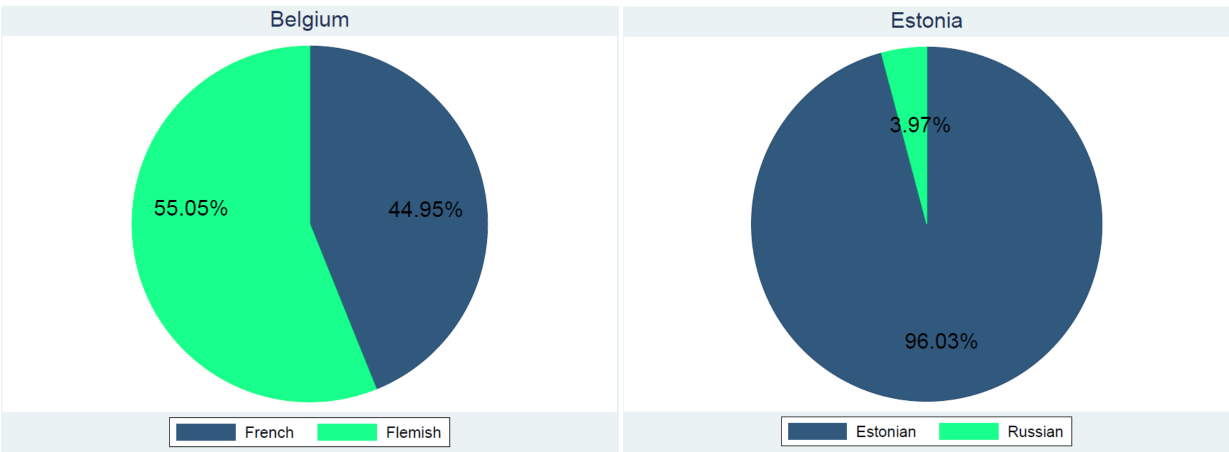
3.4 Linguistically Heterogeneous Countries

In addition to the entire set of countries, I also run separate regressions for linguistically heterogeneous countries, which are countries where individuals speak two or more different languages. There are six linguistically heterogeneous countries in SHARE, including Belgium, Estonia, Israel, Luxembourg, Spain and Switzerland, which speak 10 different languages.

The sample of observations of Belgium is characterized by a majority of Flemish speakers (55.05%), characterized by a weak Future Time Reference, and a minority of French speakers (44.95%), characterized by a strong FTR[19]. The sample for Estonia presents a large majority of Estonian speakers (96.03%), characterized by a language with weak FTR and three non-indicative moods, while the remaining 3.97% of individuals speaks Russian, with a strong FTR and four non-indicative moods. Israel is characterized by 77.70% of individuals speaking Hebrew, marked by strong FTR and no indicative moods, 11.55% speaking Arabic, marked by strong FTR and four non-indicative moods, and 10.75% speaking Russian, marked by strong FTR and four non-indicative moods. The sample of observations of Luxembourg has a large prevalence of German speakers, with a weak FTR and two “Irrealis” markers (60.36%), and a minority of French speakers, with a strong FTR and three “Irrealis” markers (39.64%). As regards Spanish “ES5 Este” region, comprehending Catalonia, Valencian Community and Balearic Islands, 67.96% of individuals speaks Catalan, characterized by a strong FTR and three non-indicative moods, and 32.04% of individuals speaks Spanish. Finally, the sample of individuals living in Switzerland includes 73.05% of German speakers, with a weak FTR and two non-indicative moods, 23.35% of French speakers, with a strong FTR and three non-indicative moods, and 3.60% of Italian speakers, with a strong FTR and six non-indicative moods.

The aim of considering these subsamples of the total sample is to analyze the effect of language on identical individuals living in countries with the same institutions who only differ for the language they speak, through Future Time Reference and “Irrealis” linguistic markers.

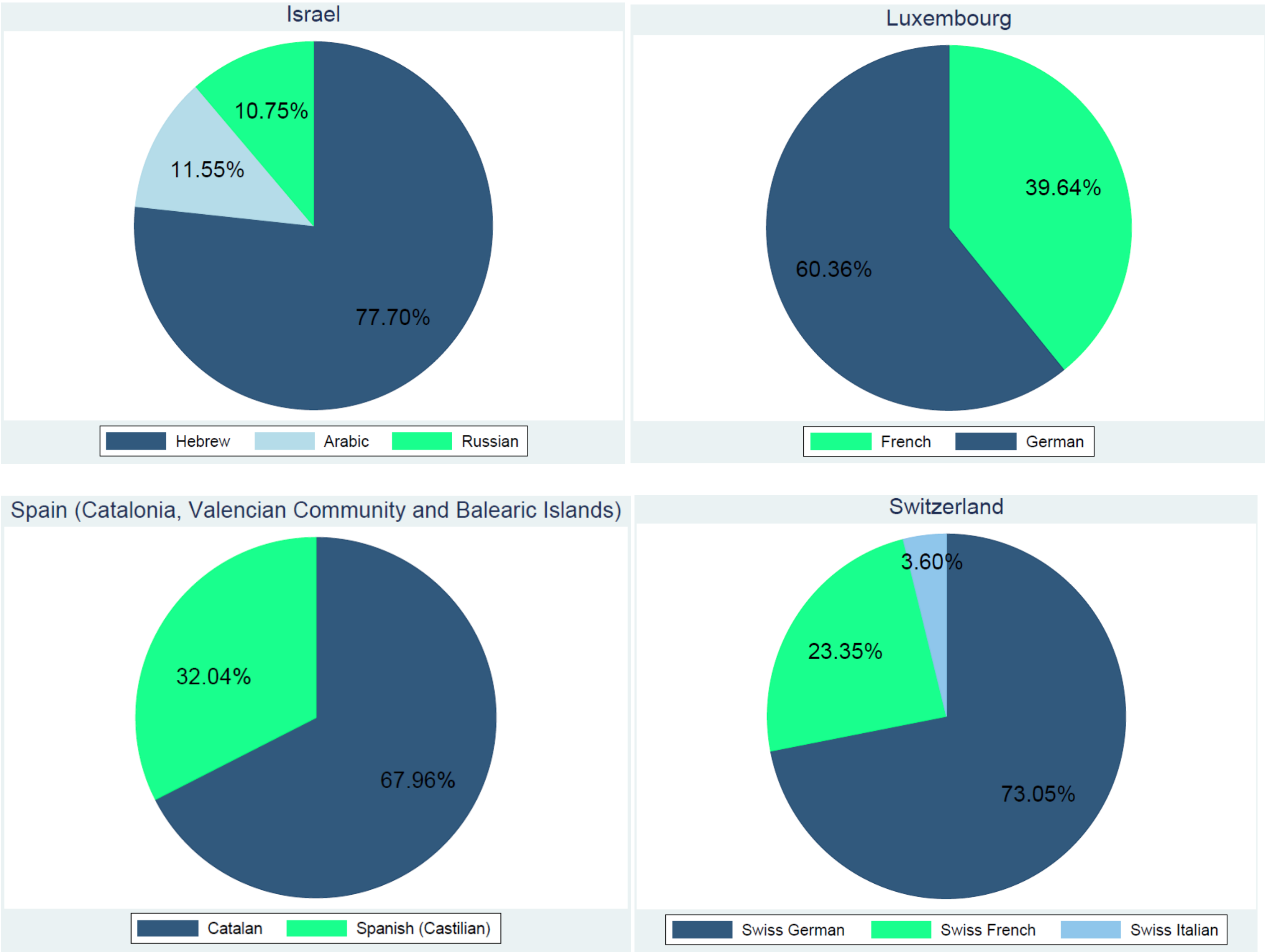
Fig. 15 – Distribution of individuals in Linguistically Heterogeneous Countries by language



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

[19]The “Irrealis” linguistic marker is not available for Flemish.

Fig. 15 – Distribution of individuals in Linguistically Heterogeneous Countries by language (continue)



Source: These figures use data from SHARE release 5.0.0 (Wave 2, 2006/07 (2009/2010, and Wave 5, 2013)); computations by the author.

4. Empirical strategy

The empirical strategy of this thesis aims at providing evidence of the causal relationship of language and Behavioral Risk Factors and includes two linguistic markers in the analysis, Strong FTR (Chen (2013)) and "Irrealis (IRR)" (Kovacic et al. (2016)).

My first set of regressions examines the relationship between Behavioral Risk Factors and "Strong FTR" through Logistic regressions. I considered three dependent variables (d) related to smoking habit, namely "Current Smoker (d)", "Have Smoked" and "Quit Smoking", five dependent variables related to alcohol consumption, namely "Heavy Drinking (d)", "Frequency Drinking", "Ever Drunk Alcohol", "Frequency Heavy Drinking 4" (Wave 2) and "Frequency Heavy Drinking 6" (Wave 5). As regards physical activity, I took into consideration "Vigorous Exercise (d)", "Moderate Exercise (d)" and "phactive" as dependent variables. Finally, concerning weight and dietary pattern, the dependent variables are "Obese (d)", "Overweight (d)", "Fruit and vegetables every day" and "Fruit and Vegetables at least 3 times". The empirical problems consist of estimating the following equation for:

1) Smoking habit

$$\Pr(CurrentSmoker)_{it} = \frac{\exp(s_{it})}{1+\exp(s_{it})} \quad [7]$$

where $s_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \varepsilon_{it}$

2) Alcohol consumption

$$\Pr(HeavyDrinking)_{it} = \frac{\exp(d_{it})}{1+\exp(d_{it})} \quad [8]$$

where $d_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \eta_{it}$

3) Physical Activity

$$\Pr(exercise)_{it} = \frac{\exp(e_{it})}{1+\exp(e_{it})} \quad [9]$$

where $e_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \varphi_{it}$

4) Overweight or Obesity

$$\Pr(Overweight/Obesity)_{it} = \frac{\exp(\mathrm{w}_{it})}{1+\exp(\mathrm{w}_{it})} \quad [10]$$

where $w_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \vartheta_{it}$

In all regression the explanatory variable is "Strong FTR" linguistic marker, which is a binary variable equal 1 if the language spoken by the individual has a strong Future Time Reference and equal 0 if the language has a weak Future Time Reference. X_{it} the vector of demographic and socio-economic characteristics of individual i, such as gender, age, occupational and marital status, household size, education, parents' education, household's income level, the number of children and life expectancy.

In addition, I estimate the model with a set of fixed-effects for individual demographic and socio-economic characteristics. In this way, it is possible to compare individuals who are identical in all features apart from language. These regression are estimated using conditional logistic (fixed-effect) model:

1) Smoking habit

$$\Pr(CurrentSmoker)_{it} = \frac{\exp(s_{it})}{1+\exp(s_{it})} \quad [11]$$

Where $s_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \beta_3 \mathrm{FE_{it}} + \varepsilon_{it}$

2) Alcohol consumption

$$\Pr(HeavyDrinking)_{it} = \frac{\exp(d_{it})}{1+\exp(d_{it})} \quad [12]$$

Where $d_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \beta_3 \mathrm{FE_{it}} + \eta_{it}$

3) Physical Activity

$$\Pr(exercise)_{it} = \frac{\exp(e_{it})}{1+\exp(e_{it})} \quad [13]$$

Where $e_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \beta_3 \mathrm{FE_{it}} + \varphi_{it}$

4) Obesity

$$\Pr(Obese)_{it} = \frac{\exp(\mathrm{w}_{it})}{1+\exp(\mathrm{w}_{it})} \quad [14]$$

Where $w_{it} = \beta_0 + \beta_1 StrongFTR + \beta_2 X_{it} + \beta_3 \mathrm{FE_{it}} + \vartheta_{it}$

As in the previous model, X_{it} is the vector of demographic and socio-economic characteristics of individual i, and $\mathrm{FE_{it}}$ is the set of individual specific fixed-effects, such as gender, age, country, wave, income, education, marital status, and number of children.

Moreover, I considered Linguistically Heterogeneous Countries and their territorial units in order to confirm my hypothesis of the importance of linguistic markers in affecting Behavioral Risk Factors not only between countries, but also within countries, excluding any influence attributable to institutions.

Furthermore, on the basis of Kovacic et al. (2016), I test the hypothesis that linguistic differences might not only "influence the individual perception of risk and uncertainty, and indirectly their investment decisions", but also individuals' attitude towards behavioral risks. Kovacic et al. (2016) demonstrated that the number of "irrealis" moods represents a strong instrument for risk aversion and that there is a strong and significant negative relationship between high risk aversion and the probability of holding risky assets. The aim of this study is to test the hypothesis that the number of non-indicative moods is a strong and significant instrument, through an IV approach, in order to explain the relationship between high risk aversion and the probability of being involved in risky behaviors related to health, widely presented in the literature (Dave and Saffer (2008), Pfeifer (2012), Komlos et al. (2004)).

In the first stage, I estimate the effect of the number of non-indicative moods in *irrealis* contexts (IRR) in the individual i's language:

$$Risk\ Aversion_i = \alpha + \gamma_{i1} IRR_i + \gamma_{i2} X_i + \gamma_{i2} CW_i + \nu_i \qquad [15]$$

where , X_i is the vector of demographic and socio-economic characteristics of individual i, such as gender, age, income, education, marital status, and number of children, and $\mathrm{CW_i}$ indicates the country-wave fixed effects.

Fitted values from the first stage are plugged in the second stage equation, leading to the following reduced models for each Behavioral Risk Factor:

1) Smoking habit

$$CurrentSmoker_i = \alpha + \beta_1 \widehat{\mathrm{RA}}_\mathrm{i} + \beta_2 X_i + \beta_3 Z_i + error_i \qquad [16]$$

2) Alcohol consumption

$$Heavy\ Drinking_i = \alpha + \beta_1 \widehat{\mathrm{RA}}_\mathrm{i} + \beta_2 X_i + \beta_3 Z_i + error_i \qquad [17]$$

3) Physical Activity

$$Exercise_i = \alpha + \beta_1 \widehat{\mathrm{RA}}_\mathrm{i} + \beta_2 X_i + \beta_3 Z_i + error_i \qquad [18]$$

4) Obesity

$$Obesity_i = \alpha + \beta_1 \widehat{\mathrm{RA}}_\mathrm{i} + \beta_2 X_i + \beta_3 Z_i + error_i \qquad [19]$$

The theory suggests a negative coefficient of high risk aversion for *current smoker* (Pfeifer (2012)), *heavy drinking* (Dave and Saffer (2008)) and *obesity* (Komlos et al. (2004), Anderson and Mellor (2008)), and a positive coefficient of high risk aversion for exercise (Komlos et al. (2004), Dohmen et al. (2005)).

5. Results

5.1 Empirical results from Logistic regressions

5.1.1 Logistic regressions with Strong FTR linguistic marker

On the basis of Chen (2013)'s analysis on Behavioral Risk Factors, I estimate logistic regressions for each dependent variable on Strong FTR linguistic marker. I report only regressions which result statistically significant, namely those with the following dependent variables: "Current Smoker", "Heavy Drinking", "Vigorous Exercise", "Moderate Exercise" and "Overweight".

