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2023 **Barbora Hrušková**

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Diet after retirement: Does working after retirement matter?

Master's thesis

Author: **Bc. Barbora Hrušková**

Study program: **Economics and Finance**

Supervisor: **PhDr. Jana Votápková Ph.D.**

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Declaration of Authorship

The author hereby declares that she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain any other academic title.

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Barbora Hrušková

Abstract

A balanced and healthy diet can prevent chronic and cardiovascular diseases, cancer deaths, and other serious health problems. Following a healthy diet is therefore essential during all stages of life and old age is no exception. This thesis examines the impact of working after retirement on the diet of retirees using data from the Survey of Health, Ageing and Retirement in Europe (SHARE). The propensity score matching and the logit methods are performed and robust standard errors are applied. Our analysis reveals that retirees who start working anew after being already retired and unemployed for some time, have by 9 pp higher probability to increase their consumption of meat, fruits & vegetables, compared to their counterparts who do not start working. No significant differences are found regarding the impact of starting to work on the change of consumption of dairy products, legumes & eggs. However, we further conclude that the probability of eating meat every day is lower by 4 pp for retirees who are working after retirement, compared to retirees who are not working after retirement. Therefore, we point out that to get a complete picture of how the diet changes based on post-retirement work, it is ideal to also observe the data regarding diet prior to retirement.

JEL Classification	I12, J14, D12
Keywords	working after retirement, retirement, healthy diet, consumption, retirees, Europe, SHARE
Title	Diet after retirement: Does working after retirement matter?

Abstrakt

Vyváženou a zdravou stravou lze předcházet chronickým, kardiovaskulárním a onkologickým onemocněním a dalším vážným zdravotním problémům. Dodržování zdravé stravy je proto nezbytné ve všech fázích života a stáří není výjimkou. Tato diplomová práce zkoumá vliv zaměstnání po odchodu do důchodu na stravování penzistů pomocí dat z průzkumu Survey of Health, Ageing and Retirement in Europe (SHARE). K analýze jsme použili párování pomocí propensity skóre a logistickou regresi, zároveň jsme aplikovali robustní standartní odchylky. Naše závěry ukazují, že penzisté, kteří začnou znovu pracovat poté, co byli již po určitou dobu v důchodu a nezaměstnaní, mají o 9 procentních bodů vyšší pravděpodobnost, že zvýší konzumaci masa, ovoce a zeleniny, ve srovnání s jejich protějšky, kteří do zaměstnání nenastoupí. Nejsou zjištěny žádné významné rozdíly ohledně vlivu nástupu do zaměstnání na změnu konzumace mléčných výrobků, luštěnin & vajec. Z výsledků však také vyplývá že pravděpodobnost každodenní konzumace masa je o 4 procentuální body nižší u penzistů, kteří pracují po odchodu do důchodu, ve srovnání s penzisty, kteří po odchodu do důchodu nepracují. Proto tedy zdůrazňujeme, že pro úplný obrázek o tom, jak se mění stravování penzistů na základě práce po odchodu do důchodu, je ideální sledovat také údaje o stravování před odchodem do důchodu.

Klasifikace JEL	I12, J14, D12
Klíèová slova	pracovní zapojení, odchod do důchodu, zdravá strava, chování, penzisté, Evropa, SHARE
Název práce	Stravování ve stáří: vliv pracovního zapojení

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This thesis uses data from SHARE Waves 1, 2, 3, 4, 5, 6, 7, and 8 (DOIs: 10.6103/SHARE.w1.800, 10.6103/SHARE.w2.800, 10.6103/SHARE.w3.800, 10.6103/SHARE.w4.800, 10.6103/SHARE.w5.800, 10.6103/SHARE.w6.800, 10.6103/SHARE.w7.800, 10.6103/SHARE.w8.800, 10.6103/SHARE.w8ca.800).

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Contents

List of Tables

List of Figures

Acronyms

ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CDF	Cumulative Distribution Function
CHD	Coronary Heart Disease
EU	European Union
HH	Household
HR	Human Resources
Kcal	Kilocalorie
LR	Likelihood ratio
NN	Nearest Neighbour
OECD	Organisation for Economic Co-operation and Development
pp	Percentage Point
PS	Propensity Score
PSM	Propensity Score Matching
SD	Standard Deviation
SHARE	Survey of Health, Ageing and Retirement in Europe
WHO	World Health Organisation

Thesis Proposal

Author:	**Bc. Barbora Hrušková**
Supervisor:	**PhDr. Jana Votápková Ph.D.**
Proposed topic:	**Working after retirement and healthy food habits**

Research Question and Motivation

The life expectancy is increasing rapidly in developed countries. In the Czech Republic, the life expectancy at birth was over 79 years in 2019, while at the beginning of the century it was less than 75 years (World Bank, 2022). As the population grows older, ensuring healthy aging for the older population should be a major public health interest not only from the ethical perspective but also from the economical perspective because the expenditures on health care account for a large proportion of the GDP and are growing continuously.

Healthy eating patterns are often associated with good health, prevention of major diseases, longevity, and thus better quality of life (Key, et al., 2004; Reddy & Katan, 2004). And the right nutrition has been proven as important at any age, including the elderly (Wolfe, 2015; Helldán, et al., 2012). Many studies focused on the relationship between retirement and healthy eating habits; however, the conclusions are not unified (Fisher, et al., 2008; Helldán, et al., 2012; Plessz, et al., 2015). The positive relationships are mostly explained by more free time for meal preparation, on the other hand, the negative ones are justified by not having enough financial resources.

Nowadays, participation in the workforce after retirement is becoming more common in Europe (Beehr & Bennett, 2015). The impact of working after retirement on different aspects of life has been analyzed; however, there is not enough research about the effect of participation in the workforce after retirement on food consumption. The additional income could be expected to be at least partly spent on higher quality, healthier, or more nutritious food. However, for example, Irz et al., 2014 found a negative or no relationship between poor dietary choices among the elderly and insufficient resources.

Studies regarding working after retirement, food, and health using SHARE data were already published; however, to my knowledge, none of them analyzed the data in order to show the effect of additional income after retirement on healthy food habits (Nie & Sousa-Poza, 2016; Dingemans & Henkens, 2019; Celidoni, et al., 2020). Therefore, I will enrich the existing literature by studying the effect of working after retirement on healthy food habits among retirees in Europe.

This thesis may be generalized as an income-substitution effect analysis. If a positive correlation between decreased income of retires and unhealthy food habits is found, we suggest that the income effect takes place indicating that food habits may improve with additional income. In case of negative correlation results, the substitution effect prevails which would most probably result from an additional time because of fewer work obligations. The income-substitution effect analysis may however be applied to the whole population with some limitations only stemming from the fact that the elderly are expected to be more interested in their health as health deteriorates with age and the elderly face fewer years left in good health than younger generations.

Hypotheses

The following hypotheses will be tested:

1. Hypothesis #1: Does working after retirement (as a measure of additional income) have a positive effect on the consumption of foods that are considered healthy?
2. Hypothesis #2: What other characteristics influence the consumption of healthy foods?
3. Hypothesis #3: Do the results change for different European regions?
4. Hypothesis #4: Do the results change for OLS and DiD methodology?

Methodology

To conduct the analysis, I will use the SHARE survey (Survey of Health, Ageing and Retirement in Europe). The data were collected between 2004 and 2021 and include health, social, and economic variables.

Multiple dependent variables will be tested, namely the consumption of fruits and vegetables, the consumption of legumes and eggs, the consumption of dairy products, and the consumption of meet. As independent variable of interest, I will use the fact, whether the individual has an additional income arising from the bridge employment, and the variables describing individual characteristics, household characteristics, and regional differences will be included as control variables. In the first model, I will employ the OLS methodology.

Secondly, I will use the difference in differences technique, which will serve as a robustness check for the former. If the results of both models differ, the effect of retirement and additional income mix in the former model. The DiD model on the other hand separates the effect of retirement and keeps only the effect of additional income after retirement.

The effect of an increase in income after retirement can hardly be captured from the data. Thus, I will inverse the model and rather test the effect of decrease in income after retirement by comparing food consumption of healthy individuals who are both working and receiving retirement pension in t1 and t2 (the control group) with healthy individuals who were previously receiving both a salary and a retirement pension in t1 and now are receiving only a retirement pension in t2 (the treatment group). Members of both treatment and control group are healthy individuals thus members of the control group have only additional income, other characteristic of the individuals in both groups are assumed to be similar. Appropriate tests will be carried out.

Expected Contribution

The thesis can contribute to the knowledge about income-substitution effect analysis capturing the change in food consumption. If income proves as important for healthy food consumption, this finding could raise public awareness of income-related eating habits. As a result, programs that aid not only seniors but also other generations in obtaining healthy and nutritious food could be developed.

Outline

1. Introduction: introduction to the topic, motivation for the thesis, and overview of the thesis structure

2. Literature review: an overview of to-date published studies and the gap for further research

3. Data: description of the data source (SHARE) and selected variables, data preparation, descriptive statistics

4. Methodology: explanation of methods used

5. Results: tables with results, discussion

6. Conclusion: summary of the findings and their possible implication, limitations of the thesis, and future research recommendations

Core Bibliography

Beehr, T. A., & Bennett, M. M. (2015). Working after retirement: Features of bridge employment and research directions. Work, Aging and Retirement, 1(1), 112-128.

Celidoni, M., Dal Bianco, C., Rebba, V., & Weber, G. (2020). Retirement and Healthy Eating. Fiscal studies, 41(1), 199-219.

Dingemans, E., & Henkens, K. (2019). Working after retirement and life satisfaction: Cross-national comparative research in Europe. Research on Aging, 41(7), 648-669.

Fisher, J. D., Johnson, D. S., Marchand, J., Smeeding, T. M., & Torrey, B. B. (2008). The retirement consumption conundrum: Evidence from a consumption survey. Economics Letters, 99(3), 482-485.

Helldán, A., Lallukka, T., Rahkonen, O., & Lahelma, E. (2012). Changes in healthy food habits after transition to old age retirement. The European Journal of Public Health, 22(4), 582-586.

Irz, X., Fratiglioni, L., Kuosmanen, N., Mazzocchi, M., Modugno, L., Nocella, G., & Zanello, G. (2014). Sociodemographic determinants of diet quality of the EU elderly: a comparative analysis in four countries. Public health nutrition, 17(5), 1177-118.

Key, T. J., Schatzkin, A., Willett, W. C., Allen, N. E., Spencer, E. A., & Travis, R. C. (2004). Diet, nutrition and the prevention of cancer. Public health nutrition, 7(1a), 187-200.