Empirical results of equation [7], related to smoking habit, are presented in Table 3. The Odds Ratio of 1.064 in regression 1 can be interpreted as strong-FTR individuals being 6% more likely to smoke currently than weak-FTR individuals. The positive effect of Strong FTR on the probability of being a smoker at present time remains significant even when adding controls (X_{it}) to the equation, apart from regression three where the effect of the linguistic marker seems to take the opposite direction. Controlling for age and gender reveals that young people are more prone to smoke with respect to old ones (Blaylock and Blisard (1992)) and that males are more inclined towards smoking habit with respect to females. The effect of education confirms past literature which affirms that increasing the level of education reduces the probability of being involved in risky behaviors such as smoking (Kemna (1987), Kenkel (1991), Di Novi (2013), Blaylock (1992)). In particular, data show that people who have a bachelor's or master's degree or a PhD are 26% less likely to smoke currently, on average. On the other hand, data on mother's level of education are not statistically significant, while father's high level of education seem to increase the probability of being a smoker by 9%, contrary to past literature (Lynch et al. (1997)). Moreover, my data support Contoyannis (2004)'s finding that people belonging to the highest socio-economic class are significantly more likely to avoid smoking habit than those in the baseline category. In fact being more wealthy and owning a house reduces the probability of smoking by, respectively, 4% and 43%. Analogously, being married leads to a 26% lower probability of tobacco use and increasing the number of children decreases the likelihood of smoking habit by 5%. Contrary to Blaylock and Blisard (1992)'s finding, the household size increases the probability of smoking, even though the coefficient is not significant. Finally, controls concerning occupational status show that being retired, unemployed, disabled or homemaker rises the likelihood of being a smoker, however only unemployment and disability seem to affect the probability strongly and significantly with an increase of the probability, respectively, of 70% and 53%.

Regarding the equation on alcohol consumption, equation [8], empirical results are showed in Table 4. Regression 1 presents evidence that a strongly grammaticalized FTR leads to a 64% higher probability of having drunk more than two drinks in a day in the three months leading up to the interview. The effect of Strong FTR on involvement in heavy drinking continues to be strong and significant even with the addition of controls (X_{it}) in the equation. Age seems not to influence the probability of heavy drinking, while being a female leads to a 6% lower probability of alcohol consumption with respect to being a male. Controlling for education shows that individuals who have a bachelor's or master's degree or a PhD are 26% less likely to be involved in alcohol abuse with respect to those who have no degree or a lower secondary education degree, on average

(Kemna (1987), Di Novi (2013)). Also father's high level of education decreases the probability of alcohol consumption by 18%, while mother's high level of education leads to the opposite effect and rises the probability by 25%, contradicting past literature prediction and remaining almost constant in the following regressions (Lynch et al. (1997)). As for smoking habit, data reveals that high socio-economic classes are significantly more likely not to be involved in alcohol abuse than baseline classes, since being more wealthy and owning a house reduces the probability of drinking by, respectively, 10% and 5%, even though the effect of owning a house is less significant in the case of alcohol consumption than in the case of tobacco use. Furthermore, married individuals are 15% less likely to be involved in episodes of heavy drinking. On the other hand, increasing the number of children and the family size have a negative effect on drinking behavior, even though not strong and significant, given that individuals with a high number of children and living in a big family are, respectively, 2% and 1% more likely to drink excessively. Finally, not being employed for causes other than retirement leads to a greater probability of alcohol consumption. In fact, the coefficient related to retirement is lower than one and significant, while the coefficients related to disability and homemaking are greater than one and significant, meaning that being retired leads to a 16% lower probability of being involved in drinking behavior, and that being disabled and homemaker leads, respectively, to a 63% and 16% higher probability of heavy drinking episodes.

Moving to results from the equation related to physical activity, equation [9], I prefer to consider variables related to exercise with respect to *phactive*, given that according to the latter almost all individuals in the sample do physical activity regularly. As mentioned in paragraph 3.3, exercise is divided into vigorous exercise and moderate exercise. *Vigorous exercise* refers to activities which require a high level of energy, such as sports, heavy housework or a job that needs physical labor, while *moderate exercise* refers to activities which require a moderate level of energy, such as gardening, cleaning the car or doing a walk. Empirical results for both types of exercise are presented, respectively, in Table 5 and Table 6. Regression 1 of Table 5 shows that individuals who speak languages with a strong FTR are 40% less likely to practice vigorous exercise than their counterparts who speak languages with a weak FTR. This effect remains nearly constant and strongly significant even when adding controls (X_{it}) to the equation. Young individuals and females are more likely to be involved in sports or other activities which require a high level of energy, on average, with respect to aged people and males by 6% and 32%, respectively.

Table 3. Logistic regressions of smoking habit on Strong FTR. All countries.

Current Smoker	CS1	CS 2	CS 3	CS 4	CS 5
Strong FTR	1.064	1.070	0.901	1.175	1.179
	(0.018)***	(0.019)***	(0.025)***	(0.068)***	(0.069)***
Age		0.938	0.933	0.929	0.930
		(0.009)***	(0.001)***	(0.003)***	(0.004)***
Female		0.681	0.671	0.932	0.946
		(0.012)***	(0.019)***	(0.048)	(0.051)
High Education			0.736	0.724	0.734
			(0.026)***	(0.047)***	(0.048)***
Mother's High Education			0.898	0.805	0.800
			(0.065)	(0.110)	(0.110)
Father's High Education			1.089	1.027	1.031
			(0.054)*	(0.094)	(0.094)
Income			0.959	0.950	0.959
			(0.005)***	(0.010)***	(0.011)***
Owner			0.567	0.627	0.641
			(0.017)***	(0.036)***	(0.037)***
Married				0.745	0.746
				(0.047)***	(0.048)***
Number of children				0.949	0.947
				(0.019)***	(0.019)***
Household size				1.022	1.026
				(0.033)	(0.033)
Retired					1.091
					(0.083)
Unemployed					1.703
					(0.222)***
Disabled					1.529
					(0.185)***
Homemaker					1.027
					(0.125)
N. Observations	79055	79053	34476	7746	7742
N. Countries	18	18	18	18	18

The dependent variable is "Current Smoker". The linguistic marker is Strong FTR. Regressions are logistic regressions with coefficients reported as Odds ratios. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. Reference categories: Male, Low Education, Not married, Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

The effect of education and the knowledge of benefits from exercising on health confirms past literature which affirms that increasing the level of education rises the probability of doing physical activity (Kemna (1987), Kenkel (1991)). Data show that people who have a bachelor's or master's degree or a PhD are 37% more likely to be involved in vigorous activities, on average. Analogously, father's high level of education seems to have a positive influence on their children and induces them to take care of their health, increasing the probability of exercising by 18%, while mother's level of education is not statistically significant (Lynch et al. (1997)).

Table 4. Logistic regression of alcohol consumption on Strong FTR. All countries.

Heavy Drinking	HD 1	HD 2	HD 3	HD 4	HD 5
Strong FTR	1.643	1.645	1.220	1.356	1.355
	(0.025)***	(0.025)***	(0.030)***	(0.061)***	(0.061)***
Age		0.999	0.993	0.993	0.999
		(0.001)	(0.001)***	(0.002)***	(0.003)
Female		0.945	0.887	0.885	0.852
		(0.014)***	(0.021)***	(0.036)***	(0.036)***
High Education			0.850	0.850	0.867
			(0.026)***	(0.044)***	(0.045)***
Mother's High Education			1.254	1.337	1.324
			(0.026)***	(0.150)***	(0.149)**
Father's High Education			0.818	0.706	0.706
			(0.035)***	(0.053)***	(0.053)***
Income			0.899	0.946	0.947
			(0.004)***	(0.008)***	(0.008)***
Owner			0.947	0.886	0.890
			(0.025)**	(0.042)**	(0.043)**
Married				0.853	0.866
				(0.042)***	(0.043)***
Number of children				1.020	1.017
				(0.015)	(0.015)
Household size				1.011	1.004
				(0.025)	(0.025)
Retired					0.837
					(0.049)***
Unemployed					1.025
					(0.119)
Disabled					1.634
					(0.187)***
Homemaker					1.158
					(0.097)*
N. Observations	76942	76936	32215	11112	11107
N. Countries	18	18	18	18	18

The dependent variable is "Heavy Drinking". The linguistic marker is Strong FTR. Regressions are logistic regressions with coefficients reported as Odds ratios. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. Reference categories: Male, Low Education, Not married, Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

Moreover, according to Contoyannis (2004)'s statement that people belonging to the highest socioeconomic classes are significantly more likely to exercise than those in the baseline category, data reveal that being more wealthy and owning a house increases the probability of practicing physical activity by, respectively, 5% and 41%. Also marital status and the number of children influence the probability of exercising, given that married individuals are 12% significantly more likely to exercise and having a high number of children increases the likelihood of being involved in vigorous activities by 2%. Analogously to smoking habit, the household size has a negative effect on health on average, since it reduces the probability of exercising by 1%, even though the coefficient is not significant. Finally, occupational status has a strong and significant effect on the probability of being involved in vigorous exercise. In fact, being retired, unemployed, disabled and homemaker leads to, respectively, a 20%, 50%, 83%, and 36% lower probability of practicing sports, doing heavy housework, being involved in jobs requiring physical labor or similar activities.

Table 5. Logistic regression of vigorous exercise (sports, heavy housework, a job that requires physical labor) on Strong FTR. All countries.

Vigorous Exercise	VE 1	VE 2	VE 3	VE 4	VE 5
Strong FTR	0.598	0.581	0.553	0.510	0.500
	(0.008)***	(0.008)***	(0.012)***	(0.021)***	(0.021)***
Age		0.943	0.948	0.950	0.948
		(0.001)***	(0.001)***	(0.002)***	(0.002)***
Female		0.684	0.743	0.770	0.784
		(0.009)***	(0.016)***	(0.029)***	(0.031)***
High Education			1.366	1.430	1.348
			(0.038)***	(0.068)***	(0.066)***
Mother's High Education			0.974	0.842	0.851
			(0.058)	(0.087)*	(0.090)
Father's High Education			1.183	1.147	1.138
			(0.048)***	(0.082)*	(0.082)*
Income			1.052	1.047	1.030
			(0.004)***	(0.008)***	(0.008)***
Owner			1.408	1.361	1.302
			(0.034)***	(0.059)**	(0.057)***
Married				1.118	1.142
				(0.051)**	(0.053)***
Number of children				1.020	1.023
				(0.014)	(0.015)
Household size				0.988	0.970
				(0.024)	(0.024)
Retired					0.804
					(0.044)***
Unemployed					0.502
					(0.051)***
Disabled					0.174
					(0.018)***
Homemaker					0.639
					(0.050)***
N. Observations	97512	97503	41262	14482	14476
N. Countries	18	18	18	18	18

The dependent variable is "Vigorous Exercise". The linguistic marker is Strong FTR. Regressions are logistic regressions with coefficients reported as Odds ratios. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. Reference categories: Male, Low Education, Not married, Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

Concerning moderate exercise, the effect of Future Time Reference is even larger than for vigorous exercise. Regression 1 of Table 6 present an Odds Ratio of 0.509, which can be interpreted as individuals speaking languages with a strong FTR being 49% less likely to practice moderate exercise than individuals speaking languages with a weak FTR. As for vigorous exercise, the effect of the linguistic marker remains nearly constant and strongly significant after the inclusion of controls (X_{it}) in the equation. Controls tend to affect the probability of being involved in moderate exercise in the same way and significance they affected the probability of being involved in vigorous exercise, apart from the number of children and the household size which affect the probability of moderate exercise, but not vigorous exercise, in a significant way, and retirement which does not seem to be a significant explanatory variable, contrary to the case of vigorous exercise. In fact, individuals with a high number of children are 4% significantly more likely to be involved in moderate exercise, such as gardening, cleaning the car, doing a walk, while individuals living in a big family are 17% less likely to do the same activities. Furthermore, being retired leads to a 2% greater probability of exercising moderately, even though the coefficient is not significant, and being unemployed has a less significant effect on moderate exercise than vigorous exercise.

Furthermore, I analyze empirical results of equation [10], presented in Table 7, related to overweight. Regression 1 shows an odds ratio of 1.108 which implies that individuals who speak a language characterized by a strong FTR are 11% more likely to be overweight than individuals who speak a language characterized by a weak FTR. As for all the previous dependent variables, the effect of Strong FTR remains significant even with the inclusion of controls (X_{it}) in the equation, and becomes even stronger. Controlling for age and gender reveals that young people are slightly more likely to be overweight and that females are 39% less inclined to be overweight with respect to males (Bakhshi et al. (2008)). As regards the effect of education, a higher knowledge of the consequences related to overweight and obesity seems to have a positive effect deriving not only from individual's high level of education but also from both parents' high level of education (Kemna (1987), Kenkel (1991), Di Novi (2013), Bakhshi et al. (2008)). In fact, according to data from regression 3, people who have a bachelor's or master's degree or a PhD are 7% less likely to be overweight, on average. Moreover, people whose mother and father have a bachelor's or master's degree or a PhD are, respectively, 15% and 9% less likely to be overweight, in accordance to past literature (Lynch et al. (1997)). Income and socio-economic class are not significant in determining overweight status, while owning a house is a good predictor of the increase of the probability of being overweight. Individuals who own a house are 9% more likely to be overweight than those who pay a rent or have other forms of contract on the house. In the same way, being married and having a high number of children leads to, respectively, a 15% and a 5% higher probability of being overweight. On the other hand, the household size decreases the probability of being overweight by 3%, even though the coefficient is not significant. Finally, occupational status seems not to be a significant explanatory variable for the probability of being overweight.

As a conclusion, speaking languages with a strong FTR leads to a greater involvement in Behavioral Risk Factors, such as smoking, drinking, being overweight and reduction of physical activity with respect to speaking languages with weak FTR[20].

[20]These results are confirmed by regressions run as robustness check and reported in Appendix A, which reveal that speaking a language with a strong FTR decreases the probability of quitting smoking (Appendix Table 3), increases the probability of drinking more than once or twice a week (Appendix Table 4) and of drinking four or more drinks at one occasion for Wave 2 and six or more drinks at one occasion for Wave 5 (Appendix Table 5), it rises the probability of being physically inactive, measured by *phactive* generated variable (Appendix Table 6) as well as the probability of being obese (Appendix Table 7).

Table 6. Logistic regression of moderate exercise (gardening, cleaning the car, doing a walk) on Strong FTR. All countries.

Moderate Exercise	ME 1	ME 2	ME 3	ME 4	ME 5
Strong FTR	0.509 (0.010)***	0.500 (0.010)***	0.598 (0.020)***	0.519 (0.034)***	0.516 (0.034)***
Age		0.931 (0.001)***	0.936 (0.001)***	0.940 (0.002)***	0.932 (0.003)***
Female		0.732 (0.015)***	0.810 (0.027)***	0.826 (0.048)***	0.859 (0.053)**
High Education			1.683 (0.084)***	1.711 (0.155)***	1.584 (0.145)***
Mother's High Education			0.880 (0.091)	0.944 (0.189)	0.977 (0.197)
Father's High Education			1.205 (0.085)***	1.140 (0.148)	1.121 (0.147)
Income			1.096 (0.007)***	1.072 (0.013)***	1.061 (0.013)***
Owner			1.356 (0.047)***	1.410 (0.089)***	1.366 (0.088)***
Married				1.447 (0.099)***	1.421 (0.101)***
Number of children				1.042 (0.021)**	1.046 (0.022)**
Household size				0.835 (0.028)***	0.830 (0.029)***
Retired					1.023 (0.096)
Unemployed					0.716 (0.131)*
Disabled					0.163 (0.020)***
Homemaker					0.699 (0.085)***
N. Observations	97520	97511	41260	14481	14475
N. Countries	18	18	18	18	18

The dependent variable is "Moderate Exercise". The linguistic marker is Strong FTR. Regressions are logistic regressions with coefficients reported as Odds ratios. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. Reference categories: Male, Low Education, Not married, Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. Logistic regression of being overweight on Strong FTR. All countries.

Overweight	OW 1	OW 2	OW 3	OW 4	OW 5
Strong FTR	1.108	1.114	1.078	1.136	1.137
	(0.015)***	(0.015)***	(0.023)***	(0.045)***	(0.046)***
Age		1.003	1.005	1.001	0.999
		(0.001)***	(0.001)***	(0.002)	(0.002)
Female		0.610	0.624	0.591	0.591
		(0.008)***	(0.013)***	(0.021)***	(0.022)***
High Education			0.933	0.903	0.900
			(0.025)***	(0.040)**	(0.040)**
Mother's High Education			0.851	0.809	0.810
			(0.048)***	(0.079)**	(0.079)**
Father's High Education			0.909	0.984	0.984
			(0.035)**	(0.064)	(0.064)
Income			0.999	0.998	0.998
			(0.004)	(0.008)	(0.008)
Owner			1.093	1.067	1.061
			(0.026)***	(0.045)	(0.045)
Married				1.154	1.147
				(0.050)***	(0.051)***
Number of children				1.048	1.048
				(0.014)***	(0.014)***
Household size				0.972	0.974
				(0.022)	(0.022)
Retired					1.053
					(0.054)
Unemployed					0.929
					(0.093)
Disabled					0.900
					(0.087)
Homemaker					1.017
					(0.078)
N. Observations	95084	95075	40262	14215	14209
N. Countries	18	18	18	18	18

The dependent variable is "Overweight". The linguistic marker is Strong FTR. Regressions are logistic regressions with coefficients reported as Odds ratios. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. Reference categories: Male, Low Education, Not married, Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.1.2 Logistic regressions with Strong FTR in Linguistically Heterogeneous Countries

After analyzing data from the total sample, on the basis of Chen (2013) and Kovacic et al. (2016), I run regressions considering only Linguistically Heterogeneous Countries, which are countries where individuals speak two or more different languages. The six Linguistically Heterogeneous Countries, present in SHARE, which I took into account include Belgium, Estonia, Israel, Luxembourg, Spain and Switzerland, speaking ten different languages. The aim of considering this subsample is to test if living in countries with the same institutions and similar characteristics, where individuals only differ for the language they speak, confirms the findings of regressions including all eighteen countries, by means of the Future Time Reference linguistic marker.

Regression 1 in Table 8 indicates that a language characterized by a strong FTR leads to a 24% higher probability of smoking currently and the coefficient is significant at 10%, confirming Chen (2013)'s finding. As regards control variables, coefficients of age and gender have the same characteristics as with the total sample considering all countries and predict that young people are more likely to smoke with respect to old ones (Blaylock and Blisard (1992)) and that males are more incline to tobacco addiction with respect to females. However, individual's level of education, household's income, marital status, and the number of children are not significant in affecting the probability of tobacco use, contrary to regression including all eighteen countries. Furthermore, in contrast with the total sample, living with a big family decreases the chances of having been a smoker at the moment of the interview by 13%, and the coefficient is significant at 10%. Supporting Contoyannis (2004)'s finding that people belonging to the highest socio-economic class are significantly more likely to avoid smoking than those in the lowest class, data show that owning a house reduces the probability of smoking by 35%. Lastly, concerning occupational status, being disabled increases strongly and significantly the probability of being involved in tobacco use, however unemployment does not rise the likelihood of smoking significantly as in the sample with all countries.

Similarly, regression 2 indicates that a strong-FTR language leads to a 48% higher probability of having drunk more than two drinks in a day in the three months leading up to the interview and the coefficient is significant at 1%. Heavy drinking behavior was not considered in Chen (2013) as a dependent variable and therefore no comparison with previous results is allowed. Concerning controls, both age and gender seem to affect the probability of heavy drinking. Young people and males are more incline to smoke than aged people and females in a significant manner. Contrary to the results considering the total sample, education is not highly significant in influencing drinking behavior. Data show that in Linguistically Heterogeneous Countries, individuals who have a bachelor's or master's degree or a PhD are 19% less likely to be involved in alcohol abuse, on average (Kemna (1987), Di Novi (2013)). Moreover, father's high level of education decreases the probability of alcohol consumption by 30%, while mother's high level of education is not significant (Lynch et al. (1997)). Accordingly to past literature, belonging to high socio-economic classes leads to avoid alcohol abuse more frequently with respect to baseline classes. Being more wealthy reduces the probability of heavy drinking by 13%, while owning a house is not significant as in the sample including all eighteen countries. Furthermore, controls for family present completely different characteristics with respect to the ones obtained using the total sample. In Linguistically Heterogeneous Countries, married individuals seem to be 16% more likely to be involved in episodes of heavy drinking, even though the coefficient is not significant. In addition, individuals with a high number of children are 10% more likely to drink excessively, and individuals living with a big family are 14% less likely to abuse of alcohol. Finally, occupational status is not significant in predicting drinking behavior, contrary to the regression with data on all countries.

As showed in regression 3, individuals who speak languages with a strong FTR are 30% less likely to practice vigorous exercise than their counterparts who speak languages with a weak FTR. Young individuals and females are more likely to be involved in sports or other activities which require a high level of energy, on average, even though gender is less significant than in the regression with all countries. Education is not a significant explanatory variable, contrary to previous regressions with the total sample. However, the effect of owning a house and marital status are greater in Linguistically Heterogeneous Countries than before. Owning a house and being married increases the probability of taking part in sports or similar activities which require a high level of energy by, respectively, 48% and 29%. These coefficients almost doubled with respect to the total sample and they are both highly significant. Moreover, having a high number of children leads to a 6% higher probability of exercising, while living with a big family leads to a 10% lower probability of exercising, both significant at 10%. Finally, occupational status has strong and significant effect on the probability of being involved in vigorous exercise. In fact, being retired, unemployed, disabled and homemaker leads to, respectively, a 23%, 43%, 84%, and 41% lower probability of practicing sports, doing heavy housework or jobs requiring physical energy, with the first two variables significant at 5% and the last two variables significant at 1%.

Even though regressions on the probability of being obese or overweight did not lead to significant results, regression 4 indicates that a language characterized by a strong FTR leads to a 32% lower probability of consuming fruit and vegetables daily and the coefficient is significant at 1%. Regressions for consumption of fruit and vegetables on Strong FTR were not reported for all countries, given that the coefficients were not significant. Control variables for age and gender are associated with coefficients of 1.027 and 1.975, which can be interpreted as aged individuals and females speaking a language with a strong FTR being more likely to eat fruit and vegetables on a daily basis. Moreover, high educated individuals who speak a strong-FTR language are 68% significantly more likely to consume fruit and vegetables every day with respect to their low educated counterparts. On the other hand, mother's high level of education leads to a 44% lower probability of following a good dietary pattern, significant at 5%, while father's high level of education does not seem to affect dietary pattern. Similarly to Behavioral Risk Factors, people belonging to the highest socio-economic class are significantly more likely to follow a healthy diet, rich in fruit and vegetables, than those in the baseline category. In fact being more wealthy rises the probability of consuming this food by 9%, confirmed by a coefficient significant at 1%. Owning a house, however, does not affect dietary pattern in a significant way. Concerning variable controls related to marital status and family composition, only being married increases the probability of consuming fruit and vegetables regularly by 30%, significant at 10%. Finally, as regards occupational status, being retired and being disabled reduce the probability of eating fruit and vegetables on a daily basis by, respectively, 27% and 41%, both significant at 5%.

As a conclusion, in accordance with Chen (2013)'s idea according to which "if obligatory FTR reduces the psychological importance of the future, we would predict that it would lead to more smoking, less exercise, and worse long-run health", the negative effect of speaking a language with a strongly grammaticalized FTR on Behavioral Risk Factors is not only confirmed in the total sample but also in the Linguistically Heterogeneous Countries subsample[21].

[21] Chen (2013)'s study is confirmed using Wave 2 and Wave 5 also for grip strength variable using linear regressions. Individuals who speak languages with a strong FTR have a reduction in grip strength of almost 3 kilograms (-2.823), significant at 1%, in the total sample, and more than a kilogram (-1.318), not significant, in Linguistically Heterogeneous Countries. This result confirms the effect of language on long-run health.

Table 8. Logistic regression of Behavioral Risk factors Strong FTR. Linguistically Heterogeneous Countries

	Current Smoker (1)	Heavy Drinking (2)	Vigorous Exercise (3)	Fruit and vegetables every day (4)
Strong FTR	1.240	1.477	0.705	0.683
	(0.155)*	(0.156)***	(0.065)***	(0.076)***
Age	0.922	0.981	0.954	1.027
	(0.009)***	(0.006)***	(0.006)***	(0.007)***
Female	0.835	0.657	0.817	1.975
	(0.109)	(0.073)***	(0.078)**	(0.230)***
High Education	0.875	0.810	1.085	1.681
	(0.134)	(0.102)*	(0.119)	(0.236)***
Mother's High Education	0.874	1.473	0.914	0.556
	(0.270)	(0.368)	(0.194)	(0.134)**
Father's High Education	1.144	0.703	1.094	1.363
	(0.254)	(0.132)*	(0.179)	(0.290)
Income	1.010	0.872	1.027	1.094
	(0.023)	(0.017)***	(0.017)	(0.022)***
Owner	0.647	0.924	1.476	0.901
	(0.094)***	(0.124)	(0.169)***	(0.125)
Married	0.940	1.158	1.285	1.299
	(0.147)	(0.150)	(0.145)**	(0.178)*
Number of children	0.981	1.095	1.055	0.990
	(0.042)	(0.040)**	(0.032)*	(0.356)
Household size	0.875	0.857	0.897	1.031
	(0.068)*	(0.053)**	(0.050)*	(0.068)
Retired	1.210	1.056	0.769	0.729
	(0.215)	(0.160)	(0.102)**	(0.116)**
Unemployed	1.476	1.126	0.567	0.676
	(0.500)	(0.394)	(0.155)**	(0.207)
Disabled	2.266	1.128	0.163	0.594
	(0.581)***	(0.293)	(0.038)***	(0.138)**
Homemaker	0.934	0.864	0.588	0.807
	(0.235)	(0.168)	(0.100)***	(0.179)
N. Observations	1417	1804	2385	2385
N. Countries	6	6	6	6

Regressions are logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. Reference categories: Male, Low Education, Not married, Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.2 Empirical results from Conditional Logit regressions

At this point, given that I am using panel data, namely information on subjects are measured at two points in time, in 2006/2007 (Wave 2), apart from Israel in 2009/2010, and in 2013 (Wave 5), I can use subjects as their own controls. With binary dependent variables, I can adopt Fixed Effects (or Conditional) Logistic models controlling for stable characteristics which do not change across time, such as gender, age, income, education, marital status, and number of children. In this way I can replicate the analysis conducted by Chen (2013) on health behaviors and measures of health, using more recent data and adding dependent variables[22].In all regression models I calculate the robust standard errors clustered by country.

Regressions 1, 2, and 3 in Table 9 which presents results of equation [11], reported in chapter 4, seem to suggest that a Strong FTR leads to almost 17% higher probability of smoking at the time of the interview, even though coefficients are not statistically significant in all three cases. Including fixed-effects for age, gender, country, wave, income, education, marital status, and the number of children leads to a coefficient of 1.130, which can be interpreted as identical individuals in all these characteristics apart from speaking a language with a strong FTR having a 13% higher probability of being a smoker currently. This result confirms Chen (2013)'s finding, despite the coefficient being slightly smaller in this case.

Table 9. Fixed-Effects Logistic regressions of smoking habit on Strong FTR. All countries.

	CS 1	CS 2	CS 3	CS 4
Strong FTR	1.166	1.135	1.177	1.130
	(0.218)	(0.204)	(0.206)	(0.047)**
Fixed Effects:				
Age x sex	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**
Income	No	**Yes**	**Yes**	**Yes**
Education	No	No	**Yes**	**Yes**
Married x Numchildren	No	No	No	**Yes**
All FE Interacted	Yes	Yes	Yes	Yes
Countries	18	18	18	18
Observations	78429	75047	67706	10182

The dependent variable is "Current Smoker". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Similarly, I consider the habit of drinking two or more drinks in a day in the three months leading up to the interview as a dependent variable. All regressions in Table 10, which presents results of equation [12], reveal that speaking a language with a strong FTR leads to a 33% higher probability of drinking heavily, on average, when considering respondents' answers to SHARE Survey identical in age, gender, country, wave, income, education, marital status, and the number of children, apart from linguistic characteristics.

[22] I replicate Table 8 in Chen, M. K. (2013). The effect of Language on Economic Behavior: Evidence from Savings Rates, Health Behaviors, and Retirement Assets. *American Economic Review*, 103(2):690-731

Table 10. Fixed-Effects Logistic regressions of alcohol consumption on Strong FTR. All countries.

	HD 1	HD2	HD 3	HD 4
Strong FTR	1.341	1.339	1.372	1.325
	[0.164]**	[0.149]***	[0.120]***	[0.113]***
Fixed Effects:				
Age x sex	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**
Income	No	**Yes**	**Yes**	**Yes**
Education	No	No	**Yes**	**Yes**
Married x Numchildren	No	No	No	**Yes**
All FE Interacted	Yes	Yes	Yes	Yes
Countries	18	18	18	18
Observations	76888	75473	70479	13732

The dependent variable is "Heavy Drinking". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

To return to dependent variables analyzed by Chen (2013), I take physical activity into account, distinguishing vigorous exercise from moderate exercise[23]. All regressions in Table 11 and 12, which show results from equation [13] in chapter 4, present strong and significant coefficients, in line with Chen (2013)'s findings. Analogously to results on smoking habit and alcohol consumption, speaking a strong-FTR language has a negative effect on health, since individuals who speak a language characterized by a grammar which distinguishes present from future tend to practice a sport or do a job which needs a certain level of strength with 92% less probability and to be involved in activities requiring moderate level of energy with 40% less probability, on average, than their counterparts speaking a language with a weak FTR.