Nie, P., & Sousa-Poza, A. (2016). Food insecurity among older Europeans: Evidence from the Survey of Health, Ageing, and Retirement in Europe (No. 03-2016). Hohenheim Discussion Papers in Business, Economics and Social Sciences.

Plessz, M., Guéguen, A., Goldberg, M., Czernichow, S., & Zins, M. (2015). Ageing, retirement and changes in vegetable consumption in France: findings from the prospective GAZEL cohort. British Journal of Nutrition, 114(6), 979-987.

Reddy, K. S., & Katan, M. B. (2004). Diet, nutrition and the prevention of hypertension and cardiovascular diseases. Public health nutrition, 7(1a), 167-186.

Wolfe, R. R. (2015). Update on protein intake: importance of milk proteins for health status of the elderly. Nutrition reviews, 73(suppl_1), 41-47.

World Bank. (2022, January 18). World Bank: Life expectancy at birth. Retrieved from https://data.worldbank.org/indicator/SP.DYN.LE00.IN

1 Introduction

The declining fertility rates and rising life expectancy are causing rapid aging of the European population. As a result, the proportion of people of working age is shrinking and such a development might bring significant issues regarding the sustainability of the public finances, labor markets, social and healthcare systems (Eurostat 2020). Moreover, the increase in life expectancy is not associated with a proportional improvement in the quality of life of the elderly. The last decades of life do come with a higher probability of developing disabilities, cancer disease, heart disease, and chronic diseases, which further result in significant economic burden due to their healthcare costs. Among other factors, which are beneficial for the health of the elderly, a balanced and healthy diet is a significant factor that can prevent major health issues (Willett 2002).

Even in advanced age, the need for nutrients in food remains the same as for younger counterparts, therefore, a diet of the elderly should be full and nourishing. However, food price is reported as one of the key barriers to healthy eating and since retirement is associated with a substantial decrease in income, retirees might face challenges to meeting healthy eating patterns (Mestral, Stringhini, and Marques-Vidal 2016; Pinho et al. 2018). Numerous studies analyzed the impact of retiring on the dietary habits of retirees and even though the results are inconclusive, a significant part of the studies reports that food quality, nutritional intake, and the proportion of healthy foods decrease after retirement (Allais, Leroy, and Mink 2020; Smed, Rønnow, and Tetens 2022; Stephens and Toohey 2018).

Despite the awareness of dietary changes after the transition to retirement, which is associated with a significant decrease in income, the effect of remaining in the labor market or re-entering the labor market in retirement after a period of unemployment, and thus maintaining (or not decreasing as significantly) the monetary income, has not yet been analyzed. Working after retirement has become more common in recent decades and the labor market offers more job opportunities for the elderly. Therefore, retirees have the possibility to choose whether to work after retirement or not, and the potential impact of additional income on the diet of retirees should be analyzed.

Hence, the primary objective of this thesis is to examine how and to what extent does working after retirement determine the diet of retirees. We hypothesize that the consumption of meat, dairy products, legumes & eggs, fruits & vegetables, and protein increases when retirees start working in retirement after a period of unemployment.

The hypotheses are tested using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), which collects information on pan-European individuals aged 50 or over. We gather information about demographic data, health, financial situation, employment and pension, and dietary habits. We focus on the last two waves of the survey which include data from 2017 and 2019-2020. Our sample is composed of healthy individuals who declare to be retired from work and for which we are not missing the variable describing the working status (our main variable of interest). Regarding dependent variables, dummy variables created for 5 different food groups - meat, dairy products, legumes & eggs, fruits & vegetables, and protein - are analyzed. The selection of control variables is based on the previous studies analyzing retirement and consumption of foods. Specifically, we control for age, gender, region, education, marital status, and financial situation of a household.

The main results are obtained using propensity score matching. We are interested in the average treatment on the treated (ATT) and radius matching is chosen as the main matching method. Robustness check includes different matching approaches (nearest neighbor, kernel, and stratification matching) and a logit estimation. Bootstrapped/robust standard errors are applied and the results are interpreted using marginal effects. First, we regress the change in consumption of specific food groups on the variable describing whether a retiree started working anew after retirement or not and the set of covariates. Subsequently, we estimate the impact of the variable describing whether a retiree works after retirement or not on the frequency of consumption of specific food groups, controlling for the set of covariates.

The remainder of this thesis is structured as follows. Section 2 provides a background for the topic. First, we describe the determinants, benefits, and drawbacks of working after retirement. Subsequently, we define what a healthy, balanced diet is and we focus on the connection between a healthy diet and retirees. Data used for the analyses are introduced in Section 3, the information about the SHARE dataset is provided and further, descriptions of the data and selected variables are presented. Section 4 describes the applied methodology, specifically the propensity score matching approach and the logit model. Subsequently, results, their robustness check, and additional comments are included in Section 5. Section 6 provides a discussion of the results and possible limitations of our study. Finally, Section 7 concludes our findings, emphasizes the main contribution of our thesis, and gives suggestions for further research.

2 Background and literature review

In this section, we first discuss the determinants, reasons, and motivations for working after retirement. Next, we comment on the benefits and disadvantages that arise from post-retirement employment. The second part is devoted to healthy eating habits and patterns. We specify which foods should be included in a healthy and balanced diet, and we discuss the main factors that determine the diet as well as the consequences associated with the diet. Finally, we summarize the current literature regarding the relationship between retirement and the consumption of foods, with a focus on healthy eating habits.

2.1 Working after retirement

The percentage of elderly workers has increased significantly in recent years. In 2021 the labor market participation rate of people over the age of 65 years reached 16% in OECD countries, a 70% growth compared to the year 2000. In the EU the percentage remains lower (6% as of 2021), however, the increasing trend is also observable (*OECD: Labour force participation rate* 2021). The main reason for this rise is population aging and thus increased pressure on public finances, supported by governments incentives to work longer and to delay retirement (Wheaton and Crimmins 2012; Staubli and Zweimüller 2013; Bloom et al. 2007).

However, also the original concept of retirement as the on-time action of leaving job and ceasing to work has changed in the last decades, as more people from developed countries continue to work after retirement. Increased participation in the labor market after retirement from the main career path can be mostly explained by growing financial incentives and by governments enhancing flexible retirement options that enable workers to gradually decrease work effort with aging (Goll 2020). Given the growing number of people who remain in or re-enter the labor market after retirement, it is important to examine the motivations and incentives that lead them to do so, so that appropriate policy measures can be put in place, not only from an economic but also from a sociological perspective.

2.1.1 Determinants of working after retirement

Retirement is a major life decision for many people and individual characteristics of retirees, their work situations, as well as country characteristics, are important determinants of continuing to work after retirement.

One of the main aspects affecting labor market participation is health. Studies agree on a positive correlation between good physical and mental health and working after retirement age

(E. A. A. Dingemans 2016; Kim and Feldman 2000; Demou et al. 2017; Zwaan et al. 2019). This is to be expected as people in poor health are more likely to retire early even before reaching the statutory retirement age. At the same time, health status is closely linked to age. It is not only for this reason that younger individuals are associated with a higher probability of participating in the labor market after the statutory retirement age, as people usually keep working directly after retirement (E. A. A. Dingemans 2016; Kim and Feldman 2000).

The traditional gender division of labor in the household also affects work after retirement. Women are, on average, less prone to remain in the labor market after retirement than men (Anxo, Ericson, and Herbert 2019). When controlling for marital status, gender differences play an important role, because marital status appears to be an important determinant, especially for women (E. Dingemans and Möhring 2019). Divorced and widowed women are more likely to work after retirement. This can be explained mainly by financial difficulties (Pleau 2010), others further argue that insufficient finances are a consequence of the lack of experience caused by previously provided unpaid care (E. Dingemans and Möhring 2019). According to Anxo, Ericson, and Herbert (2019), being married is negatively correlated with post-retirement work for women, because husbands, on average, retire earlier than wives (as they are usually older and sooner reach the statutory retirement) and in the interest of spending leisure time together, women do not prolong their labor market participation or even prefer to retire earlier. On the other hand, Kim and Feldman (2000) conclude that being married to a working man is positively related to wives' post-retirement work. In addition, E. Dingemans and Möhring (2019) find that the positive correlation between divorce and post-retirement work disappears for remarried women. In contrast to women, the association between marriage and post-retirement work turns out to be positive for men (Beehr and M. M. Bennett 2015). However, not only individual characteristics but also spousal characteristics are important to consider. Regarding husbands' and wives' different retirement expectations, Pienta and Hayward (2002) conclude that within a marriage, wives' retirement expectations are more influenced by husbands' financial resources than vice versa. As for other household members, studies agree that having financially dependent children significantly increases the likelihood of remaining in the labor market after retirement (Anxo, Ericson, and Herbert 2019).

According to E. A. A. Dingemans (2016), retirees who participate in the labor market tend to be highly educated individuals. This is in line with Anxo, Ericson, and Herbert (2019) and Aaron and Callan (2011) who report a positive correlation between university degree and longer labor market stay.

Less clear is the effect of salary level at the time of retirement. While Beutell and Schneer (2021) and M. Wang et al. (2008) find that income plays no role in deciding whether to work after retirement, Anxo, Ericson, and Herbert (2019) show that higher income has a positive impact on work after retirement, but only for women. According to Wind et al. (2016), poor or precarious financial circumstances force people to seek employment and re-enter the labor market after retirement. A negative correlation between the salary level and the probability of post-retirement work is found by Kim and Feldman (2000) and this is consistent with the conclusion of G. G. Fisher, Chaffee, and Sonnega (2016) who identify that insufficient financial resources are a reason to participate in labor market after retirement (G. G. Fisher, Chaffee, and Sonnega 2016). E. A. A. Dingemans (2016) conclude that approximately 15 percent of retirees continue to work due to financial needs. For other retirees, financial security is not the most important reason for continuing to work, but the additional income is more than welcomed, as the financial benefit allows them to maintain their standard of living and enjoy leisure activities even after retirement (Sewdas et al. 2017; Bratun and Zurc 2020). Although it remains unclear how wages affect participation in the labor market after retirement, the decision to continue working might be based also on other economic reasons, such as employer-provided health insurance (G. G. Fisher, Ryan, et al. 2016; Sewdas et al. 2017; Wind et al. 2016).