Table 11. Fixed-Effects Logistic regressions of vigorous exercise (sports, heavy housework, a job that requires physical labor) on Strong FTR. All countries.

	VE 1	VE 2	VE 2
Strong FTR	0.757	0.742	0.085
	[0.078]***	[0.065]***	[0.083]***
Fixed Effects:			
Age x sex	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**
Income	**Yes**	**Yes**	**Yes**
Education	No	**Yes**	**Yes**
Married x Numchildren	No	No	**Yes**
All FE Interacted	Yes	Yes	Yes
Countries	18	18	18
Observations	95848	91032	19459

The dependent variable is "Vigorous Exercise". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

[23]Regressions for vigorous exercise and moderate exercise which consider only age, sex, country, and wave fixed-effects are not available through Stata 13.

Table 12. Fixed-Effects Logistic regression of moderate exercise (gardening, cleaning the car, doing a walk) on Strong FTR. All countries.

	ME 1	ME 2	ME 3
Strong FTR	0.685	0.641	0.605
	[0.055]***	[0.039]***	[0.035]***
Fixed Effects:			
Age x sex	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**
Income	**Yes**	**Yes**	**Yes**
Education	No	**Yes**	**Yes**
Married x Numchildren	No	No	**Yes**
All FE Interacted	Yes	Yes	Yes
Countries	All	All	All
Observations	91277	75756	9918

The dependent variable is "Moderate Exercise". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Furthermore, regression 1 in Table 13, which presents results of equation [14], suggests that a Strong FTR leads to almost 8% higher probability of being obese, when comparing individuals identical in age, gender, country and wave and speaking languages which differ in Future Time Reference. The effect of Strong FTR on obesity is less strong than in Chen (2013) and is not significant after the inclusion of income, education, marital status, and number of children fixed-effects. Moreover, speaking a language with a strong FTR seems to reduce the probability of being overweight, as shown in Appendix Table 8 (Appendix A). As a conclusion, according to my data the impact of Strong FTR linguistic marker on weight is not clear.

Table 13. Fixed-Effects Logistic regression of being obese on Strong FTR. All countries.

	OB 1	OB 2	OB 3	OB 4
Strong FTR	1.077	1.047	1.079	1.094
	[0.036]**	[0.050]	[0.056]	[0.111]
Fixed Effects:				
Age x sex	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**
Income	No	**Yes**	**Yes**	**Yes**
Education	No	No	**Yes**	**Yes**
Married x Numchildren	No	No	No	**Yes**
All FE Interacted	Yes	Yes	Yes	Yes
Countries	18	18	18	18
Observations	94742	92238	84414	15698

The dependent variable is "Obese". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

As a robustness check, I consider the regressions reported above including fixed-effects for age, gender, country, and wave, and control variables for occupational status, trust, life expectancy and Social Security Wealth and I report the results in Table 14. With these additional controls, Strong FTR seems not to affect smoking habit and vigorous exercise behavior in a significant way, even though the sign predicted is in line with previous results, on the other hand this linguistic marker impacts on the probability of drinking two or more drinks in a day in the three months leading up to the interview and being obese. In fact, speaking a language with a Strong FTR rises the probability of being involved in heavy drinking episodes and being obese by, respectively, 32% and 8%, both significant at 10%. Furthermore, regression 5 confirms the negative effect of Strong FTR on moderate exercise in Linguistically Heterogeneous Countries, with a coefficient significant at 1%. Finally, it is worth to remark that when comparing individuals with the same demographic characteristics, occupational status, trust, life expectancy and Social Security Wealth are all strongly significant with respect to Behavioral Risk Factors.

As regards occupational status, unemployment, disability and being a homemaker lead to have unhealthy lifestyles. In fact, belonging to one of these categories of occupational status leads to a higher probability of being involved in smoking and heavy drinking behaviors, and being obese, and to a lower probability of vigorous exercise, in the sample with all countries, and of moderate exercise, in the subsample of Linguistically Heterogeneous Countries.

On the other hand, trusting other people has a positive impact on health, reducing involvement in risky behaviors related to health. High levels of trust lead to 4% lower likelihood of tobacco use, drinking two or more drinks in a day and being obese and to a 3% higher likelihood of doing vigorous exercise, in the total sample, and a 7% higher probability of doing activities requiring a moderate level of energy, in Linguistically Heterogeneous Countries.

Analogously, high values of self-assessed life expectancy of living in ten years from the moment of the interview lead to almost 1% lower probability of being involved in smoking and heavy drinking behaviors and of being obese. Moreover, predicting a higher chance of living in ten years leads to a 1% higher probability of doing physical activity, both in the sample considering all countries and in the subsample of Linguistically Heterogeneous Countries.

Finally, coefficients for Social Security Wealth, which is computed through self-reported information about pension amounts received by retired individuals or predicted information about pension amounts that will be received assuming that the individual will retire at current age from the labor market, are in line with coefficients for income relatively to Behavioral Risk Factors. In fact, individuals who speak a strong-FTR language are almost 6% less likely to smoke at the moment of the interview, to have drunk two or more drinks in a day in the three months leading up to the interview and to exceed weight threshold of 30 kg/m^2 for obesity. On the other hand, individuals with the same linguistic feature are almost 5% more likely to do vigorous exercise, in the total sample, and moderate exercise, in Linguistically Heterogeneous Countries.

As a conclusion, trust, life expectancy and Social Security Wealth affect Behavioral Risk Factors positively, hindering smoking habit, alcohol consumption, and obesity, and fostering physical activity.

Table 14. Fixed-Effects Logistic regression on Strong FTR with additional controls. All countries (1,2, 3,4) and Linguistically Heterogeneous Countries (5).

	Current Smoker (1)	Heavy Drinking (2)	Vigorous Exercise (3)	Obesity (4)	Moderate Exercise (5)
Strong FTR	1.002	1.319	0.766	1.078	0.653
	(0.168)	(0.220)*	(0.126)	(0.042)*	(0.094)***
Retired	1.033	1.057	0.632	1.288	0.547
	(0.053)	(0.071)	(0.050)***	(0.065)***	(0.130)**
Unemployed	1.527	1.256	0.601	1.256	0.464
	(0.103)***	(0.114)**	(0.045)***	(0.139)**	(0.063)***
Disabled	1.798	1.476	0.190	1.936	0.163
	(0.106)***	(0.184)***	(0.012)***	(0.108)***	(0.034)***
Homemaker	0.828	1.218	0.616	1.409	0.576
	(0.051)***	(0.075)***	(0.032)***	(0.106)***	(0.171)*
Trust	0.957	0.963	1.031	0.957	1.072
	(0.008)***	(0.010)***	(0.009)***	(0.008)***	(0.022)***
Life Expectancy	0.995	0.998	1.009	0.998	1.009
10 years	(0.001)***	(0.001)***	(0.001)***	(0.005)***	(0.004)**
SSW	0.943	0.945	1.048	0.947	1.046
	(0.009)***	(0.007)***	(0.006)***	(0.010)***	(0.037)
Fixed Effects:					
Age x sex	Yes	Yes	Yes	Yes	Yes
Country x wave	Yes	Yes	Yes	Yes	Yes
N. Observations	46799	38629	50503	49406	13998
N. Countries	18	18	18	18	6

Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.3 Empirical results from Linguistically Heterogeneous Countries

Similarly to regressions for the entire set of countries, I also run separate regressions for linguistically heterogeneous countries, in order to analyze the effect of language on identical individuals living in countries with the same institutions who only differ for the language they speak, through Future Time Reference. Four out of six Linguistically Heterogeneous Countries available in SHARE differ in Future Time Reference including Belgium, Estonia, Luxembourg, and Switzerland. I adopt Fixed-Effects (or Conditional) Logistic models, in analogy to regressions run for all countries. Moreover, I increase the level of spatial control, in the case of Switzerland and Belgium, by including fixed-effects for intra-country regions.

Starting from Luxembourg, individuals are divided into German speakers, with a weak FTR and a French speakers, with a strong FTR. Table 15 shows that speaking a strong-FTR language, like French, has a negative effect on heavy drinking behavior with respect to weak-FTR language, like German. The negative effect on health is confirmed by an increase in individuals who declare to be overweight and to do less vigorous and moderate exercise, even though associated with coefficients which are not significant. When comparing French speakers and German speakers with identical of the same gender and age, French speakers are 43% more likely to declare to have drunk two or more drinks in the three months leading up to the interview. The effect distinguishing present from future implied by a Strong FTR seems to increase when considering individuals living in Luxembourg with the same socio-demographic characteristics as well as same levels of wealth and education. In fact, comparing individuals with this identical characteristics apart from the language they speak leads to a 48% higher probability of being involved in alcohol abuse for French speakers with respect to German speakers.

Table 15. Fixed-Effects Logistic regression on Behavioral Risk Factors. Luxembourg.

	Heavy Drinking (1)	Heavy Drinking (2)	Heavy Drinking (3)
Strong FTR	1.416	1.429	1.480
	(0.210)**	(0.216)**	(0.260)**
Fixed Effects:			
Age x sex	No	Yes	Yes
Country x wave	No	Yes	Yes
Income	No	No	Yes
Education	No	No	Yes
N. Observations	757	753	659

The dependent variable is "Heavy Drinking". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Moving to case of Estonia, I compare the effect of speaking Estonian, which is a language with a weak FTR, and Russian, which is a language with a strong FTR, on Behavioral Risk Factors. Table 16 shows that speaking Russian has a negative effect on physical activity and obesity with respect to speaking Estonian. From the comparison of individuals living in Estonia who are identical in all characteristics, such as age, gender, income and education, apart from language, results that speaking Russian leads to a 36% lower probability of being involved in sports or jobs which require a high level of strength, a 56% lower probability of doing activities related to moderate exercise, and almost 70% higher probability of being obese, on average, with respect to speaking Estonian.

On the basis of Chen (2013), in the cases of Switzerland and Belgium, I do not only run a regression at a country level, but also include fixed-effects for intra-country regions, allowing to examine whether language may be proxying for unobserved institutional differences between regions.

Switzerland is characterized from being an heterogeneous territory divided into cantons, speaking German, French and Italian. It is the perfect environment to test the hypothesis that language might affect Behavioral Risk Factors, given that French and Italian are languages with strongly grammaticalized FTR while German is characterized by a weak FTR. Table 17 shows that individuals speaking languages which differ in Future Time Reference, but are identical in gender and age, are 75% less likely to do activities involving moderate level of energy, and the percentage reaches 66% even when including also individuals with the same level of income and education.

Table 16. Fixed-Effects Logistic regression on Behavioral Risk Factors. Estonia.

	Vigorous Exercise (1)	Moderate Exercise (2)	Obesity (3)	Vigorous Exercise (1)	Moderate Exercise (2)	Obesity (3)
Strong FTR	0.638 (0.087)***	0.443 (0.069)***	1.297 (0.188)*	0.650 (0.096)***	0.441 (0.075)***	1.289 (0.194)*
Fixed Effects:						
Age x sex	No	No	No	Yes	Yes	Yes
Country x wave	No	No	No	Yes	Yes	Yes
Income	No	No	No	Yes	Yes	Yes
Education	No	No	No	Yes	Yes	Yes
N. Observations	5639	5641	5497	5488	5185	5347

The dependent variable are "Vigorous Exercise", "Moderate Exercise" and "Obesity". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 17. Fixed-Effects Logistic regression on Behavioral Risk Factors. Switzerland.

	Moderate Exercise (1)	Moderate Exercise (2)	Moderate Exercise (3)	Moderate Exercise (4)	Moderate Exercise (5)
Strong FTR	0.254 (0.178)**	0.255 (0.255)***	0.309 (0.180)**	0.339 (0.195)*	0.703 (0.548)
Fixed Effects:					
Age x sex	No	Yes	Yes	Yes	Yes
Country x wave	No	Yes	Yes	Yes	Yes
Income	No	No	No	Yes	Yes
Education	No	No	No	Yes	Yes
Sub-Reg FEs	No	1	7	1	7
N. Observations	590	544	544	133	133

The dependent variable is "Moderate Exercise". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Moreover, the addition of finer spatial controls represented by level 2 of nuts 2003 (region)[24], does not appear to attenuate the effect of language on moderate exercise significantly.

Analogously, Belgium is characterized by a population speaking both French and Flemish. Table 18 shows that speaking a strong-FTR language, like French, has a negative effect on all Behavioral Risk Factors with respect to a weak-FTR language, like Flemish. Individuals living in Belgium with same age, gender, level of wealth and education, who only differ for the language they speak, are 48% more likely to smoke at present, 59% more likely to drink two or more drinks in a day, 34% less likely to practice sports or do vigorous exercise, 41% less likely to do moderate exercise, and

[24]The 7 regions included in NUTS2 (2003) for Switzerland are: Iemanique (CH01), Espace Mittelland (CH02), Nordwestschweiz (CH03), Zurich (CH04), Ostschweiz (CH05), Zentralschweiz (CH06), Ticino (CH07).

60% more likely to be obese if they speak French with respect to Flemish. Furthermore, including intra-country regions fixed effects represented by level 2 of nuts 2010 (provinces)[25] does not alter the impact of language on Behavioral Risk Factors. In fact, individuals living in the same province with same age, gender, level of wealth and education, who only differ for the language they speak, are 59% more likely to be involved in smoking habit, 56% more likely to abuse of alcoholic beverages, 32% less likely to do vigorous exercise, 37% less likely to do moderate exercise, and 45% more likely to be obese if they speak French with respect to Flemish, excluding any influence that might be connected to institutions.

Table 18. Fixed-Effects Logistic regression on Behavioral Risk Factors. Belgium.

	Current Smoker (1)	Current Smoker (2)	Heavy Drinking (1)	Heavy Drinking (2)	Vigorous Exercise (1)	Vigorous Exercise (2)
Strong FTR	1.484	1.589	1.562	1.556	0.664	0.681
	(0.315)*	(0.337)**	(0.285)**	(0.291)**	(0.098)***	(0.102)***
Fixed Effects:						
Age x sex	Yes	Yes	Yes	Yes	Yes	Yes
Country x wave	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Sub-Reg FEs	1	11	1	11	1	11
N. Observations	424	424	667	667	994	994

The dependent variable are "Current Smoker", "Heavy Drinking", "Vigorous Exercise", "Moderate Exercise", and "Obesity". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 18. Fixed-Effects Logistic regression on Behavioral Risk Factors. Belgium. (continue)

	Moderate Exercise (1)	Moderate Exercise (2)	Obesity (1)	Obesity (2)
Strong FTR	0.590	0.627	1.597	1.450
	(0.142)**	(0.153)**	(0.296)**	(0.280)**
Fixed Effects:				
Age x sex	Yes	Yes	Yes	Yes
Country x wave	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Sub-Reg FEs	1	11	1	11
N. Observations	606	606	857	857

The dependent variable are "Current Smoker", "Heavy Drinking", "Vigorous Exercise", "Moderate Exercise", and "Obesity". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Immigrants are excluded from all regressions. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

[25]The 11 provinces included in NUTS2 (2010) for Belgium are: Region de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest (BE10), Antwerpen (BE21), Limburg (BE22), Oost-Vlaanderen (BE23), Vlaams-Brabant (BE24), West-Vlaanderen (BE25), Brbant Wallon (BE31), Hainaut (BE32), Liege (BE33), Luxembourg (BE34), Namur (BE35).