Additionally, work experience accumulated over a lifetime proved crucial for late-career decision-making (J. Bennett and Moehring 2015; Damman, Henkens, and Kalmijn 2011). Therefore, E. Dingemans and Möhring (2019) examine the impact of work experience in the course of peoples' lives on the decision to remain in the labor force after retirement, using the SHARE data. The results show that the number of years in the labor market is positively related to work after retirement because of greater interest in workers with demonstrable track records (Oude Mulders et al. 2016). They further find that men with previously high occupational status, compared to men with lower status, tend to stay attached to the labor market even after retirement. Wahrendorf et al. (2018) support this finding in their study analyzing English workers.

Regarding the type of contract, E. Dingemans and Möhring (2019) find that previous part-time contracts increase the likelihood of working after retirement - mainly because part-time contracts are associated with insufficient financial resources. Another strong predictor of work beyond the standard retirement age is being self-employed (Anxo, Ericson, and Herbert 2019). Concerning the occupation type, monotonous and physically demanding jobs decrease the probability of late labor market exit (Anxo, Ericson, and Herbert 2019).

Enjoyment of a job is another common reason for being employed beyond retirement (E. A. A. Dingemans 2016; Bratun and Zurc 2020; Henkens and Solinge 2013). Older people are often attached to the stereotypes and routines that employment brings to them and maintaining their routines and social networks is very important for their psychical stability (E. A. A. Dingemans 2016; Schlosser, Zinni, and Armstrong-Stassen 2012; Sewdas et al. 2017). While some find work fulfilling, others fear the loss of their main purpose in life or the loss of their status or identity if fully retired (Schlosser, Zinni, and Armstrong-Stassen 2012; Sewdas et al. 2017; Manor and Holland 2022). Sewdas et al. (2017) as well as Wind et al. (2016) find that employed retirees often work because they enjoy contributing to and participating in society and relish the feeling of being needed. Other frequent reasons for staying in work beyond retirement age are continued personal development and the opportunity for further learning (Sewdas et al. 2017; Reynolds, Farrow, and Blank 2012).

The decision to work after retirement is also significantly influenced by work practices or the work environment in an organization (Zwaan et al. 2019; Bal et al. 2012; Armstrong-Stassen 2008). Retirees often seek a job that they would find interesting and that would allow them to keep learning, so training and development opportunities are highly valued (Kim and Feldman 2000; Armstrong-Stassen 2008). Topa, J. A. Moriano, et al. (2009), in their meta-analysis, identify a positive correlation between higher work involvement and the intention to remain employed in older age. Studies by Wind et al. (2016) and Topa and Alcover (2015) support this by finding an association between post-retirement employment and work involvement and attachment. Taking on tasks that involve mentoring younger colleagues also contributes to retirees' workplace satisfaction (Zwaan et al. 2019). Flexibility in working hours is another important aspect, as part-time contracts are more popular among retirees than full-time contracts (Wind et al. 2016). HR practices that accommodate the needs of older workers are particularly important to workers when making decisions about remaining employed beyond retirement (Armstrong-Stassen 2008). Further, Veth et al. (2018) conclude that high-quality workplace relationships are highly desired by older workers and the way the elderly are treated in an organization is closely related to the probability that they will continue to work after retirement.

The retirement timing is affected not only by individual and job characteristics but also by country characteristics. Axelrad (2018) analyses the determinants of retirement timing at the country level. Based on a comparison of 20 European countries, he concludes that higher unemployment rates and higher rates of long working hours are associated with later retirement. Similarly, higher pension spending, a higher percentage of people with no pension plan, and low social security retirement benefits correlate with a higher probability of late retirement (Axelrad 2018). Analysis of American workers by Beutell and Schneer (2021) shows that people with health care benefits at work are more likely to continue working after retirement. A country's traditions and culture also play an important role in the desire to remain at work beyond retirement age (Axelrad 2018).

2.1.2 Benefits and drawbacks of working after retirement

Mental health is an essential topic at any age, but especially after retirement many people experience a decline in their mental health (Dave, Rashad, and Spasojevic 2008; Heller-Sahlgren 2017). However, the studies analysing the impact of work beyond retirement on mental health are not unified. The conclusions on this topic also vary depending on the gender and marital status of individuals (Picchio and Ours 2020).

Maimaris, Hogan, and Lock (2010) in their review of published evidence focusing on the effects of post-retirement work on mental health do not find any study that would conclude that post-retirement employment is detrimental to mental health, and few studies were found to show a positive impact on mental health outcomes. Post-retirement work was associated with favourable effect primarily because of the continuous role and social contact. They admit that reasons for the positive impact might vary between individuals and also among countries, however, they further consider stable income, social support, and social connections resulting from employment as some of the reasons for better mental health (Maimaris, Hogan, and Lock 2010). Herzog, House, and Morgan (1991) propose that it is primarily the ability to make one's own decisions and choices to work that has a significant positive impact on mental health rather than the work itself. In addition, a study of Dutch retirees points out that retirees who seek employment but remain unemployed are less satisfied with their lives than those who do not consider working (E. Dingemans and Henkens 2014).

Life satisfaction is an important indicator of well-being and has been proven to be closely related to mortality (Chida and Steptoe 2008; Kim and Feldman 2000). Financial security can be considered one of the determinants of overall life satisfaction. A study by Choi (2001) finds that mainly financial resources and subjective financial satisfaction arising from work after employment are determinants of higher life satisfaction, but only for women. It cannot be omitted that the quality, as well as the quantity of employment, also affects the life satisfaction of retirees (Depolo, J. L. Moriano, Morales, et al. 2009).

Similarly to mental health, also the impact on physical health might vary depending on individual characteristics and incentives for working. Westerlund et al. (2010), Plouvier et al. (2011), and Heide et al. (2013) conclude that there are mainly negative impacts of working after the statutory retirement age on physical health. However, the conclusions are not unified and straightforward. Nemoto et al. (2020) find that depending on the working incentives, retirees who work only for financial reasons rate their health lower than workers with non-financial reasons. Other studies report physical health benefits resulting from employment in old age (Fujiwara et al. 2016; Dave, Rashad, and Spasojevic 2008; Zhan et al. 2009), and Yin et al. (2022) even conclude that participation in the labor force after retirement is associated with a lower risk of all-cause mortality.

2.2 Eating habits: Healthy, balanced diet

Being overweight or obese represents one of the fastest-developing health problems in developed countries (Price 2005). The prevalence of obesity among adults in the EU almost doubled since the beginning of this century (OECD 2019) and nowadays, it represents one of the main risk factors for comorbidities, diseases, disabilities, and decreased quality of life (Ricci et al. 2018; Di Bonaventura et al. 2018).

Excess weight is the result of many elements, such are genetics, eating patterns, physical activity levels, and individual routines, however, a balanced and healthy diet is a significant factor that can prevent as well as control overweight and obesity (Kopp 2019). Further, a balanced diet or changes in dietary patterns could prevent 30% of cancer deaths and contribute to a decrease in chronic and cardiovascular diseases and other major causes of mortality (Willett 2002). In addition, higher levels of energy, stronger immunity, and longevity are associated with healthy and balanced eating (Chakrabarty, Kaveri, and Chakrabarty 2019).

From the economic perspective, unhealthy eating results in a substantial economic burden, as significant direct and indirect costs are associated with the treatment of related conditions (Müller-Riemenschneider et al. 2008; Anekwe and Rahkovsky 2013). Not only unhealthy diet increases medical care and institutional costs, but overweight people are also overall less productive, or even unable to participate in the labor market.

2.2.1 Components of a healthy, balanced diet

The dietary and nutrition patterns changed significantly over the past 40 years. The consumption of a higher energy density diet including more fatty and sugary foods increased so did the consumption of meat and the proportion of portion sizes. On the other hand, the intake of fruits, vegetables, complex carbohydrates, and fiber was reduced (Chan and Woo 2010). A significant number of individuals do not follow a healthy, balanced diet although they are aware of the connection between diet and health. This is among others a result of insufficient health policies, marketing, and lacking education (WHO et al. 2013). Therefore, institutions around the world publish dietary guidelines to increase awareness of healthy eating and provide sufficient knowledge.

European Commission publishes the Food-Based Dietary Guidelines, which are science-based recommendations for healthy eating for the European population. They are consistent, appropriate for each country, easy to understand, and practical to implement. The recommendations focus on the most commonly encountered food or nutrient groups (carbohydrates, fruit & vegetables, dairy products, legumes, meat & fish, eggs, fats & oils). Sufficient hydration and the recommended intake of salt and sugar are also proposed (EC 2022). Similarly, also the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO) summarize information about national dietary guidelines (United Nations FAO 2022; W. H. O. WHO 2022).

Carbohydrates are an integral part of a diet. However, whole grain foods, which are rich in dietary fiber, resistant starch, minerals, and vitamins, should be preferred to highly processed grains (Skerrett and Willett 2010). Immoderate consumption of a highly processed grains diet is associated with raising triglycerides and reducing high-density lipoprotein (HDL) cholesterol. Raised triglyceride levels contribute to obesity, the development of type-2 diabetes, and a higher risk of coronary heart disease (CHD) and gastrointestinal cancers (Willett and Stampfer 2013; Slavin 2000).

Dietary fat is essential for a balanced diet as it enhances the absorption of vitamins A, D, E, and K and supports cell function. Monounsaturated and polyunsaturated fats from vegetable sources and fish should be preferred to saturated fats (Skerrett and Willett 2010). Similarly, proteins with the greatest health benefits should be consumed as a priority. Meat is a great source of protein, iron, zinc, and vitamin B12, however, especially red meat provides the most saturated fats and can increase the risk of CHD and colorectal cancer (Willett and Stampfer 2013; Aykan 2015). Therefore, red meat should be at least partially replaced by other animal or vegetable sources of protein such as fish (which is particularly high in long-chain omega-3 fatty acids), eggs, legumes, soy products, nuts, and seeds (Hertzler et al. 2020). Dairy products might be good sources of protein as well. In addition, dairy products are high in calcium and vitamin D (Willett and Stampfer 2013). Their daily consumption contributes to bone health as well as lower probability of colorectal cancer (Alvarez-León, Román-Vinas, and Serra-Majem 2006).

In the majority of EU countries, the recommended daily intake of fruits or vegetables is 5 portions per day (EC 2022). Fruits and vegetables are excellent source of fiber, vitamins and minerals (especially vitamin C and potassium) and frequent consumption of fruits and vegetables is associated with lower probability of cardiovascular disease, slower disablement processes, and better cognitive and mental health (Gehlich et al. 2020; Angelino et al. 2019).

Overall, strong evidence supports the need to consider not only the amount of food, but mainly its quality, sources, and processing. The inclusion of all types of food in sufficient, but not excessive amounts, is necessary for proper body functioning (Chakrabarty, Kaveri, and Chakrabarty 2019). Further, an overall healthy lifestyle is important for disease prevention, but healthy nutrition is an integral part (Skerrett and Willett 2010).

2.2.2 Determinants of a healthy, balanced diet

Many people encounter difficulties when considering healthy eating and a balanced diet, others do not even try to change their poor eating habits. In this subsection, we summarize the main determinants of a healthy, balanced diet and the barriers to adopting or subsequently following such a diet.

Food price is reported as one of the key barriers to healthy eating (Mestral, Stringhini, and Marques-Vidal 2016; Pinho et al. 2018). Mostly women and low-income individuals perceive the higher price of healthy foods as a reason to consume them in lower amounts (Beydoun, May, and Y. Wang 2008). Rao et al. (2013) conclude, in their meta-analysis of prices of healthier versus less healthy foods, that the differences in prices are largest with regards to a serving of meat, while the differences in prices of grains, dairy, and fats are smaller. They further identify that the price difference between a healthy diet (e.g. Mediterranean-type diet including fruits, vegetables, and fish) and an unhealthy diet (including processed foods and refined grains) equals about 1.5 dollars per day. This also holds when standardized to 2000 kcal per day. This is in line with the conclusion of Darmon and Drewnowski (2015) who find evidence that healthier diets are associated with higher costs on a per calorie basis. They also report that the differences in prices result in the preference of low nutritional value foods (often short of fruit and vegetables) by consumers with lower socioeconomic status. On the other hand, Maillot, Darmon, and Drewnowski (2010) point out, that diets that meet energy and nutrient requirements can be created at very low cost. Nevertheless, such diets deviate from the mainstream norms.

According to Macdiarmid et al. (2013), even though there are numerous factors influencing food patterns, knowledge plays a pivotal role in healthy eating. Overall, consumers are usually aware of the relationship between diet and health as well as the basic principles of healthy eating (e.g. balance and variability). However, the knowledge of foods' specific nutrient content and the correct portion size is often lacking (S. Chambers et al. 2008). Moreover, nowadays, it might be difficult to interpret dietary messages and incorporate them into everyday life (Nutbeam 2000). The availability of fast foods, as well as advertising and marketing of unhealthy options, contribute to even less straightforward food considerations. Therefore, informational campaigns should be funded to educate the public (Macdiarmid et al. 2013). Regarding education attainment, according to Boylan et al. (2011), the level of education is positively associated with healthy food habits.

The barriers to adopting a healthy diet also tend to focus around the opportunity cost of time. Lack of time to prepare and eat meals results in the increasing popularity of convenience foods and fast foods (Macdiarmid et al. 2013). This supports the findings of Pinho et al. (2018) who further show that insufficient time is related to skipping breakfast and not cooking meals at home.

Habit, convenience, preferences, and taste are important determinants of a diet. The human organism has strong preferences for specific flavors, sweet, and salt tastes. Palatable foods or foods which contain an excessive amount of sugar have highly addictive potential and can be easily consumed in excess (Fortuna 2012). Consumers often perceive a balanced healthy diet as unappealing and boring. Others are not willing to change their habits or do not want to give up their preferred foods. Many people desire to eat healthfully, however, they are are lacking motivation or willpower (Chance, Gorlin, and Dhar 2014). The immediate benefits compared to the uncertain and far-in-time costs of unhealthy options are one of the causes of low motivation to stick to a healthy diet (Wertenbroch 1998).

Attitudes, motivations, and behaviors regarding healthy eating change throughout life. Younger consumers are more likely to eat more processed and sugary foods and devote less time to cooking. On the other hand, they are more informed about healthy diet trends and follow more information regarding healthy consumption (S. Chambers et al. 2008). Food consumption also differs with marital status, compared to married, singles tend to consume more fast food (Schoeppe et al. 2018). Demographics also plays a role. Compared to men, women are more likely to eat enough fiber and fruit, limit salt intake, and avoid unhealthy fats (Bogue, Coleman, and Sorenson 2005; Wardle et al. 2004).

2.2.3 Retirement & Healthy, balanced diet

Retirement is a major life change and its impacts on health and well-being have received increasing attention these days. Still, there is limited research regarding changes in health behaviors such as food habits after retirement.

After retirement, the expenditures on food consumption usually decline (J. D. Fisher et al. 2008; Stephens and Toohey 2018). The decline might be caused by the purchase of cheaper foods of the same quality (shopping for bargains), cooking at home, or substituting market goods with goods produced at home. However, some studies find that not only the expenditure on food declines, but also the amount purchased, food quality, nutritional intake, or the proportion of healthy foods decrease (Allais, Leroy, and Mink 2020; Smed, Rønnow, and Tetens 2022; Stephens and Toohey 2018). Further, Allais, Leroy, and Mink (2020) conclude that the descrease in food quality is observable in households with low pre-retirement income.

Regarding specific types of foods, the results of studies are inconclusive. Ali-Kovero et al. (2020), analyzing data from Helsinki Health Study, report that retirement is associated with a decrease in vegetable consumption among women, and with increased consumption of fruits among men. French studies find that less fruits and more bread and alcohol are consumed after retirement (Lauque et al. 1998; Si Hassen et al. 2017). And Swedish study by Steen et al. (1988) shows that mainly the consumption of sweets and pastries increased with the transition to retirement.

Gustafsson and Sidenvall (2002) in their study analyzing the food habits of older women identify that mainly older widowed women are at risk of poor nutritional intake. Similarly, Quandt et al. (2000) conclude that single, retired women are particularly prone to malnutrition because they are often cooking fewer meals, simplifying cooking, or missing appetite. Although energy needs decrease with age, older people have the same need for nutrients as their younger counterparts. Malnutrition might result in frailty, diminished cognitive skills, and ability to care for oneself (WHO 2015).

Some studies identify positive impact of retirement on the healthy diet. Finnish study concludes that healthy food habits increase after the transition to old age retirement, compared to those continuously employed, but only for women. Neither health nor socio-demographic factors could explain this difference and thus unobserved factors such as time constraints probably play important roles (Helldan et al. 2012). Similarly, Dutch study finds that retirees start to eat healthier after the transition to retirement without any decrease in food expenditure (Zantinge et al. 2014). Nevertheless, these result might be only country specific since the proportion of pension income to the income before retirement is probably a significant indicator.

Even though the results of studies focusing on the association between the transition to retirement and eating habits are inconsistent, the decline in food consumption, food quality, nutritional intake, or the proportion of healthy foods is mostly attributed to the decrease in income that follows after retirement. For this reason, we decided to analyze the effect of working after retirement and thus maintaining (or not decreasing as significantly) the monetary income on the diet of retirees.

3 Data and descriptive statistics

The first part of this section introduces the source of our data, which is the 'Survey of Health, Ageing and Retirement in Europe' (SHARE) database. SHARE collects information about individuals aged 50 and above and focuses on health and socio-economic conditions. We describe the data used, present the dependent, explanatory, and control variables, and provide their descriptive statistics. Finally, we discuss the correlation between the variables and the potential issue caused by omitting important variables.

3.1 SHARE data and sample selection

We use data from the two latest waves of the 'Survey of Health, Ageing and Retirement in Europe' (SHARE) cross-national panel. The freely available SHARE research infrastructure is the largest pan-European social science panel study which provides insights into the fields of public health and socio-economic living conditions. The data collection through interviews has begun in 2004 and to date, 8 waves are available to the public. In the first wave, only 8 countries participated, but the number of countries involved in the study is increasing with each wave and up to the present time 28 different European countries and Israel participated in at least one wave. Subjects are individuals aged 50 and above, however, as SHARE focuses also on subjects' partners, even people younger than 50 can be observed. The nationally representative household samples are selected and interviewed by SHARE national survey organizations. The questions cover different topics, such as individual's demographics, health, social networks, behavior, employment and pension, finance, saving, and consumption. Country differences regarding public policy, social security systems, culture, and others, are also subject to the interviews. [1]

Although the variables of our interest are included in different SHARE questionnaires, all of these questionnaires were completed at approximately the same time. Namely, we use variables from the following sections: demographics and networks, physical health, behavioral risks, and employment and pensions. For the analysis, we use the two latest waves (wave 7 and wave 8) of the SHARE survey which include data from 2017 and 2019-2020, respectively. Earlier waves were not suitable for the analysis as our variables of interest concerning diet were missing for the majority of observations. Nevertheless, waves 1-6 were also used to obtain basic demographic information (e.g.: birth year, education), as the entry interview containing these types of questions is made only during the first occurrence of the individual in the SHARE survey.

Even in wave 7, the number of observations for which variables regarding diet are available is

[1] More information about the SHARE panel can be found at: `http://www.share-project.org/home0.html`.

limited. This is caused by the fact that wave 7 focused mainly on extending information about life histories (SHARELIFE). Thus, the regular panel module in wave 7, which includes specific questions about consumption and work characteristics, was only asked of respondents who had already participated in a previous SHARELIFE interview in 2008-2009 (only 18% of the total number of respondents). This leads to a significantly lower number of observations from wave 7 compared to wave 8.

We restricted our sample only to retirees who retired because they either become eligible for a public pension, private pension, or private occupational pension. Further, we omit individuals who did not respond to the questions about food consumption (diet) and additional income from paid work, and individuals who evaluated their health as poor. The last restriction enables us to cover only individuals in good health who are able to work - the fact whether they work or not is less likely to be influenced by health reasons.

We construct two datasets, a panel dataset, and a cross-sectional dataset. Our panel dataset uses data from both, wave 7 and wave 8. It comprises retirees who did not have any additional income except retirement pension in wave 7 and either continued having retirement pension as the only income in wave 8 (the control group) or started having additional income from paid work in wave 8 (the treatment group). Regarding the number of observations, it consists of 4,431 observations (111 and 4,320 observations for the treatment and control groups, respectively). This panel dataset which tracks each individual at two points in time enables us to include the measurements over time and thus explore dynamic concepts. Further, we also focus only on cross-sectional data from one wave. The cross-sectional dataset includes all retirees from wave 8 who received retirement pension and either had additional income from paid work or not. The cross-sectional sample consists of 22,402 observations. The number of observations is significantly higher than in the panel dataset since, compared to the panel dataset, the condition that the individual had to be interviewed in two waves was relaxed here.

3.2 Variables

First, we present the dependent variables and comment on the descriptive statistics. Next, we describe the variables of interest and subsequently, the control variables related to the individual, work, and household characteristics.