5.4 Empirical results from IV regressions

Kovacic et al. (2016) sustain that languages which require a high intensive use of non-indicative moods lead to higher levels of risk aversion and, therefore, to lower involvement in risky behaviors, such as investing in risky assets. Given that Behavioral Risk Factors are risky behaviors related to health, I would like to test the hypothesis that linguistic differences directly affect the individual perception of risk and uncertainty, and indirectly their health behaviors. As a consequence, individuals speaking languages with a high intensive use of non-indicative moods should be more likely to be involved in Behavioral Risk Factors, such as smoking, heavy drinking, less physical activity and being obese. This part of the study includes only Wave 5, given that question related to risk aversion was not available in Wave 2, and the sample is restricted to 15 countries.

In Table 19 and 20 I estimate conditional Logistic model controlling for gender, age, income, education, marital status, and number of children, for both total sample and Linguistically Heterogeneous Countries[26]. All coefficients are reported as odds ratios.

First of all, I consider the effect of “Irrealis” on risk aversion for individuals of the same gender and age, and I find that individuals speaking languages with a high intensive use of non-indicative moods are 36% more likely to be highly risk averse than individuals speaking “moodless” languages[27]. Occupational status controls do not change the effect significantly, and retirement, unemployment, disability and being a homemaker tend to increase risk aversion significantly. Moreover, both owning a house and trusting other people seem to decrease the level of risk aversion and to enlarge the size of the influence of non-indicative moods on risk aversion, in conformity with Kovacic et al. (2016)’s findings. In addition, controlling for health status and cognitive ability does not alter the size or the significance of the coefficient, which reveals that even when including all fixed effects in the regression and after controlling for health and cognitive ability, speakers of a language where non-indicative moods are used more intensively are 57% more likely to show high levels of risk aversion. All these effects do not change significantly when restricting the sample to Linguistically Heterogeneous Countries, as shown in Table 20, even though the inclusion of marital status and number of children fixed-effects in the regression make the coefficient of “Irrealis (IRR)” become less significant. In the same way, being homemaker, owning a house and trusting other people seem to be less significant in Linguistically Heterogeneous Countries than in regressions which consider the total sample.

In order to make accurate predictions about the causal relationship between risk aversion and Behavioral Risk Factors, I need to overcome simultaneity and omitted variables problems. Reverse causality may arise if the number of non-indicative moods influences the level of risk aversion, but *simultaneously* risk aversion impacts on the number of non-indicative moods. The second problem that could arise in the estimation is related to unobservable variables excluded from the model that jointly shape risk aversion, creating a correlation between risk aversion and the error term. On the

[26]Table 23 and 24 replicate Table 9 and 10 in Kovacic, M, Costantini, F., and Bernhofer, J. (2016). Risk attitudes, investment behavior and linguistic variation: an IV approach. *University Ca’ Foscari of Venice, Dpt. of Economics Research Paper Series No. 34/15.*http://ssrn.com/abstract=2708465.

[27]“Languages than do not require non-indicative moods in any *irrealis* context are called “moodless” languages” Kovacic, M, Costantini, F., and Bernhofer, J. (2016).

basis of Kovacic et al. (2016), I estimate the causal relationship between risk aversion and Behavioral Risk Factors through Instrumented Variable approach, using "Irrealis" as an instrument for risk aversion. In the first stage, reported in Table 25, I estimate the effects of socio-economic and linguistic characteristics on individual self-assessed risk aversion. Fitted values from the first stage are plugged in the second stage equation, leading to a reduced model for each Behavioral Risk Factor. The theory suggests an inverse causal relationship between risk aversion and smoking habit (Pfeifer (2012)), heavy drinking (Dave and Saffer (2008)) and obesity (Komlos et al. (2004), Anderson and Mellor (2008)), and a direct causal relationship between risk aversion and exercise (Komlos et al. (2004), Dohmen et al. (2005)). In order to use the number of non-indicative moods as an instrument for risk aversion, IRR needs to be strong and valid. As remarked by Kovacic et al. (2016), "IRR linguistic marker must be correlated with the endogenous variable (instrument relevance), it must be uncorrelated with the error term (independence), and it should not have any direct impact on the probability of *smoking, drinking heavily, exercising and being obese* than through its first stage of impact on risk aversion (exclusion restriction)".

Table 19. Fixed-Effects Logistic regressions. Odds ratios. Discrete "Irrealis" variable. All countries.

Risk Aversion	RA1	RA2	RA3	RA4	RA5
IRR	1.360	1.288	1.293	1.568	1.574
	(0.040)***	(0.060)***	(0.060)***	(0.299)**	(0.300)**
Retired		1.237	1.222	1.401	1.409
		(0.055)***	(0.055)***	(0.156)***	(0.158)***
Unemployed		1.417	1.387	1.241	1.246
		(0.126)***	(0.124)***	(0.257)	(0.258)
Disabled		1.582	1.516	1.656	1.688
		(0.138)***	(0.133)***	(0.344)**	(0.352)**
Homemaker		1.188	1.185	1.325	1.319
		(0.090)**	(0.090)**	(0.225)*	(0.224)*
Owner		0.822	0.836	0.851	0.847
		(0.028)***	(0.283)***	(0.071)*	(0.071)*
Trust			0.921	0.914	0.913
			(0.006)***	(0.014)***	(0.014)***
Cognitive, Health	No	No	No	No	Yes
Fixed Effects:					
Sex x Age	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Income x Education	No	**Yes**	**Yes**	**Yes**	**Yes**
MarStatus x Numchildren	No	No	No	**Yes**	**Yes**
N. Observations	57650	33813	33589	4933	4926
N. Countries	15	15	15	15	15

The dependent variable is "High Risk Aversion". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. Reference categories: No Irrealis Moods, and Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 20. Fixed-Effects Logistic regressions. Odds ratios. Discrete "Irrealis" variable. Linguistically Heterogeneous Countries.

Risk Aversion	RA1	RA2	RA3	RA4	RA5
IRR	1.343	1.237	1.237	1.094	1.102
	(0.041)***	(0.060)***	(0.060)***	(0.285)	(0.287)
Retired		1.267	1.260	1.806	1.798
		(0.112)***	(0.113)**	(0.591)*	(0.588)*
Unemployed		1.1.267	1.253	2.767	2.725
		(0.237)	(0.236)	(1.436)*	(1.414)*
Disabled		1.531	1.467	7.152	7.386
		(0.268)**	(0.257)**	(5.568)**	(5.778)**
Homemaker		0.894	0.0909	1.942	1.865
		(0.127)	(0.129)	(0.849)	(0.818)
Owner		0.771	0.783	1.558	1.535
		(0.060)***	(0.062)***	(0.490)	(0.488)
Trust			0.929	0.990	0.989
			(0.013)***	(0.043)	(0.032)
Cognitive, Health	No	No	No	No	Yes
Fixed Effects:					
Sex x Age	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Income x Education	No	**Yes**	**Yes**	**Yes**	**Yes**
MarStatus x Numchildren	No	No	No	**Yes**	**Yes**
N. Observations	15535	8288	8211	628	627
N. Countries	6	6	6	6	6

The dependent variable is "High Risk Aversion". Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. Reference categories: No Irrealis Moods, and Employed. * significant at 10%; ** significant at 5%; *** significant at 1%.

Results of the first stage of the IV approach (equation [15] reported in chapter 4) estimating the effect of the number of non-indicative moods in *irrealis* contexts (IRR) on risk aversion are reported in Table 21, and test statistics confirm the validity and the strength of the instrument for all Behavioral Risk Factors. First of all, in all specifications, the value of F-statistic is largely higher than the commonly used threshold of 10 or 16, reaching values close to 100 for regressions related to physical activity. Therefore, IRR instrument is highly correlated with the endogenous variable even with the inclusion of additional control variables. Secondly, Sargan test for overidentification presents a value of zero, meaning that the validity of the instrument is exactly identified. Thirdly, exogeneity of the instrument cannot be directly tested, nonetheless there is no reason to believe in a reverse causality of Behavioral Risk Factors on the number of non-indicative moods. Given the high number of controls the instrument should not have any direct impact on Behavioral Risk Factors than through its first stage of impact on risk aversion. Since all the three requirements are satisfied, "Irrealis" linguistic marker can be considered a strong and valid instrument for risk aversion and I can proceed with the second stage.

Table 22 shows the second stage estimates from a recursive bivariate probit model. I adopt this method since dependent variables take on value 1 if the respondent to the Survey smokes at the time of the interview, has drunk two or more drinks in a day in the three months leading up to the interview, declares to practice physical activity, and is obese, and they equal 0 otherwise. All regressions are reported in marginal effects and include control for country and wave fixed-effects in order to capture the institutional and country-specific heterogeneous characteristics. The instrumented risk aversion is strongly significant in all regressions, even though only coefficients for heavy drinking behavior and for obesity are in line with my prediction. Individuals with similar characteristics who differ in the intensity of use of non-indicative moods in *irrealis* contexts tend to reduce heavy drinking episodes by 24% and are 23% less likely to be obese, on average. On the other hand, results for smoking habit and physical activity are in contrast with past literature which predict an inverse relationship between risk aversion and smoking habit and a direct relationship between risk aversion and exercise. While Pfeifer (2012) argues that more risk lover individuals are associated with a higher probability of smoking cigarettes, given that risk takers tend to underestimate the consequences from smoking, my data suggest that risk averse individuals are 34% more likely to be involved in tobacco use. Analogously, for individuals with similar socio-economic characteristics, being highly risk averse reduces the probability of doing physical activity by approximately 30%. In addition, I run separate regressions of Behavioral Risk Factors on Strong FTR, using a Probit model, in order to compare the effect of risk aversion to the effect of individual time preferences. Table 23 shows that all dependent variables are in line with previous results, apart from obesity, but the effect of Strong FTR on weight is confirmed by overweight, as in logistic regressions reported in Table 8. In fact, individuals with similar characteristics who differ in Future Time Reference tend to be more incline to smoking and heavy drinking behaviors by 3% and 7%, respectively, and tend to do less physical activity, both vigorous (16%) and moderate (5%). The effect of Strong FTR seems to be more wide and significant relatively to health. On the other hand, analogously to Kovacic et al. (2016)'s finding relative to a comparison in size of linguistic markers on asset accumulation, the effect of risk aversion on heavy drinking is approximately four times larger than the effect of individual subjective discount rate. All other coefficients are in line with results found with Strong FTR as linguistic marker, apart from the one related to disability which seems to reveal that being disable increases the probability of being obese and the coefficient for female which reveals that females are more likely to be involved in activities which require moderate level of energy and to be obese, in this case. Confirming previous results, young individuals and females tend to maintain healthier lifestyles than aged individuals and males. On the contrary, being more wealthy, owning a house, being married and education induce individuals to be wholesome. Moreover, being retired, unemployed, disabled or homemaker implies a greater probability of being involved in risky behaviors related to health. Finally, trust and life expectancy tend to reduce involvement in smoking habit and alcohol consumption, and to foster exercise in order to contrast or prevent obesity.

As a conclusion, individuals speaking a language with a strongly grammaticalized FTR are more incline to be involved in Behavioral Risk Factor, furthermore, speaking a language with a high number of non-indicative moods in *irrealis* contexts makes individual perceive reality as more uncertainty and increases the level of risk aversion. As a consequence, the higher the risk aversion the more the individual will avoid risky behaviors, such as heavy drinking, contrasting the effect of Future Time Reference.

Table 21. IV regressions: First Stage Estimation and Test Statistics. All countries.

	High RA1 [Current Smoker]	High RA 2 [Heavy Drinking]	High RA 3 [Vigorous Exercise]	High RA 4 [Moderate Exercise]	High RA 5 [Obesity]
IRR	0.230 (0.077)***	-0.023 (0.063)	0.128 (0.032)***	0.057 (0.027)**	-0.149 (0.099)
Age	0.007 (0.002)***	0.003 (0.001)***	0.004 (0.001)***	0.003 (0.001)***	0.001 (0.001)
Female	0.170 (0.025)***	0.100 (0.042)**	0.120 (0.010)***	0.109 (0.009)***	0.082 (0.017)***
Owner	-0.186 (0.041)***	0.008 (0.040)	-0.089 (0.021)***	-0.047 (0.018)**	0.071 (0.058)
Income	0.055 (0.019)***	-0.024 (0.016)	0.013 (0.008)	-0.005 (0.007)	-0.057 (0.025)**
Household size	-0.097 (0.030)***	0.021 (0.020)	-0.028 (0.011)**	-0.005 (0.010)	0.060 (0.032)*
Married	0.035 (0.020)*	0.016 (0.012)	0.026 (0.010)**	0.023 (0.010)**	0.016 (0.013)
High Education	-0.089 (0.022)***	-0.133 (0.017)***	-0.104 (0.012)***	-0.118 (0.011)***	-0.154 (0.021)***
Mother’s High Education	0.071 (0.051)	-0.021 (0.034)	0.030 (0.025)	0.007 (0.024)	-0.050 (0.041)
Father’s High Education	-0.042 (0.027)	-0.032 (0.018)*	-0.043 (0.015)***	-0.045 (0.015)***	-0.056 (0.018)***
Retired	0.040 (0.024)	0.067 (0.014)***	0.052 (0.013)***	0.054 (0.012)***	0.060 (0.015)***
Unemployed	0.122 (0.043)***	0.044 (0.028)	0.090 (0.024)***	0.077 (0.023)***	0.042 (0.032)
Disabled	0.177 (0.043)***	0.077 (0.033)**	0.122 (0.025)***	0.101 (0.024)***	0.039 (0.039)
Homemaker	-0.211 (0.079)***	0.099 (0.043)**	-0.005 (0.028)	0.043 (0.025)*	0.183 (0.071)**
Trust	0.008 (0.008)	-0.021 (0.006)***	-0.008 (0.004)**	-0.015 (0.003)***	-0.035 (0.010)***
Life Expectancy 10 years	0.002 (0.001)	-0.0001 (0.0002)	0.000003 (0.0002)	-0.00009 (0.0002)	-0.0003 (0.0002)
Numeracy score	-0.021 (0.010)**	-0.044 (0.010)***	-0.027 (0.006)***	-0.036 (0.005)***	-0.061 (0.014)***
Country Wave FE	Yes	Yes	Yes	Yes	Yes
N. Observations	5452	8393	11152	11151	10992
N. Countries	18	18	18	18	18
Strong Instrument	27.17	19.72	90.12	118.35	12.03
Endogenous RA	0.0000	0.0000	0.0000	0.0000	0.0000
Overidentification	-	-	-	-	-

The dependent variable is “High Risk Aversion”. The method is ivreg2 (only the first stage estimates reported). Robust standard errors are reported in parentheses. Reference categories: No Irrealis Moods, Male, Not Married, Low Education, and Retired. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 22. IV regressions: Second Stage Estimation. Bivariate Probit, Marginal Effects. All countries.