3.2.1 Dependent variables

As dependent variables, we choose five variables describing the frequency of consumption of different food groups. These food groups are considered part of a healthy, balanced diet because they provide essential vitamins, minerals, fiber, protein, and fat. Four of the variables, namely consumption of meat, diary products, legumes & eggs, and fruits & vegetables, were directly available in the SHARE questionnaire. All of them are originally categorical variables consisting of 5 categories which describe weekly consumption. Each variable takes value '1' if the type of food is consumed every day, '2' if 3-6 times a week, '3' if twice a week, '4' if once a week, or '5' if less than once a week. Further, we created variable protein as a sum of consumption of meat, dairy products, and legumes & eggs. By analyzing this variable we account for substituting similar types of products (in this case high protein products). All the dependent variables are summarized in Table 3.1.

Table 3.1: Dependent variables overview

Dependent variable: Survey question	
Meat	*In a regular week, how often do you eat meat, fish or poultry?*
Dairy	*In a regular week, how often do you have a serving of dairy products such as a glass of milk, cheese in a sandwich, a cup of yogurt or a can of high protein supplement?*
Legumes & Eggs	*In a regular week, how often do you have a serving of legumes, beans or eggs?*
Fruits & Vegetables	*In a regular week, how often do you consume a serving of fruits or vegetables?*
Dependent variable: Additional (not survey) variable	
Protein	*Consumption of dairy, legumes & eggs, and meat*

For a more straightforward interpretation of the results and due to the distribution of the original variables, we additionally constructed dummy variables that describe the consumption of food groups displayed in Table 3.1. The meat, dairy products, and fruits & vegetables variables take value '1' if consumed every day and '0' if consumed less frequently. The variable legumes & eggs takes value '1' if consumed 3 times a week or more and '0' if consumed less frequently. Additionally created variable protein equals '1' if the individual consumes protein more frequently than the sample average and '0' if the individual consumes protein less frequently than the sample average (before the dummy was created, this variable consisted of integers, hence the values of '0' and '1' are not equally distributed). Descriptive statistics of the dummy dependent variables can be seen in Table 3.2.

First, we focus on the panel dataset. In wave 7, around 34% of retirees eat meat, fish, or poultry every day. Almost twice as frequent is the consumption of dairy products on a daily basis (67%), and more than 3/4 of retirees eat a serving of fruits or vegetables every day. Consumption of legumes, beans, and eggs is significantly less frequent, just slightly above 40% of respondents eat a serving at least 3 times a week or more. 57% of retirees are encoded as eating protein 'more often than the sample average'. If we compare changes over time in the panel dataset (from wave 7 to wave 8), we can observe that the frequent consumption (every day, 3 times a week or more, or more often than the sample average) of all food groups either decreased or remained the same over time. Meat and legumes & eggs consumption decreased the most, however, the decreasing trend over time reaches only 2 pp difference at maximum. If we compare the frequency of consumption in wave 8 between the panel and cross-sectional datasets, we can observe lower everyday consumption of meat, dairy products, and fruits & vegetables in the cross-sectional dataset where it reaches around 31%, 63%, and 75%, respectively. The frequency of consumption of protein is the same in both datasets, and consumption of legumes & eggs 3 times a week or more is by 4 pp higher in the cross-sectional dataset.

Moreover, Table A.1 in Appendix provides descriptive statistics of the original categorical dependent variables that were observed directly from the questionnaire responses. The table is followed by Figure A.1 - Figure A.4 which graphically represent the distribution of consumption of foods in the cross-sectional dataset in wave 8.[2] We can notice that the consumption of dairy products and legumes & eggs is right skewed as the vast majority of retirees eat these products every day. The most frequent response regarding the consumption of meat and legumes & eggs is '3-6 times a week' and the distribution of legumes & eggs is closest to the normal distribution. The lower consumption of legumes & eggs can be explained by its substitution for other foods that are also high in protein such as meat or dairy products.

Concerning the panel dataset, we are interested in the frequency change of foods consumption across waves. Therefore, additional dependent variables which capture the increase in consumption or the decrease in consumption were created by subtracting the value of the original categorical variable (composed of 5 categories) in wave 7 from the value of the original categorical variable

[2]Since the distribution is very similar in cross-sectional and panel datasets as well as across waves, we do not provide individual figures for each wave and dataset.

(composed of 5 categories) in wave 8. Since a lower number corresponds to more frequent consumption, negative numbers were coded as an increase, positive numbers as a decrease, and zeros as no change. For each of our 5 food types, we then constructed a dummy variable capturing an increase in consumption ('1' if an increase, '0' if a decrease or no change) and a dummy variable for a decrease in consumption frequency ('1' if a decrease, '0' if an increase or no change). The descriptive statistics are also provided in Table 3.2. The biggest changes in consumption (increase or decrease between waves) can be noticed for the consumption of legumes & eggs and protein (around 30% increase as well as decrease for legumes & eggs, 34% increase and 38% decrease for protein). Overall, regarding any type of food, at least 12% of respondents experienced a change in consumption between waves.

Table 3.2: Dependent variables

		Panel dataset				Cross-sectional dataset	
		Wave 7 (4,431 obs.)		Wave 8 (4,431 obs.)		Wave 8 (22,402 obs.)	
Dependent variable		N	%	N	%	N	%
Meat - every day:	*yes*	1,516	34%	1,439	32%	6,949	31%
	no	2,915	66%	2,992	68%	15,453	69%
Dairy - every day:	*yes*	2,980	67%	2,922	66%	14,139	63%
	no	1,451	33%	1,509	34%	8,263	37%
Legumes & Eggs - 3 times a week or more:	*yes*	1,804	41%	1,741	39%	9,533	43%
	no	2,627	59%	2,690	61%	12,869	57%
Fruits & Vegetables - every day:	*yes*	3,460	78%	3,455	78%	16,908	75%
	no	971	22%	976	22%	5,494	25%
Protein - more often than the sample average:	*yes*	2,536	57%	2,479	56%	12,506	56%
	no	1,895	43%	1,952	44%	9,896	44%
Meat - increase:	*yes*	*n/a*	*n/a*	852	19%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,579	81%	*n/a*	*n/a*
Dairy - increase:	*yes*	*n/a*	*n/a*	665	15%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,766	85%	*n/a*	*n/a*
Legumes & Eggs - increase:	*yes*	*n/a*	*n/a*	1,240	28%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,191	72%	*n/a*	*n/a*
Fruits & Vegetables - increase:	*yes*	*n/a*	*n/a*	528	12%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,903	88%	*n/a*	*n/a*
Protein - increase:	*yes*	*n/a*	*n/a*	1,490	34%	*n/a*	*n/a*
	no	*n/a*	*n/a*	2,941	66%	*n/a*	*n/a*
Meat - decrease:	*yes*	*n/a*	*n/a*	1,015	23%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,416	77%	*n/a*	*n/a*
Dairy - decrease:	*yes*	*n/a*	*n/a*	737	17%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,694	83%	*n/a*	*n/a*
Legumes & Eggs - decrease:	*yes*	*n/a*	*n/a*	1,288	29%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,143	71%	*n/a*	*n/a*
Fruits & Vegetables - decrease:	*yes*	*n/a*	*n/a*	531	12%	*n/a*	*n/a*
	no	*n/a*	*n/a*	3,900	88%	*n/a*	*n/a*
Protein - decrease:	*yes*	*n/a*	*n/a*	1,677	38%	*n/a*	*n/a*
	no	*n/a*	*n/a*	2,754	62%	*n/a*	*n/a*

Note: The panel dataset consists of retirees who participated in both wave 7 and wave 8.
The cross-sectional dataset consist of retirees who participated in wave 8.

3.2.2 Independent variables of interest

The descriptive statistics of variables of interest are provided in Table 3.3.

Started working: Concerning our panel dataset, we want to analyze the change in post-retirement employment status in time, therefore, variable 'Started working' was constructed. It takes value '1' if the retiree did not have any additional income except retirement pension in wave 7 and started having additional income from paid work in wave 8 (i.e.: started working). Value '0' corresponds to retirees who did not have any additional income except retirement pension in wave 7 and continued having retirement pension as the only income also in wave 8 (i.e.: did not start working). In wave 8, 3% of retirees started working in comparison to wave 7.

Working: A dummy variable 'Working' describes whether the retiree receiving a pension has an additional income from dependent employment, self-employment, or work for a family business (equal to 1), or not (equal to 0). Variable 'Working' will be analyzed in the cross-sectional dataset, where the vast majority of retirees (92%) do not have any income from paid employment and receive only retirement pension. However, 8% of retirees do have additional income from employment above pension. There is a 1% difference between our data and the percentage of working retirees that E. Dingemans and Möhring (2019) report in their paper focusing on post-retirement work using SHARE data. This discrepancy might be caused by the inclusion of different waves.

Hours worked: Our third variable of interest describes the number of hours a retiree works per week. With the use of this variable, we are able to examine whether the amount of work plays a role in the frequency of foods consumption (diet). 'Hours worked' is a categorical variable consisting of 5 categories and ranging from 0 (not working any hours) to 5 (working more than 20 hours per week). Unfortunately, the data about working hours were missing for many observations. Therefore, we coded 'Hours worked' as 0 for the individuals who did not receive income from paid work in addition to their pension income, and the remaining missing values were coded as 'missing'. In total, 92% of retirees are working 0 hours, 3% of the data are missing, 2% of retirees work more than 20 hours, and the remaining categories each cover 1% of the individuals.

Table 3.3: Independent variables (explanatory)

		Panel dataset				Cross-sectional dataset	
		Wave 7 (4,431 obs.)		Wave 8 (4,431 obs.)		Wave 8 (22,402 obs.)	
Independent variable (explanatory)		N	%	N	%	N	%
Started working:	*yes*	*n/a*	*n/a*	111	3%	*n/a*	*n/a*
	no	*n/a*	*n/a*	4,320	97%	*n/a*	*n/a*
Working:	*yes*	0	0%	111	3%	1,776	8%
	no	4,431	100%	4,320	97%	20,626	92%
Hours worked:	*0*	*n/a*	*n/a*	*n/a*	*n/a*	20,626	92%
	1-5	*n/a*	*n/a*	*n/a*	*n/a*	270	1%
	6-10	*n/a*	*n/a*	*n/a*	*n/a*	231	1%
	11-20	*n/a*	*n/a*	*n/a*	*n/a*	254	1%
	more than 20	*n/a*	*n/a*	*n/a*	*n/a*	448	2%
	missing	*n/a*	*n/a*	*n/a*	*n/a*	573	3%

Note: The panel dataset consists of retirees who participated in both wave 7 and wave 8. The cross-sectional dataset consist of retirees who participated in wave 8.