	Current Smoker (1)	Heavy Drinking (2)	Vigorous Exercise (3)	Moderate Exercise (4)	Obesity (5)
High RA	0.336	-0.239	-0.307	-0.320	-0.226
	(0.038)***	(0.088)***	(0.036)***	(0.026)***	(0.051)***
Retired	-0.014	-0.025	-0.026	0.026	0.059
	(0.015)	(0.016)	(0.012)**	(0.010)***	(0.011)***
Unemployed	0.074	0.017	-0.100	0.001	0.028
	(0.026)***	(0.028)	(0.022)***	(0.019)	(0.020)
Disabled	0.051	0.107	-0.254	-0.123	0.098
	(0.025)**	(0.027)***	(0.024)***	(0.015)***	(0.018)***
Homemaker	-0.004	0.053	-0.061	-0.010	0.057
	(0.024)	(0.021)**	(0.017)***	(0.014)	(0.016)***
Age	-0.014	0.00005	-0.007	-0.004	-0.003
	(0.001)***	(0.0008)	(0.001)***	(0.0004)***	(0.001)***
Female	-0.047	-0.015	-0.012	0.024	0.017
	(0.011)***	(0.017)	(0.010)	(0.008)***	(0.009)*
Owner	-0.071	-0.009	0.021	0.017	-0.011
	(0.011)***	(0.011)	(0.009)**	(0.007)**	(0.008)
Income	0.003	-0.022	0.008	0.001	-0.009
	(0.002)	(0.002)***	(0.002)***	(0.002)	(0.002)***
Household size	0.002	0.010	-0.010	-0.016	0.001
	(0.007)	(0.006)	(0.005)**	(0.004)***	(0.005)
Married	-0.065	-0.028	0.020	0.032	0.006
	(0.013)***	(0.012)**	(0.010)**	(0.008)***	(0.009)
High Education	-0.006	-0.064	0.005	-0.015	-0.081
	(0.015)	(0.017)***	(0.012)	(0.010)	(0.011)***
Mother's High	-0.025	0.051	-0.049	-0.013	-0.024
Education	(0.027)	(0.026)**	(0.022)**	(0.020)	(0.020)
Father's High Education	0.012	-0.089	0.022	0.009	-0.054
	(0.018)	(0.018)***	(0.0150)	(0.013)	(0.014)***
Trust	-0.001	-0.006	0.0002	-0.0002	-0.009
	(0.002)	(0.003)**	(0.0019)	(0.001)	(0.002)***
Life Expectancy 10	-0.001	-0.0004	0.002	0.0008	-0.001
years	(0.0002)***	(0.0002)**	(0.0001)***	(0.0001)***	(0.0001)***
Country Wave FE	Yes	Yes	Yes	Yes	Yes
N. Observations	6839	9480	12558	12557	12369
N. Countries	18	18	18	18	18

The dependent variables are: smoking at present time ("Current Smoker"), having drunk two or more drinks in a day in the three months leading up to the interview ("Heavy Drinking"), "Vigorous Exercise", "Moderate Exercise" and "Obese". The method of estimation is Recursive Bivariate Probit (only second stage estimates reported). Robust standard errors are reported in parentheses. Reference categories: No Irrealis Moods, Male, Not Married, Low Education, and Retired. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 23. Probit Model: Behavioral Risk Factors and Strong FTR, Marginal Effects. All countries.

	Current Smoker (1)	Heavy Drinking (2)	Vigorous Exercise (3)	Moderate Exercise (4)	Obesity (5)
Strong FTR	0.034	0.070	-0.162	-0.050	-0.002
	(0.013)**	(0.012)***	(0.010)***	(0.005)***	(0.008)
Retired	0.012	-0.041	-0.058	0.004	0.047
	(0.017)	(0.015)***	(0.013)***	(0.007)	(0.010)***
Unemployed	0.108	0.004	-0.165	-0.024	0.016
	(0.030)***	(0.029)	(0.025)***	(0.013)*	(0.019)
Disabled	0.099	0.094	-0.378	-0.125	0.084
	(0.028)***	(0.028)***	(0.025)***	(0.010)***	(0.018)***
Homemaker	0.009	0.038	-0.101	-0.028	0.043
	(0.028)	(0.021)*	(0.019)***	(0.009)***	(0.015)***
Age	-0.016	-0.001	-0.010	-0.0044	-0.003
	(0.001)***	(0.001)	(0.001)***	(0.0002)***	(0.001)***
Female	-0.014	-0.046	-0.064	-0.012	-0.005
	(0.012)	(0.011)***	(0.009)***	(0.004)**	(0.007)
Owner	-0.092	-0.029	0.056	0.019	-0.016
	(0.013)***	(0.012)**	(0.011)***	(0.005)***	(0.008)*
Income	-0.006	-0.012	0.005	0.003	-0.004
	(0.003)**	(0.002)***	(0.002)**	(0.001)***	(0.002)***
Household size	0.003	-0.003	-0.004	-0.012	-0.003
	(0.008)	(0.006)	(0.006)	(0.003)***	(0.005)
Married	-0.072	-0.035	0.023	0.025	0.005
	(0.015)***	(0.013)***	(0.011)	(0.006)***	(0.009)
High Education	-0.065	-0.037	0.060	0.030	-0.052
	(0.015)***	(0.013)***	(0.012)***	(0.007)***	(0.009)***
Mother’s High Education	-0.049	0.063	-0.042	0.001	-0.026
	(0.031)	(0.028)**	(0.025)*	(0.014)	(0.020)
Father’s High Education	0.003	-0.088	0.034	0.014	-0.045
	(0.021)	(0.019)***	(0.017)**	(0.009)	(0.014)***
Trust	-0.010	-0.00002	0.004	0.003	-0.005
	(0.002)***	(0.00210)	(0.002)*	(0.001)***	(0.001)***
Life Expectancy 10 years	-0.001	-0.0004	0.0021	0.0006	-0.0006
	(0.0002)***	(0.0001)**	(0.0001)***	(0.0001)***	(0.0001)***
Country Wave FE	Yes	Yes	Yes	Yes	Yes
N. Observations	7162	9922	13144	13143	12942
N. Countries	18	18	18	18	18

The dependent variables are: smoking at present time (“Current Smoker”), having drunk two or more drinks in a day in the three months leading up to the interview (“Heavy Drinking”), “Vigorous Exercise”, “Moderate Exercise” and “Obese”. The method of estimation is Probit. Robust standard errors are reported in parentheses. Reference categories: No Irrealis Moods, Male, Not Married, Low Education, and Retired. * significant at 10%; ** significant at 5%; *** significant at 1%.

6. Conclusions

The idea that the language we speak affects our choices dates back to the early twentieth century, when Sapir-Whorf hypothesis of linguistic relativity arose, maintaining that the native language has a strong impact on the way people think and that certain thoughts of individuals cannot be fully understood by individuals who speak a different language. In fact, given the difference in semantic expressions related to colors and spatial cognition, speakers of different languages select the categories across the continuum of the spectrum in different ways and show cognitive performance on spatial memory tasks. Analogously, grammatical characteristics such as distinction between present and future tenses and the use of non-indicative moods in *irrealis* contexts tend to affect choices about savings, smoking, drinking, exercise, weight and dietary pattern, as well as attitude toward immigration.

By means of Strong FTR (Chen (2013)) and "Irrealis (IRR)" (Kovacic et al. (2016)) linguistic markers this thesis analyzes the effects of linguistic features on Behavioral Risk Factors, testing the hypothesis that speaking languages characterized by a Strong FTR and an intensive use of non-indicative moods in *irrealis* contexts might affect health behaviors in a negative way. On the one hand, speaking a language which strongly distinguish between present and future makes individuals perceive the future as more distant than "futureless" languages and foster the involvement in risky behaviors related to health. On the other hand, speaking a language which uses a high number of non-indicative moods in *irrealis* contexts makes individuals perceive the world as more mutable and uncertain inducing higher levels of risk aversion and, as a consequence, the avoidance of risky behaviors related to health.

The association between linguistic markers and Behavioral Risk Factors seems to be very robust. Data from Wave 2 and Wave 5 of the Survey of Health, Ageing and Retirement in Europe (SHARE) (release 5.0.0) analyzed through Logistic regression with demographic and socio-economic controls for gender, age, occupational and marital status, household size, education, parents' education, household's income level, the number of children and life expectancy, show that individuals speaking a language with strongly grammaticalized FTR (Strong FTR) are 18% more likely to be involved in smoking behavior, 36% more likely to drink two or more drinks in a day, 50% less likely to do vigorous exercise and 48% less likely to do moderate exercise, and 14% more likely to be overweight. Moreover, restricting the sample to Linguistically Heterogeneous Countries, including Belgium, Estonia, Israel, Luxembourg, Spain and Switzerland, does not alter the results significantly. In fact, living in countries with the same institutions and similar characteristics, where individuals only differ for the language they speak induce individuals speaking a strong-FTR language to be 24% more likely to smoke, 48% more likely to drink heavily, 30% less likely to practice sports or do activities requiring vigorous exercise, and 32% less likely to consume fruit and vegetables every day.

In order to make accurate predictions about the causal relationship between Future Time Reference and Behavioral Risk Factors, I adopted Fixed-Effects (or Conditional) Logistic models, controlling for age, gender, income, education, marital status, and number of children, to allow comparisons between individuals with similar demographic and socioeconomic characteristics, who only differ in the language they speak. Through these models, I found that individuals with identical features apart from speaking a language with Strong FTR have, respectively, a 13% and a 33% higher probability of being involved in smoking and drinking habit, a 92% and 40% lower probability of practicing vigorous and moderate activities, and a 9% higher probability of being obese. These effects are confirmed for heavy drinking and obesity, in the total sample, and for moderate exercise, in the Linguistically Heterogeneous Countries, when adding controls for occupational status, trust, life expectancy and Social Security Wealth. Moreover, it is remarkable that trust, life expectancy and Social Security Wealth affect Behavioral Risk Factors positively, hindering smoking habit, alcohol consumption, and obesity, and fostering physical activity. Furthermore, the relationship between Strong FTR and Behavioral Risk Factors is confirmed within-country in Luxembourg, Estonia, Switzerland and Belgium and when considering sub-regions fixed-effects, in the cases of Switzerland and Belgium, excluding any influence that might be connected to institutions.

In order to analyze the effect of risk aversion on Behavioral Risk Factors, using the number of non-indicative moods used in *irrealis* contexts as an instrument, I adopted an Instrumental Variables (IV) approach. “Irrealis (IRR)” is found to be a valid and significant instrument for risk aversion, and individuals with similar characteristics who differ in the intensity of use of non-indicative moods in *irrealis* contexts, proxying for risk aversion, tend to reduce heavy drinking episodes by 24% and to be 23% less likely to be obese, on average. However, risk averse individuals are 34% more likely to be involved in tobacco use and 30% less likely to do physical activity. In contrast to Kovacic et al. (2016)’s finding on asset accumulation, according to which the effect of risk aversion on the probability of investing in risky assets is almost three times larger than the effect of Strong FTR linguistic marker, in the case of Behavioral Risk Factors the effect of risk aversion on health is approximately four times larger than the effect of individual subjective discount rate only for heavy drinking.

As a conclusion, the results obtained in this thesis support the effect of language on behavioral and socio-economic choices, suggesting the importance of language as a predictor of people’s behavior, not only relatively to savings, retirement assets, and immigration, but also to Behavioral Risk Factors, and that effect of Strong FTR linguistic marker on the probability of smoking, drinking, exercising and being obese seems to be wider and more significant with respect to the linguistic marker based on the number of non-indicative moods.

7. Appendices

The appendices provide some deeper aspects about the concepts discussed in the thesis. In particular, Appendix A shows linguistic mapping according to Weak/Strong FTR (or prediction FTR) used in Chen (2013) and in the first part of the thesis and according to the number of non-indicative moods used in Kovacic et al. (2016) and in the second part of the thesis. Moreover, it provides regressions on Behavioral Risk Factors used as robustness check. In Appendix B, I report the expressions of questions on Behavioral Risk Factors submitted to respondents from SHARE Survey. Finally, in Appendix C some mathematical expressions related to Life-Cycle hypothesis and individuals' saving behavior are reported.

7.1 Appendix A: Linguistic markers and Data

This appendix reports Strong FTR (Appendix Table 1) and "Irrealis (IRR)" (Appendix Table 2) linguistic markers by country, used for the construction of the dataset. Moreover, it provides robustness checks to the regressions in Chapter 5 concerning Behavioral Risk Factors, and providing evidence that speaking a language with a strong FTR decreases the probability of quitting smoking (Appendix Table 3), rises the probability of drinking more than once or twice a week (Appendix Table 4) , it increases the probability of drinking four or more drinks at one occasion for Wave 2 and six or more drinks at one occasion for Wave 5 (Appendix Table 5), the probability of being physically inactive, measured by *phactive* generated variable (Appendix Table 6) as well as the probability of being obese (Appendix Table 7).

Furthermore, I report Appendix Table 8 which reveals that speaking a language with a strong FTR seems to reduce the probability of being overweight and confirms that the effect of Strong FTR on obesity is less strong than in Chen (2013) and is not significant after the inclusion of income, education, marital status, and number of children fixed-effects in Table 13. Therefore, the impact of Strong FTR on weight is not clear.

Finally, Appendix Table 9 and 10 report fixed-Effects Logistic regressions using a categorized version of the "Irrealis" variable, for all countries and for Linguistically Heterogeneous Countries, respectively. In both cases, the effect of non-indicative moods on risk aversion become smaller and not significant with respect to using a discrete version of the "Irrealis" variable, as in Table 19 and 20. Appendix Table 11 report the second stage of the IV approach using a categorized version of the "Irrealis" variable, for all countries. The signs of coefficients are in line with the ones of regressions using a discrete version of the "Irrealis" variable reported in Table 22, even though significant only for heavy drinking, at 1% level, and moderate exercise, at 10% level.

Appendix Table 1. Linguistic mapping according to Online Future Time Reference (FTR) ratios

Language	Prediction FTR	Inflectional FTR	Any FTR
Catalan	Strong	Strong	Strong
Hebrew	Strong	Strong	Strong
Greek	Strong	Weak	Strong
French	Strong	Strong	Strong
Slovenian	Strong	Weak	Strong
English	Strong	Weak	Strong
Italian	Strong	Strong	Strong
Russian	Strong	Weak	Strong
Spanish	Strong	Strong	Strong
Czech	Strong	Weak	Strong
Arabic	Strong	Strong	Strong
Polish	Strong	Weak	Strong
Danish	Weak	Weak	Strong
Swedish	Weak	Weak	Strong
Dutch	Weak	Weak	Strong
Estonian	Weak	Weak	Weak
German	Weak	Weak	Strong
Flemish	Weak	Weak	Strong

Source: Chen, M. K. (2013). The effect of Language on Economic Behavior: Evidence from Savings Rates, Health Behaviors, and Retirement Assets. *American Economic Review*, 103(2):690-731 (Appendix B, Table 1, page. 40). "Languages_Data_File.dta". Note: Prediction FTR is used in this thesis.