3.2.3 Control variables

We control for 6 variables concerning individual characteristics and financial situation. Their descriptive statistics can be observed in Table 3.4.

Age: Three categories were created in order to capture the age of retirees. From wave 7 in the panel dataset, we can see, that almost half of the sample (42%) are retirees older than 75 years. 31% of the sample is less than 70 years old and the age of 27% of the sample ranges between 70-75 years. Naturally, the average age increases from wave 7 to wave 8. In the cross-sectional dataset, overall younger individuals are present in wave 8 compared to the panel dataset. This is caused by the condition that individuals in the panel dataset have to be already retired in wave 7.

Gender: 'Gender' is a dummy variable equal to '1' for males and to '0' for females. 47% and 48% of our sample are males in the panel and cross-sectional datasets, respectively.

Region: To account for cultural characteristics and customs, we created the categorical variable 'Region' by dividing 28 European countries into four regions - Northern Europe, Southern Europe, Central+Eastern Europe, and Western Europe. In the panel dataset, the most represented region is Western Europe with 38% of the sample, followed by Southern Europe (25%), Northern Europe (19%), and Central+Eastern Europe (18%). The distribution across regions changes with a focus on cross-sectional dataset, where the proportion of Western and Southern Europe decreases to 32% and 21%, respectively. This decrease is compensated by an increase in the proportion of Northern and Central+Eastern European countries. This discrepancy is caused by the fact that mainly Southern and Western European countries participated in the initial waves.

Education: 'Education' is a categorical variable describing the number of completed years of education. In both our datasets, almost half of our samples has 11-15 years of education, and only around 5% of retirees have less than 5 years of education.

Spouse/partner: Marital status of the subjects is characterized by a dummy variable 'Spouse/partner'. It equals '1' if the individual is married or in partnership and lives together with the spouse/partner, and '0' otherwise. More than 2/3 of retirees in both our datasets are living in one household with spouse or partner.

Hh gets by financially: Financial situation of a household is reflected by the categorical variable 'Household gets by financially'. A significant number of responses regarding the financial situation of the household was missing, therefore, we created an additional category for the missing values. Missing values account for approximately 30% of the data in both datasets. Mainly for this reason, we decided not to include this variable in some of our models. Considering other categories, in wave 7 in the panel dataset, 43% of retirees responded that they can make ends meet fairly easily or easily. 17% have some difficulty and 7% have great difficulty to get by financially. However, the financial situation improves over time. In wave 7 only 19% of individuals responded they get by easily, while in wave 8 it was 26%.

Table 3.4: Independent variables (control)

		Panel dataset				Cross-sectional dataset	
		Wave 7 (4,431 obs.)		Wave 8 (4,431 obs.)		Wave 8 (22,402 obs.)	
Independent variable (control)		N	%	N	%	N	%
Age:	*less than 70 years*	1,389	31%	806	18%	6,302	28%
	70-75 years	1,198	27%	1,217	27%	6,164	28%
	75 years or more	1,844	42%	2,408	54%	9,936	44%
Gender - male:	*yes*	2,092	47%	2,092	47%	10,647	48%
	no	2,339	53%	2,339	53%	11,755	52%
Region:	*Northern*	846	19%	846	19%	5,112	23%
	Southern	1,120	25%	1,120	25%	4,594	21%
	Central+Eastern	785	18%	785	18%	5,543	25%
	Western	1,680	38%	1,680	38%	7,153	32%
Education:	*less than 5 years*	191	4%	191	4%	1,263	6%
	5-10 years	1,263	28%	1,263	28%	5,667	25%
	11-15 years	2,023	46%	2,023	46%	10,994	49%
	more than 15 years	954	22%	954	22%	4,478	20%
Spouse/partner:	*yes*	3,107	70%	3,001	68%	15,082	67%
	no	1,324	30%	1,430	32%	7,320	33%
Hh gets by financially:	*great difficulty*	322	7%	225	6%	1,199	5%
	some difficulty	733	17%	633	14%	3,752	17%
	fairly easily	1,048	24%	1,070	24%	5,213	23%
	easily	857	19%	1,150	26%	5,266	24%
	missing	1,471	33%	1,323	30%	6,972	31%

Note: The panel dataset consists of retirees who participated in both wave 7 and wave 8. The cross-sectional dataset consist of retirees who participated in wave 8.

3.2.4 Correlation between variables and potentially omitted variables

To test for collinearity in regressors, the Variance Inflation Factor (VIF) method is used. VIF is the overall model variance divided by the variance of a model with only one independent variable and the calculation is repeated for every variable independently. The VIF results are shown in Table 3.5. As no value exceeds the threshold of 5 (the highest value is 1.21 for the spouse/partner variable), we conclude that there is no perfect collinearity in regressors. In addition, no presence of collinearity is supported also by the results of correlation matrix provided in Table A.2 in Appendix.

We are aware of the fact that some variables which affect the diet of the retirees might be omitted. Omitting important variables would result in biased estimates. Specific examples of potentially omitted variables and the problem of bias are discussed in Section 6.

Table 3.5: Variance Inflation Factors

	Panel dataset		Cross-sectional dataset
	Wave 7	Wave 8	Wave 8
Age:	1.06	1.06	1.05
Gender:	1.08	1.08	1.09
Region:	1.02	1.02	1.02
Education:	1.04	1.05	1.05
Spouse/partner:	1.19	1.15	1.21
Hh gets by financially:	1.11	1.09	1.15

4 Methodology

This section outlines the approach for hypotheses testing. First, we focus on the main estimation technique - propensity score matching (PSM). We describe methodology as well as motivation for selection of PSM and the average treatment effect on the treated (ATT). Assumptions, their fulfillment, and subsequently different matching algorithms (nearest neighbours matching, radius matching, kernel matching, stratification matching) are explained and commented on. Next, as our dependent variable is binary, we discuss the logit regression model which will be used as a robustness check.

4.1 Propensity score matching

To make sure that we compare retirees with the same baseline covariates, we use a matching method. Further, in our main model, we analyze panel data and apply PSM difference-in-differences approach to account for the changes in the foods consumption over time. Retirees, who did not have any additional income except retirement pension in wave 7 and continue having retirement pension as the only income in wave 8, are included in the control group. The treatment group consists of retirees who did not have any additional income except retirement pension in wave 7 but started having additional income from paid work in wave 8. Next, we apply the PSM method on cross-sectional data (single wave only) and we compare our results with the outcomes of the logit model, which is introduced in Section 4.2. In this case, the treatment group consists of retirees who have paid work, and the group of retirees without paid work serves as the control group.

We focus on the effect of the treatment ($T = 1$), in our case 'started working', relative to no treatment ($T = 0$), in our case 'did not start working'. [3] It is not possible to capture the retiree's outcome both with and without the treatment (the retiree either started working or not), thus we estimate the average treatment effect on the treated (ATT) which is defined as the average of the individual treatment effects of those who received the treatment (hence not the entire sample). An alternative could be the average treatment effect (ATE) defined as the average of the individual treatment effects of the sample under consideration.

The propensity score matching method can be divided into two steps. In the first step, we separate the retirees from the treatment group into specific categories based on the covariates,

[3] We describe the matching approach for $T = 1$ if the retiree started working and $T = 0$ if the retiree did not start working. However, the same would apply to our model on cross-sectional data, where $T = 1$ if the retiree is working and $T = 0$ if the retiree is not working.

and next we assign the observations from the control group into the same categories based on their covariates, because the logic behind the matching approach is that the distribution of covariates must be balanced for the treatment and control group. Therefore, in the first step, the main focus is on our control variables. Consequently, as a second step, we compare the dietary outcomes for the treatment and control groups.

4.1.1 Average treatment effect on the treated

There are two possible outcomes for each individual i, either $Y_i(1)$ or $Y_i(0)$, which represent the outcome for a retiree i when the retiree started working or did not start working, respectively. The treatment effect for an individual i can be defined as $\alpha_i = Y_i(1) - Y_i(0)$, however, it is not possible to estimate α_i, since always only one outcome is observable for individual i. Therefore, as already mentioned, we are interested in the average treatment effect on the treated (ATT).

ATT is defined as

$$\alpha_{ATT} = E[\alpha \mid X, T = 1] = E[Y(1) - Y(0) \mid X, T = 1] = E[Y(1) \mid X, T = 1] - E[Y(0) \mid X, T = 1], \tag{4.1}$$

where X is the set of covariates (Caliendo and Kopeinig 2008).

$Y(0)$ is not observable for the treatment group and thus the mean outcome of treated ($E[Y(0) \mid X, T = 1]$) is unobservable in our sample (counterfactual). After adjusting the equation we get

$$\alpha_{ATT} = E[Y(1) \mid X, T = 1] - E[Y(0) \mid X, T = 1]$$

$$\alpha_{ATT} + E[Y(0) \mid X, T = 1] = E[Y(1) \mid X, T = 1]$$

$$\alpha_{ATT} + E[Y(0) \mid X, T = 1] - E[Y(0) \mid X, T = 0] = E[Y(1) \mid X, T = 1] - E[Y(0) \mid X, T = 0] \tag{4.2}$$

Using the mean outcome of untreated ($E[Y(0) \mid X, T = 0]$) is not recommended, because the factors that influence the treatment decision may also influence the outcome decision, meaning that the difference between the outcomes of the treatment and control groups would be present even without the treatment (Caliendo and Kopeinig 2008).

The expression $E[Y(0) \mid X, T = 1] - E[Y(0) \mid X, T = 0]$ from the Equation4.2 represents the self-selection bias. The true parameter α_{ATT} is only identified, if the self-selection bias is not present, i.e.

$$E[Y(0) \mid X, T = 1] - E[Y(0) \mid X, T = 0] = 0. \tag{4.3}$$

In that case, ATT can be estimated as

$$\alpha_{ATT} = E[Y(1) \mid X, T = 1] - E[Y(0) \mid X, T = 0]. \tag{4.4}$$

4.1.2 Requirements for validity

One of the strongest assumptions is the conditional independence assumption (CIA) also called assumption of unconfoundedness (Caliendo and Kopeinig 2008). The CIA states that, after conditioning on a set of observed covariates X which are not affected by the treatment, potential outcomes are independent of treatment status:

$$Y(0), Y(1) \amalg T \mid X, \quad \forall \quad X. \tag{4.5}$$

This assumption requires that all control variables that have an impact on both the potential outcomes and the probability or receiving treatment are observed. By fulfilling this, it is possible to use the untreated observations to construct an unbiased counterfactual for the treatment group. In Section 4.1.3, CIA based on propensity scores is introduced.