Appendix Table 2. Linguistic mapping according to the number of non-indicative moods (IRR marker)

Language	Family	Sub-Family	a	b	c	d	e	f	g	Number of non-indicative moods
Arabic	Semitic	-	1	1	1	1	0	0	0	4
Catalan	Indo-Euro	Romance	1	1	0	0	0	1	0	3
Czech	Indo-Euro	Slavic	1	1	0	0	0	1	1	4
Danish	Indo-Euro	Germanic	0	0	0	0	0	0	0	0
Dutch	Indo-Euro	Germanic	0	0	0	0	0	1	1	2
English	Indo-Euro	Germanic	0	0	0	0	0	0	0	0
Estonian	Indo-Euro	Finno-Ugric	0	1	0	0	0	1	1	3
French	Indo-Euro	Romance	1	1	0	1	0	0	0	3
German	Indo-Euro	Germanic	0	0	0	0	0	1	1	2
Greek	Indo-Euro	-	0	1	0	0	0	0	1	2
Hebrew	Semitic	-	0	0	0	0	0	0	0	0
Italian	Indo-Euro	Romance	1	1	1	1	0	1	1	6
Polish	Indo-Euro	Slavic	1	1	0	0	0	1	1	4
Russian	Indo-Euro	Slavic	1	1	0	0	0	1	1	4
Slovenian	Indo-Euro	Slavic	0	1	0	0	0	1	1	3
Spanish	Indo-Euro	Romance	1	1	0	1	0	1	0	4
Swedish	Indo-Euro	Germanic	0	0	0	0	0	0	0	0

Source: Kovacic, M, Costantini, F., and Bernhofer, J. (2016). Risk attitudes, investment behavior and linguistic variation: an IV approach. *University Ca' Foscari of Venice, Dpt. of Economics Research Paper Series No. 34/15* (Appendix A, Table 3, page. 31).

Appendix Table 3. Logistic regressions of quitting smoking on Strong FTR. All countries. Robustness check.

Quit Smoking	QS 1	QS 2	QS 3
Strong FTR	0.509	0.510	0.574
	(0.115)***	(0.115)***	(0.185)*
Age		0.996	0.997
		(0.012)	(0.018)
Female		0.882	0.735
		(0.196)	(0.238)
High Education			0.770
			(0.320)
Mother's High Education			2.203
			(2.371)
Father's High Education			1.318
			(0.870)
Income			1.098
			(0.067)
Owner			0.872
			(0.312)
N. Observations	1433	1433	638
N. Countries	18	18	18

Regressions are logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 4. Logistic regressions of frequency of drinking alcohol on Strong FTR. All countries. Robustness check.

Frequency Drinking	FD 1	FD 2	FD 3	FD 4	FD 5
Strong FTR	0.837	0.839	1.286	1.144	1.144
	(0.012)***	(0.012)***	(0.032)***	(0.051)***	(0.051)***
Age		0.995	1.005	1.004	0.995
		(0.001)***	(0.001)***	(0.002)*	(0.003)*
Female		0.330	0.333	0.328	0.334
		(0.005)***	(0.008)***	(0.013)***	(0.014)***
High Education			1.313	1.447	1.449
			(0.037)***	(0.068)***	(0.068)***
Mother's High Education			0.960	1.040	1.051
			(0.057)	(0.104)	(1.451)
Father's High Education			1.383	1.445	1.451
			(0.056)***	(0.098)***	(0.098)***
Income			1.127	1.072	1.078
			(0.005)***	(0.009)***	(0.009)***
Owner			1.001	1.098	1.098
			(0.027)	(0.052)**	(0.052)*
Married				1.207	1.167
				(0.059)***	(0.058)***
Number of children				0.965	0.965
				(0.015)**	(0.149)**
Household size				0.904	0.919
				(0.023)***	(0.024)***
Retired					1.378
					(0.079)***
Unemployed					1.363
					(0.148)***
Disabled					0.847
					(0.098)
Homemaker					1.079
					(0.103)
N. Observations	97512	97503	41255	14476	14470
N. Countries	18	18	18	18	18

Regressions are logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 5. Logistic regressions of frequency of heavy drinking on Strong FTR. All countries. Robustness check.

Frequency Heavy Drinking	4 drinks (1)	6 drinks (1)	6 drinks (2)	6 drinks (3)	6 drinks (4)	6 drinks (5)
Strong FTR	1.033	1.393	1.344	1.164	1.888	1.907
	(0.093)	(0.070)***	(0.068)***	(0.077)**	(0.221)***	(0.224)***
Age			0.990	0.989	0.986	0.991
			(0.003)***	(0.003)***	(0.006)**	(0.008)
Female			0.370	0.310	0.325	0.337
			(0.021)***	(0.022)***	(0.038)***	(0.041)***
High Education				0.847	0.931	0.935
				(0.068)**	(0.123)	(0.123)
Mother's High Education				1.019	0.854	0.865
				(0.175)	(0.262)	(0.266)
Father's High Education				1.042	1.123	1.119
				(0.120)	(0.214)	(0.213)
Income				0.906	0.885	0.890
				(0.011)***	(0.019)***	(0.020)***
Owner				0.842	0.763	0.783
				(0.059)***	(0.091)**	(0.094)**
Married					1.096	1.115
					(0.144)	(0.148)
Number of children					0.902	0.903
					(0.040)**	(0.040)**
Household size					0.880	0.879
					(0.063)*	(0.064)*
Retired						0.948
						(0.147)
Unemployed						1.548
						(0.334)**
Disabled						1.33
						(0.310)
Homemaker						0.783
						(0.274)
N. Observations	22887	42443	42436	28060	10252	10247
N. Countries	15	15	15	15	15	15

Regressions are logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Note: 15 countries in total given that question on frequency of drinking 4 or more drinks was available only for Wave 2 (15 countries) and question on frequency of drinking 6 or more drinks was available only for Wave 5 (15 countries).

Appendix Table 6. Logistic regressions of phisical inactivity on Strong FTR. All countries. Robustness check.

Physical Inactivity (phactive)	PI 1	PI 2	PI 3
Strong FTR	1.563	1.568	1.489
	(0.407)*	(0.408)*	(0.874)
Age		0.996	0.983
		(0.012)	(0.026)
Female		0.764	1.267
		(0.202)	(0.687)
High Education			1.813
			(1.413)
Income			0.864
			(0.091)
Owner			0.739
			(0.492)
N. Observations	98057	98048	36586
N. Countries	18	18	18

Regressions are logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Note: mother's level of education and father's level of education omitted.

Appendix Table 7. Logistic regressions of obesity on Strong FTR. All countries. Robustness check.

Obese	OB 1	OB 2	OB 3
Strong FTR	1.171	1.171	0.968
	(0.019)***	(0.993)***	(0.025)
Age		0.993	0.985
		(0.008)***	(0.001)***
Female		1.076	1.050
		(0.018)***	(0.027)**
High Education			0.678
			(0.023)***
Mother's High Education			0.951
			(0.070)
Father's High Education			0.744
			(0.038)***
Income			0.928
			(0.004)***
Owner			0.914
			(0.026)***
N. Observations	95084	95075	40262
N. Countries	18	18	18

Regressions are logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 8. Fixed-Effects Logistic regression of being overweight on Strong FTR. All countries.

	OW 1	OW 2	OW 3	OW 4
Strong FTR	0.871	0.887	0.914	0.963
	[0.027]***	[0.023]***	[0.019]***	[0.043]
Fixed Effects:				
Age x sex	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**
Income	No	**Yes**	**Yes**	**Yes**
Education	No	No	**Yes**	**Yes**
Married x Numchildren	No	No	No	**Yes**
All FE Interacted	Yes	Yes	Yes	Yes
N. Observations	90052	94155	90272	20830
N. Countries	18	18	18	18

Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 9. Fixed-Effects Logistic regressions. Odds ratios. Categorized "Irrealis" variable. All countries.

Risk Aversion	RA1	RA2	RA3	RA4	RA5
CatIRR1	1.022	1.043	0.977	1.363	1.369
	(0.061)	(0.085)	(0.080)	(0.380)	(0.382)
CatIRR2	1.948	1.557	1.498	1.457	1.471
	(0.162)***	(0.196)***	(0.189)***	(0.545)	(0.550)
Retired		1.242	1.227	1.386	1.395
		(0.054)***	(0.054)***	(0.154)***	(0.155)***
Unemployed		1.411	1.382	1.247	1.252
		(0.122)***	(0.120)***	(0.250)	(0.251)
Disabled		1.616	1.548	1.661	1.693
		(0.136)***	(0.131)***	(0.338)**	(0.346)**
Homemaker		1.208	1.204	1.280	1.276
		(0.088)***	(0.088)**	(0.211)	(0.211)
Owner		0.810	0.824	0.845	0.841
		(0.027)***	(0.027)***	(0.070)**	(0.069)**
Trust			0.922	0.911	0.910
			(0.006)***	(0.014)***	(0.011)
Cognitive, Health	No	No	No	No	Yes
Fixed Effects:					
Sex x Age	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Income x Education	No	**Yes**	**Yes**	**Yes**	**Yes**
MarStatus x numchildren	No	No	No	**Yes**	**Yes**
N. Observations	60304	35469	35239	5087	5080
N. Countries	15	15	15	15	15

Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 10. Fixed-Effects Logistic regressions. Odds ratios. Categorized "Irrealis" variable. Linguistically Heterogeneous Countries.

Risk Aversion	RA1	RA2	RA3	RA4	RA5
CatIRR1	1.004	1.036	0.979	1.386	1.395
	(0.062)	(0.085)	(0.081)	(0.392)	(0.394)
CatIRR2	2.092	1.524	1.475	1.396	1.416
	(0.203)***	(0.104)***	(0.217)***	(0.541)	(0.549)
Retired		1.279	1.274	1.576	1.579
		(0.104)***	(0.104)***	(0.483)	(0.485)
Unemployed		1.286	1.273	2.237	2.212
		(0.214)	(0.213)	(0.968)*	(0.957)*
Disabled		1.646	1.577	4.510	4.699
		(0.253)***	(0.243)***	(2.842)**	(2.979)**
Homemaker		1.011	1.026	1.509	1.472
		(0.127)	(0.129)	(0.563)	(0.549)
Owner		0.727	0.741	1.221	1.214
		(0.052)***	(0.054)***	(0.328)	(0.330)
Trust			0.931	0.942	0.943
			(0.012)***	(0.037)	(0.029)
Cognitive, Health	No	No	No	No	Yes
Fixed Effects:					
Sex x Age	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Country x Wave	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Income x Education	No	**Yes**	**Yes**	**Yes**	**Yes**
MarStatus x numchildren	No	No	No	**Yes**	**Yes**
N. Observations	18189	9944	9861	782	781
N. Countries	6	6	6	6	6

Regressions are fixed-effects (or conditional) logistic regressions with coefficients reported as Odds ratios. The linguistic marker is Strong FTR. Robust standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 11. IV regressions: Second Stage Estimation. Bivariate Probit, Marginal Effects. Categorized "Irrealis" variable. All countries.

	Current Smoker (1)	Heavy Drinking (2)	Vigorous Exercise (3)	Moderate Exercise (4)	Obesity (5)
High RA	0.068	-0.324	-0.015	-0.090	0.010
	(0.051)	(0.038)***	(0.046)	(0.048)*	(0.042)
Retired	0.015	-0.012	-0.042	0.011	0.030
	(0.017)	(0.014)	(0.012)***	(0.009)	(0.011)***
Unemployed	0.010	0.022	-0.133	-0.016	0.007
	(0.028)***	(0.026)	(0.023)***	(0.016)	(0.020)
Disabled	0.108	0.119	-0.300	-0.132	0.052
	(0.027)***	(0.025)***	(0.022)***	(0.012)***	(0.019)***
Homemaker	0.016	0.062	-0.091	-0.028	0.035
	(0.026)	(0.020)***	(0.018)***	(0.011)**	(0.016)**
Age	-0.015	0.001	-0.008	-0.005	-0.003
	(0.001)***	(0.001)	(0.006)***	(0.0003)***	(0.001)***
Female	-0.021	-0.002	-0.050	-0.003	-0.006
	(0.012)*	(0.012)	(0.010)***	(0.007)	(0.009)
Owner	-0.078	-0.010	0.017	0.009	-0.010
	(0.012)***	(0.010)	(0.002)*	(0.006)	(0.008)
Income	-0.005	-0.023	0.017	0.007	-0.005
	(0.003)	(0.002)***	(0.002)***	(0.001)***	(0.002)***
Household size	0.005	0.010	-0.017	-0.017	0.001
	(0.007)	(0.006)*	(0.005)***	(0.003)***	(0.005)
Married	-0.070	-0.025	0.018	0.026	0.003
	(0.014)***	(0.012)**	(0.010)*	(0.007)***	(0.009)
High Education	-0.054	-0.075	0.053	0.019	-0.053
	(0.016)***	(0.013)***	(0.012)***	(0.010)**	(0.011)***
Mother's High Education	-0.047	0.045	-0.048	-0.010	-0.017
	(0.029)	(0.025)*	(0.022)**	(0.017)	(0.020)
Father's High Education	0.00009	-0.087	0.040	0.020	-0.045
	(0.019)	(0.017)***	(0.016)**	(0.011)*	(0.014)***
Trust	-0.008	-0.008	0.007	0.004	-0.004
	(0.002)***	(0.002)***	(0.002)***	(0.001)***	(0.002)**
Life Expectancy 10 years	-0.001	-0.0004	0.002	0.001	-0.0005
	(0.0002)***	(0.0002)**	(0.0001)***	(0.00009)***	(0.0001)***
Country Wave FE	Yes	Yes	Yes	Yes	Yes
N. Observations	6839	9480	12558	12557	12369
N. Countries	18	18	18	18	18

The dependent variables are: smoking at present time ("Current Smoker"), having drunk two or more drinks in a day in the three months leading up to the interview ("Heavy Drinking"), "Vigorous Exercise", "Moderate Exercise" and "Obese". The method of estimation is Recursive Bivariate Probit (only second stage estimates reported). Robust standard errors are reported in parentheses. Reference categories: Male, Not Married, Low Education, and Retired. * significant at 10%; ** significant at 5%; *** significant at 1%.

7.2 Appendix B: SHARE Survey on Behavioral Risk Factors

This appendix reports the expressions of questions related to Behavioral Risk Factors submitted to respondents from SHARE Survey, which are identical for Wave 2 and Wave 5, except for the question about the frequency of episodes of heavy drinking, given the different number of drinks considered as threshold.

<u>Smoking</u>

Ever Smoked Daily (BR001_)

The following questions are about smoking and drinking alcoholic beverages. Have you ever smoked cigarettes, cigars, cigarillos or a pipe daily for a period of at least one year?

1. Yes
2. No

Still Smoking (BR002_)

Do you smoke at the present time?

1. Yes
2. No

Stopped Smoking (BR022_)

Have you stopped smoking since we interviewed you?

1. Yes, I stopped after last interview
2. No, I did not smoke by last interview
3. No, I still smoke nowadays

How Many Years Smoked (BR003_)

For how many years have you smoked all together?

IWER:
Don't include periods without smoking
Code 1 if respondent smoked for less than one year

<u>Drinking</u>

Drinks In A Day (BR019_)

In the last three months, on the days you drank, about how many drinks do you have?

IWER:
As a rule of thumb, you can estimate that one drink is: 1 bottle/can of beer=33cl, 1 glass table wine=12cl, 1 glass fortified wine=8cl, and 1 glass spirits=4cl

Alcoholic Beverages Last Three Months (BR010_)

During the last 3 months, how often have you drunk any alcoholic beverages, like beer, cider, wine, spirits or cocktails?

1. Daily or almost daily
2. Five or six days a week
3. Three or four days a week
4. Once or twice a week
5. Once or twice a month
6. Less than once a month
7. Not at all in the last 3 months

Four or More Drinks (BR020_, Wave 2)

In the last three months, on how many days have you had four or more drinks on one occasion?

Six Or More Drinks (BR023_, Wave 5)

In the last three months, how often did you have six or more drinks on one occasion?
(As a rule of thumb, you can estimate that one drink is: 1 bottle/can of beer=33cl, 1 glass table wine=12cl, 1 glass fortified wine=8cl, and 1 glass spirits=4cl)

1. Daily or almost daily
2. Five or six days a week
3. Three or four days a week
4. Once or twice a week
5. Once or twice a month
6. Less than once a month
7. Not at all in the last 3 months

Ever Drunk Alcoholic Beverages (BR021_)

Have you ever drunk alcoholic beverages?

1. Yes
2. No

<u>Physical Activity</u>

Sports or activities that are vigorous (BR015_)

We would like to know about the type and amount of physical activity you do in your daily life. How often do you engage in vigorous physical activity, such as sports, heavy housework , or a job that involves physical labour?

1. More than once a week
2. Once a week
3. One to three times a month
4. Hardly ever, or never

Moderate Sports or Activities (BR016_)

How often do you engage in activities that require a moderate level of energy such as gardening, cleaning the car, or doing a walk ?

1. More than once a week
2. Once a week
3. One to three times a month
4. Hardly ever, or never

Consumption of fruit and vegetables

Fruits and Vegetables per Week (BR029_)

In a regular week , how often do you consume a serving of fruits or vegetables?

1. Every day
2. 3-6 times a week
3. Twice a week
4. Once a week
5. Less than once a week

7.2 Appendix C: Life Cycle Hypothesis

This appendix provides some mathematical expressions related to the derivation of Euler equation [6] obtained when including habits in the consumer's problem, as in paragraph 2.4.3, and shows the consumer's problem when introducing uncertainty about the duration of life and bequests in the Life-Cycle Model, as in paragraph 2.4.4.

7.3.1 Habits

We consider the following consumer's problem, with uncertainty about income and infinite planning horizon:

$$\max E_t \sum_{\tau=0}^{\infty} (1+\delta)^{-\tau} u(C_{t+\tau}, C_{t+\tau-1})$$

$$\text{s.t. } a_{t+1} = (1+r)(a_t + y_t - C_t)$$

which leads to the following Value Function:

$$V_t(a_t, C_{t-1}) = \max_{a_{t+1}, C_t} u(C_t, C_{t-1}) + \frac{1}{1+\delta} E_t V_{t+1}(a_{t+1}, C_t)$$

Given the first order condition [A1] and the Value Function which considers $C_t^{\,*}(a_t, C_{t-1})$ as the optimal solution of the consumer's problem [A2]:

$$\frac{\partial u}{\partial C_t} - \frac{1}{1+\delta}(1+r)E_t \frac{\partial V_{t+1}}{\partial a_{t+1}} + \frac{1}{1+\delta}\frac{\partial V_{t+1}}{\partial C_t} = 0 \qquad \text{[A1]}$$

$$V_t(a_t, C_{t-1}) =$$

$$= u\,[C_t^{\,*}(a_t, C_{t-1}), C_{t-1}] + \frac{1}{1+\delta} E_t V_{t+1}\{(1+r)[a_t + y_t - C_t^{\,*}(a_t, C_{t-1})], [C_t^{\,*}(a_t, C_{t-1})]\} \qquad \text{[A2]}$$

Deriving [A2] with respect to a_t and using [A1] leads to the following expression:

$$\frac{\partial V_t}{\partial a_t} = \frac{\partial u_t}{\partial C_t^{\,*}}\frac{\partial C_t^{\,*}}{\partial a_t} + \frac{1+r}{1+\delta} E_t \frac{\partial V_{t+1}}{\partial a_{t+1}} - \frac{1}{1+\delta}(1+r)E_t \frac{\partial V_{t+1}}{\partial a_{t+1}}\frac{\partial C_t^{\,*}}{\partial a_t} + \frac{1}{1+\delta}\frac{\partial V_{t+1}}{\partial C_t^{\,*}}\frac{\partial C_t^{\,*}}{\partial a_t}$$

$$\frac{\partial V_t}{\partial a_t} = \frac{\partial C_t^{\,*}}{\partial a_t}\left[\frac{\partial u_t}{\partial C_t^{\,*}} - \frac{1}{1+\delta}(1+r)E_t \frac{\partial V_{t+1}}{\partial a_{t+1}} + \frac{1}{1+\delta}\frac{\partial V_{t+1}}{\partial C_t^{\,*}}\right] + \frac{1+r}{1+\delta} E_t \frac{\partial V_{t+1}}{\partial a_{t+1}}$$

Given the first order condition [A1], the first component of the right side is equal to zero and therefore:

$$\frac{\partial V_{t+1}}{\partial a_t} = \frac{1+r}{1+\delta} E_t \frac{\partial V_{t+1}}{\partial a_{t+1}} \qquad \text{[A3]}$$

Deriving [A2] with respect to $C_{t-1}$and using [A1] leads to the following expression:

$$\frac{\partial V_t}{\partial C_{t-1}} = \frac{\partial u_t}{\partial C_t{}^*}\frac{\partial C_t{}^*}{\partial C_{t-1}} + \frac{\partial u_t}{\partial C_{t-1}} - \frac{1}{1+\delta}(1+r)E_t\frac{\partial V_{t+1}}{\partial a_{t+1}}\frac{\partial C_t{}^*}{\partial C_{t-1}} + \frac{1}{1+\delta}\frac{\partial V_{t+1}}{\partial C_t{}^*}\frac{\partial C_t{}^*}{\partial C_{t-1}}$$

$$\frac{\partial V_t}{\partial C_{t-1}} = \frac{\partial C_t{}^*}{\partial C_{t-1}}\left[\frac{\partial u_t}{\partial C_t{}^*} - \frac{1}{1+\delta}(1+r)E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} + \frac{1}{1+\delta}\frac{\partial V_{t+1}}{\partial C_t{}^*}\right] + \frac{\partial u_t}{\partial C_{t-1}}$$

Given the first order condition [A1], the first component of the right side is equal to zero and therefore:

$$\frac{\partial V_t}{\partial C_{t-1}} = \frac{\partial u_t}{\partial C_{t-1}} \qquad \text{[A4]}$$

Using [A4] we can rewrite the first order condition as:

$$\frac{\partial u_t}{\partial C_t} + \frac{1}{1+\delta}\frac{\partial u_{t+1}}{\partial C_t} = \frac{1}{1+\delta}(1+r)E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} \qquad \text{[A5]}$$

and, using [A3], as:

$$\frac{\partial u_t}{\partial C_t} + \frac{1}{1+\delta}\frac{\partial u_{t+1}}{\partial C_t} = \frac{\partial V_t}{\partial a_t} \qquad \text{[A6]}$$

Moving [A6] to time t+1 and using the law of iterated expectation at period t leads to:

$$E_t\frac{\partial u_{t+1}}{\partial C_{t+1}} + \frac{1}{1+\delta}E_t\frac{\partial u_{t+2}}{\partial C_{t+1}} = E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} \qquad \text{[A7]}$$

and multiplying both sides of [A7] by $(1+r)(1+\delta)^{-1}$:

$$\frac{1+r}{1+\delta}\left[E_t\frac{\partial u_{t+1}}{\partial C_{t+1}} + \frac{1}{1+\delta}E_t\frac{\partial u_{t+2}}{\partial C_{t+1}}\right] = \frac{1+r}{1+\delta}E_t\frac{\partial V_{t+1}}{\partial a_{t+1}} \qquad \text{[A8]}$$

Finally, given that the right sides of equation [A5] and [A8] are equal, the Euler equation which takes into account of habits of consumption is the following:

$$\frac{\partial u_t}{\partial C_t} - \frac{1}{1+\delta}E_t\frac{\partial u_{t+1}}{\partial C_t} = \frac{1+r}{1+\delta}\left[E_t\left(\frac{\partial u_{t+1}}{\partial C_{t+1}} + \frac{1}{1+\delta}\frac{\partial u_{t+2}}{\partial C_{t+1}}\right)\right] \qquad \text{[A9]}$$

7.3.2 Uncertainty about the duration of life

Supposing a multi-period model and the time frame [0,T], where T represents the oldest reachable age. The expected life of an individual who plans their consumption at time t is represented by the formula:

$$V = \int_0^T p(t|0)dt$$

Where $p(t|0)$ indicates the probability of surviving until age t conditional to the fact of having reached age 0.

The consumer's problem, with the introduction of uncertainty, becomes:

$$\max_{C_t} \int_0^T p(t|0)u(C_t)e^{-\delta t}\,dt$$

$$\text{s.t. } \dot{a}_t = ra_t + y_t - c_t$$

$$a_t \geq 0$$

$$a_T = 0$$

The Hamilton's function of the problem is:

$$H_t = p(t|0)u(C_t)e^{-\delta t} + \mu_t(ra_t + y_t - c_t)$$

With the following maximization condition:

(i) $p(t|0)u'(C_t)e^{-\delta t} = \mu_t$

(ii) $\mu_t r = -\dot{\mu}_t$

Taking the logarithm of (i), deriving with respect of time (t) and substituting the result in (ii) we obtain the following expression for the growth rate of consumption:

$$\frac{\dot{C}_t}{C_t} = -\frac{u'(C_t)}{u''(C_t)C_t}\left[r - \delta + \dot{p(t)}\right] = ESI[r - \delta - m(t)]$$

where: ESI = $-\frac{u'(C_t)}{u''(C_t)C_t}$ is the inter-temporal elasticity of substitution in consumption

$m(t)$ is the instantaneous mortality rate.

The second equation is due to the relationship between surviving function and mortality function, $m(t) = \frac{d(1-p(t))}{dt}$.

7.3.3 Bequests as a reason for saving

Considering the bequests as a constraint, the so-called *joy of giving*, leads to the same consumer's problem as in the Life Cycle Model (with r = δ):

$$max_{Co,c1,\dots,cT-1} = \sum_{t=0}^{T-1} U(C_t)$$

$$\text{s.t. } \sum_{t=0}^{T-1} C_t + a_T = \sum_{t=0}^{N-1} y_t + a_0$$

where N is the time at which retirement stage begins

a_0 are the bequests received from the previous generation

a_T are the assets of the last period of time, and that will be transferred to the future generation.

Considering the bequests as a good of consumption, the so-called *bequests as consumption*, leads to a modification of the consumer's problem with uncertainty on the life duration by taking into account not only consumption in each period of time but also assets bequeathed to future generations (Hurd 1989). The consumer's objective function and constraints become:

$$\max_{C_t} \int_0^T p(t|0)u(C_t)e^{-\delta t}dt + \int_0^T m(t)e^{-\delta t}v(a_t)dt$$

s.t. a_0 is exogeneous

$$\dot{a_t} = ra_t + y_t - c_t$$

$$a_t = a_0 e^{rt} + \int_0^t (y_t - C_t)e^{r(s-t)}ds \geq 0$$

The first part of the objective function is the same considered in the consumer's problem with uncertainty on the life duration and considers the utility discounted at the inter-temporal rate of preference δ of consumption between 0 and T. The second part represents the utility discounted at the new inter-temporal rate of preference δ of bequests. The third constraint impose the bequests to be positive, avoiding the case of leaving debts to future generations.

The Hamilton's function of the problem is:

$$H_t = p(t|0)u(C_t)e^{-\delta t} + m(t)v(a_t)e^{-\delta t} + \mu_t(ra_t + y_t - c_t)$$

With the following maximization condition:

(i) $p(t|0)u'(C_t)e^{-\delta t} = \mu_t$

(ii) $\mu_t r + m(t)v'(a_t)e^{-\delta t} = -\dot{\mu_t}$

Multiplying both sides of (ii) by e^{rt} and integrating it between two moments t and τ, τ > t, we find:

$$\int_t^\tau m(s)e^{(r-\delta)s}v'^{(a_s)}ds = -\int_t^\tau (\dot{\mu_s} + r\mu_s)\, e^s ds$$

$$\int_t^\tau m(s)e^{(r-\delta)s}v'^{(a_s)}ds = -(\mu_\tau e^{r\tau} - \mu_t e^{rt})$$

Analogously, multiplying both sides of (i) by e^{rt} and considering two moments t and τ, τ > t, we find:

$$p(t|0)e^{(r-\delta)t}u'(C_t) = \mu_t e^{rt}$$

$$p(\tau|0)e^{(r-\delta)\tau}u'(C_\tau) = \mu_\tau e^{r\tau}$$

Subtracting the second equation from the first one, we obtain:

$$p(\tau|0)e^{(r-\delta)\tau}u'(C_\tau) - p(t|0)e^{(r-\delta)t}u'(C_t) = \mu_\tau e^{r\tau} - \mu_t e^{rt}$$

The final Euler equation is:

$$u^{'}(C_t)\, p(t|0) = u^{'}(C_\tau)p(\tau|0)e^{(r-\delta)(\tau-t)} + \int_t^\tau m(s)v^{'}(a_s)e^{(r-\delta)(s-t)}ds$$

which shows that postponing consumption from time t to time τ increases the expected value of future consumption or the possibility to leave a certain amount as bequest to future generations. The model with *bequests as consumption* shows that bequests increase $u^{'}(C_\tau)$ thanks to the non-negative assets constraint, represented by the integral in the Euler equation, and reduces present consumption in favor of future consumption. Focusing on old people, in the case with uncertainty on the life duration and no bequests, uncertainty on the life duration increases consumer's rate of impatience and creates a decreasing pattern of consumption. On the other hand, the introduction of bequests produces the opposite effect on consumption, by postponing consumption to the future and creating a pattern of consumption less steep than before. This approach provides an explanation for the evidence which shows that old individuals do not destock their assets completely at the end of their life, and that the destocking of assets is slower for aged individuals than predicted by Life-Cycle Model without bequests.

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