Further, common support or overlap condition assumption requires that for every set of observable covariates X, there is a positive probability of being both treated and untreated, in other words that the perfect predictability of T given X is prevented (Caliendo and Kopeinig 2008):

$$0 < P(T = 1 \mid X) < 1. \tag{4.6}$$

This condition ensures that it is possible to find adequate matches because there is sufficient overlap in the characteristics of treated and untreated units.

For a causal inference with propensity scores, stable unit treatment value assumption (STUVA) must hold. Under STUVA, the potential outcome for each subject i is independent of the treatment status of other subjects given observed covariates X. Additionally, SUTVA implies that there are no unrepresented versions of the treatments so that the outcome for each subject i is independent of which version of treatment was administered (Rubin 2005).

Having introduced the key assumptions, we discuss their validity in our sample. According to the CIA, only variables that are not influenced by the treatment participation, or its anticipation, can be included in the set of covariates X. Among our set of control variables, we include individual characteristics such as gender, age, region, or education. These variables are in our datasets fixed over time or deterministic with respect to time. Variable describing whether an individual shares a household with spouse or partner is not stable, however, we measure it before the treatment participation, so that it is not confounded with the treatment or outcome. We decided not to include variable describing household ability to get by financially, due to the high number of missing variables and potential influence of the treatment. The selection of variables was evaluated using statistical significance. Further, the difference between the outcomes of the treated group and the control groups can be attributed only to the fact of being treated. We use propensity scores as balancing scores and by applying the propensity score method, we account for the unconfoundedness. Nevertheless, if important variables are omitted, it leads to bias in the results.

The conditional independence assumption can be partially addressed by using difference-in-differences matching on panel data. Retirees are most likely selected to the treatment group (started working) based on unmeasured characteristics that we do not account for since they are not observable. Such an example can be for example the motivation for working (financial situation, loneliness, work environment, and others). We tackle this issue by including also pre-treatment data (data from wave 7). The main assumption of this approach is the equal trends assumption. Because we have only two-period data, it is not possible to inspect this assumption visually, thus we suppose, that there are no time-varying differences between the treatment and control groups (the difference between the treatment and control group is constant over time) and the time effect can be canceled out by taking the differences between two waves (Heinrich, Maffioli, Vazquez, et al. 2010).

In the difference-in-differences model, we include the outcome as a change between the pre-treatment and post-treatment period

$$\Delta Y_i = Y_{it'} - Y_{it} \tag{4.7}$$

where t' is the pre-treatment period and t is the post-treatment period.

By the inclusion of differences between periods, the CIA assumption can be relaxed to

$$E[Y_{t'}(0) - Y_t(0) \mid X, T = 1] - E[Y_{t'}(0) - Y_t(0) \mid X, T = 0] = 0. \tag{4.8}$$

Under the assumption that the trend is stable over time for both groups (treated and untreated), the outcome of the treated retirees can now differ from the outcome of the untreated, and bias resulting from the differences can be eliminated. The propensity score is calculated on the pre-treatment period and a set of covariates X which do not change over time or which are measured prior to treatment are included (Heinrich, Maffioli, Vazquez, et al. 2010).

We suppose that the common support condition is not violated, meaning that all individuals with the same values of covariates X have a positive probability of either working or not working after retirement and that this probability does not equal 0 or 1. This assumption is also eased because of the use of propensity scores.

In simple terms, there cannot be any spill-over effect for the STUVA to be fulfilled. It can be assumed, that if retiree i starts working in time t, it does not have any impact on the consumption of foods (our outcome variable) of any other individual at any given time, because we do not include more individuals from the same household.

4.1.3 Propensity score

Propensity scores (PS) are used to adjust for confounders in non-randomized studies. They describe the conditional (predicted) probability of being assigned to the treatment group conditional on the observed covariates X (Caliendo and Kopeinig 2008). With the use of PS, biases due to observable components are not present.

The propensity score is defined as

$$P(X) = P(T = 1 \mid X). \tag{4.9}$$

Rosenbaum and Rubin (1983) showed that if $Y(0), Y(1) \amalg T \mid X, \quad \forall \quad X$, then also the potential outcomes are independent of treatment conditional on a propensity score (or other balancing scores), i.e.:

$$Y(0), Y(1) \amalg T \mid P(X), \quad \forall \quad X. \tag{4.10}$$

If CIA as well as overlap condition hold, the propensity score matching (PSM) estimator for ATT is defined as

$$\alpha_{ATT}^{PSM} = E_{P(X)|T=1} E[Y(1) \mid P(X), T = 1] - E[Y(0) \mid P(X), T = 0]. \tag{4.11}$$

For ATT it is sufficient to assume that for every X

$$Y(0), Y(1) \amalg T \mid P(X) \tag{4.12}$$

and

$$P(T = 1 \mid X) < 1. \tag{4.13}$$

4.1.4 Propensity score matching implementation

First, propensity scores need to be estimated. For the binary treatment, the logit or probit model is usually employed to estimate the propensity scores, rather than the linear probability model. According to Smith (1997), the results of both logit and probit models are mostly similar. In this thesis, we use the logit model for the estimation of PS. Subsequently, the right set of covariates X needs to be selected so that the CIA holds. Moreover, it is possible to put greater emphasis on specific variables, in case some of the variables are more important in determining the outcome or treatment decision. If the CIA holds, the overlap and common support conditions also need to be ensured. We will analyze the density distribution of the PS and the overlap of the PS visually. If necessary, the region of common support might be determined by omitting the observations which have PS out of the interval [min (PS of treated, PS of control), max (PS of treated, PS of control)] or by trimming procedure (Caliendo and Kopeinig 2008).

Next, it is essential to choose the right matching algorithm. Although all PSM algorithms compare the outcomes of individuals included in the treated versus control group, they differ regarding the definition of the neighborhood as well as the neighborhoods' weights. In the ideal case (with a growing sample size), all matching algorithms would yield the same results, but in the case of small sample sizes, the results might differ significantly.

The most common is nearest neighbour (NN) matching. It pairs the treatment unit with the closest eligible control unit in terms of the propensity score. It can be run either with replacement (each unit from the control group can be matched with more than one unit from the treatment group) or without replacement (each unit from the control group can be used only once). Allowing for replacement is recommended when the propensity score distribution differs significantly between the treatment and control groups. Another possibility is to use more than one nearest neighbour. However, both of these specifications pose a trade-off between efficiency and bias. Another specification is radius matching which avoids the risk of poor matches associated with the NN matching because it assigns a limit (propensity range) to which the units can be paired. Units with a larger distance than the radius width remain unmatched and are dropped from the sample (Caliendo and Kopeinig 2008).

Kernel matching compares the outcome of each treated subject with the weighted average of the outcomes of all untreated subjects. The weights are based on the distance of the propensity scores of untreated subjects to that of the treated subjects. The highest weight is assigned to those with scores closest to the treated subject. Compared to NN and radius matching, kernel matching uses more information and thus lowers the variance, on the other hand, there is a higher risk of bad matches, therefore it is important that the common support condition holds (Caliendo and Kopeinig 2008).

Another type of matching is stratification matching. Stratification matching divides the common support of the propensity score into different intervals (stratas) and calculates the impact within each interval by taking the mean difference in outcomes between treated and control subjects (Caliendo and Kopeinig 2008). The number of stratas needs to be chosen properly, Cochran and S. P. Chambers (1965) conclude that 95% of bias associated with one single covariate are removed by using 5 intervals.

There is no clear conclusion about which matching estimator is overall the best one; therefore, the data structure must be considered not only for the estimator selection but also in order to decide on the size of propensity range (radius matching) or stratas (stratification matching). Moreover, the trade-off between efficiency and bias must be considered.

Finally, after the PSM, it is necessary to evaluate whether the distribution of the variables in the treatment and control group is balanced (whether matching was successful or not). One possibility is to make sure that additional conditioning on the set of covariates X does not add any new information about the treatment decision. Because if there remains some dependence on X after the conditioning on PS, probably either the CIA condition is violated or the specification of the model used to estimate the PS is incorrect. The matching quality can be also assessed by using a two-sample t-test to check if there are significant differences in the covariates X for the treatment and control group before and after matching. After matching, no significant differences should be observed as the covariates should be balanced. Another way is to re-estimate the PS on the matched sample and compare the pseudo R-squared with the pseudo R-squared of the same model before matching. After matching, the pseudo R-squared should be low, because there should be no systematic differences in the distribution of covariates X among the treatment and control group.

4.2 Logit model

The logit model is carried out during the first step in PSM to calculate the propensity scores. In addition, we also use the logit model as a robustness check of our PSM results. In addition, with logistic model, we are able to capture and discuss also the impact of other variables on the diet of retirees, not only the effect of post-retirement work.

Our main objective is to estimate the impact of working after retirement on the consumption of different foods (diet). Several models in the following form will be introduced as a robustness check:

$$\text{food consumption}_i = \beta_0 + \beta_1 \text{ working after retirement}_i + \mathbf{X}\boldsymbol{\beta} + \mu_i, \tag{4.14}$$

where food consumption stands for consumption of meat, dairy, legumes & eggs, fruits & vegetables, and protein - separate models are tested for each of this variables. **X** represents the vector of control variables and μ_i is the error term that is assumed to be identically independently and normally distributed.

Logit model is chosen since the dependent variables are qualitative. Other possibility would be to use linear probability model, but in order to avoid its main drawbacks - the predicted probabilities can fall out of the interval [0,1] and the partial effect of any explanatory variable is constant - we use binary response model. For the estimation of binary response models that are nonlinear, the Maximum Likelihood Estimation (MLE) is used. According to Wooldridge (2015), even under very general conditions, MLE can be assumed as consistent, asymptotically normal, and asymptotically efficient. The methodology of this subsection is based on Wooldridge (2015).

Given the probability

$$\mathrm{P}(y=1 \mid \mathbf{X}) = \mathrm{P}\left(y=1 \mid x_1, x_2, \ldots, x_k\right) \tag{4.15}$$

where y is the binary dependent variable, and **X** denotes the full set of explanatory variables, we specify the response probability as

$$\mathrm{P}(y=1 \mid \mathbf{X}) = G\left(\beta_0 + \mathbf{X}\boldsymbol{\beta}\right) \tag{4.16}$$

where $G\left(\beta_0 + \mathbf{X}\boldsymbol{\beta}\right) = G\left(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k\right)$, G is a function with values strictly between zero and one for all real numbers. This avoids one of the drawbacks of the LPM.

In the logit model, function G is defined as

$$G(z) = \frac{1}{1+e^{-z}} = \frac{e^z}{1+e^z}. \tag{4.17}$$

This is the increasing cumulative distribution function (CDF) for a standard logistic random variable that ranges between zero and one for all real numbers z.

Using a latent variable model, we can derive the logit model. For this, let y^* be a latent variable and ε an independent error term with the standard normal distribution, such that

$$y^* = \mathbf{X}\boldsymbol{\beta} + \varepsilon, \quad y = 1[y^* > 0]. \tag{4.18}$$

The notation $1[\cdot]$ defines binary outcome by taking value 1 if the event in brackets is true, and zero otherwise. Because ε is symmetrically distributed around zero, $1 - G(-z) = G(z)$ for all real numbers z.

Using the assumptions and Equation4.18 we can derive the response probability for y as

$$\mathrm{P}(y = 1 \mid \mathbf{X}) = \mathrm{P}(y^* > 0 \mid \mathbf{X}) = \mathrm{P}[\varepsilon > -(\beta_0 + \mathbf{X}\boldsymbol{\beta}) \mid \mathbf{X}] = 1 - G[(-\beta_0 + \mathbf{X}\boldsymbol{\beta})] = G(\beta_0 + \mathbf{X}\boldsymbol{\beta}). \tag{4.19}$$

The interpretation of the estimates is not straightforward due to the nonlinear nature of $G(\cdot)$. Using the specification of the response probability, we can interpret the sign of the coefficients which indicates the positive or negative effect on the dependent variable, however, the latent variable y^* does not have a well-defined value of measurement and thus the magnitudes of the coefficients cannot be directly interpreted.

The partial effect (marginal effect), which enables more straightforward interpretation, can be calculated using partial derivative

$$\frac{\partial P(y = 1 \mid \mathbf{X})}{\partial x_j} = \frac{\partial p(\boldsymbol{X})}{\partial x_j} = g\left(\beta_0 + \mathbf{X}\boldsymbol{\beta}\right)\beta_j, \quad where \quad g(z) = \frac{dG}{dz}(z) \tag{4.20}$$

Where g is a probability density function as G is the CDF of a continuous random variable, and so $g(z) > 0$ for all z. Thus, the partial effect of x_j will always have the same sign as β_j for all j.

Assumptions, Tests & Significance measures

Pseudo R-squared can be used to measure binary response. McFadden (1974) suggests the measure $1 - \mathcal{L}_{ur}/\mathcal{L}_o$, where $\mathcal{L}_{ur}$ is the log-likelihood function for the estimated model, and $\mathcal{L}_o$ is the log-likelihood function in the model with only an intercept. Models with larger pseudo R-squared are preferred.

Log-likelihood ratio test or Wald test can be used to assess the significance of the independent variables in the model. The Wald test is essentially the same as F statistics and only the unrestricted model estimates are required to perform the Wald test. Log-likelihood ratio test compares the difference between the log-likelihood functions for the unrestricted and restricted models considering that as MLE maximized the log-likelihood function, decreasing the number of variables cannot lead to larger-log-likelihood. Both tests follow a chi-square distribution, with df equal to the number of restrictions being tested, and the null hypothesis is that the restricted model fits better than the unrestricted (Wooldridge 2015).

Logistic regression assumes the observations to be independent of each other, further, it requires that there is no severe multicollinearity among the independent variables and that there are no extreme outliers. In addition, if the fact of whether a retiree is working or not is correlated with the food consumption habits as well as the error term, an endogeneity problem would arise (Wooldridge 2015). Although we try to include all the relevant control variables, there still might be some variables omitted - they either were not collected by the SHARE questionnaire or a high proportion of them was missing in our dataset. The problem of potentially missing variables is discussed in Section 6.

5 Results

In this chapter, we present the results. First, we describe the results of propensity score matching using the main panel dataset. Subsequently, we analyze also the cross-sectional dataset by implementing the propensity score matching as well as the logit model. The logit model serves as a robustness check but in addition, it enables us to comment on other variables that might have an impact on the diet of retirees. Last, we compare the results and provide a discussion.

STATA statistical software was used to undertake statistical analysis on our data and to produce graphical visualizations. Specifically, for the propensity score calculation, subsequent matching, and for generating treatment effect estimates, we use *psmatch2* program developed by Leuven and Sianesi (2003).

5.1 Propensity score matching - Panel dataset

First, we analyze the panel dataset using the propensity score matching method. Our treatment group consists of retirees who did not have any additional income except retirement pension in wave 7 and started having additional income from paid work in wave 8 (i.e.: started working). Retirees who did not have any additional income except retirement pension in wave 7 and continued having retirement pension as their only income also in wave 8 (i.e.: did not start working) are our control group. There are 111 and 4,320 observations in our treatment and control groups, respectively.

5.1.1 Characterizing the propensity scores

We estimate the propensity scores using the logit model. Age, gender, region, education, and marital status are included as covariates that relate to the treatment status (started working or did not start working) as well as the outcomes (changes in foods consumption). In the logit model, the dependent variable is the treatment variable describing whether an individual started working or not.

Table A.3 in the Appendix shows the results of the logit model. Variable 'age' is negatively correlated with the probability of treatment (started working). Older individuals have a significantly lower probability to start working. We see significant positive parameters for gender which implies that men have a higher probability to start working than women. Regarding region, compared to Western Europeans, retirees from Northern Europe tend to start working after retirement with a higher probability. The opposite is true for retirees from Southern Europe, who have a lower probability to start working in retirement. Variables describing years of education and whether a retiree is living together with a spouse or partner are not significant indicators for starting to work after retirement. Despite the insignificance of these variables we still include them in our models because we expect them to have an impact on the outcome (diet of retirees). As next, the predicted probabilities are calculated based on the propensity scores.

5.1.2 Results of matching

We use radius matching as our main matching method to assign comparison units to treated units based on the propensity scores. The radius matching method was chosen due to the low number of treatment observations in our dataset compared to the high number of control observations. Radius matching allows more than one match to be used for each treatment variable and thus more information from the data is utilized. On the other hand, specifying the radius avoids the risk of poor matches as it defines the maximum propensity score distance by which a match can be made. We allow for sampling with replacement and the estimator was conducted with different values of radii. However, since the results were robust, here we only present the results based on the radius of 0.001.

Nearest neighbour matching, kernel matching, and stratification matching were also performed to serve as a robustness check. Again, we conducted the matching processes with different specifications and the results of specific matching methods were robust. Standard errors for all effects are calculated by the bootstrapping method using 100 replications. All the results can be seen in Table 5.1 where each row represents a different matching method.

Most of the results seem robust as the effects of the treatment and their significance levels are similar under different matching methods. The only exception is the significance of the increase in meat consumption. While the estimates of radius matching and NN matching are significant at 5% significance level, the estimate of kernel matching is significant only at 10% significance level, and regarding the stratification matching method, the estimate is not significant even at 10%. However, our main method is supported by at least one other matching alternative and the estimates of the remaining matching alternatives have the same direction, thus we consider the result robust also in this case. Overall, the results support the hypothesis that starting to work in retirement (i.e.: starting to have additional income from paid work besides retirement pension) increases the consumption of meat and fruits & vegetables. Specifically, the expected probability of retiree increasing meat and fruits & vegetables consumption is greater by 9 pp for those who start working after being already retired and unemployed for some time, compared to those who do not start working. No significant impact of the treatment is found on the increased

Table 5.1: PSM - Panel dataset: Results

Variable of interest: Started working						
	Meat - increase	Dairy - increase	Legumes & Eggs - increase	Fruits & Vegetables - increase	Protein - increase	Obs.
Radius matching:	0.09* (0.05)	0.02 (0.04)	0.05 (0.05)	0.09* (0.04)	-0.08 (0.06)	4,431
NN matching:	0.12* (0.05)	0.04 (0.04)	0.05 (0.05)	0.08* (0.05)	0.09 (0.06)	4,431
Kernel matching:	0.07· (0.04)	0.00 (0.03)	0.06 (0.05)	0.10* (0.04)	0.06 (0.05)	4,431
Stratification matching:	0.07 (0.04)	0.01 (0.03)	0.07 (0.05)	0.10** (0.04)	0.06 (0.05)	4,431
	Meat - decrease	Dairy - decrease	Legumes & Eggs - decrease	Fruits & Vegetables - decrease	Protein - decrease	Obs.
Radius matching:	0.01 (0.05)	-0.00 (0.04)	0.02 (0.06)	0.04 (0.03)	-0.04 (0.04)	4,431
NN matching:	0.02 (0.05)	0.03 (0.05)	0.00 (0.05)	0.01 (0.05)	-0.03 (0.05)	4,431
Kernel matching:	0.01 (0.04)	-0.01 (0.04)	0.01 (0.04)	0.02 (0.04)	-0.02 (0.04)	4,431
Stratification matching:	0.00 (0.04)	-0.01 (0.04)	0.01 (0.04)	0.01 (0.03)	-0.02 (0.05)	4,431

Note: Marginal effects; Bootstrapped standard errors provided in brackets;
**** p<0.001, ** p<0.01, * p<0.05, · p<0.1*

consumption of dairy products, legumes & eggs, and protein. However, the direction of the treatment's impact is positive for all cases and in the case of legumes & eggs and protein higher than 0.05. Regarding the decline in consumption, there does not appear to be any relationship between starting to work after retirement and decreased consumption of any of the analyzed foods, since none of the results is significant and in addition, the estimates are low in magnitude.

To assess the quality of performed matching, the differences in the means of the propensity scores between the treatment and the control groups are compared in Table 5.2. Although there were not many significant differences in the covariate means before matching, the differences after matching are even lower, do not exceed 0.03 for any of the covariates, and are not statistically significant. Therefore, we conclude that with matching we are able to reduce the bias associated with the observable characteristics.

Table 5.2: PSM - Panel dataset: Differences in means before and after matching

		BEFORE MATCHING			AFTER MATCHING		
		T	C	Diff	T	C	Diff
Age:	70-75 years	0.297	0.311	-0.01	0.300	0.295	0.00
	75 years or more	0.387	0.385	0.00	0.390	0.398	-0.01
Gender - male:		0.554	0.554	0.04	0.558	0.514	0.00
Region:	Northern	0.342	0.249	0.09	0.336	0.358	-0.02
	Southern	0.099	0.240	-0.14**	0.100	0.072	0.03
	Central+Eastern	0.171	0.161	0.01	0.172	0.163	0.01
Education:	less than 5 years	0.027	0.042	0.02*	0.027	0.023	0.00
	5-10 years	0.198	0.205	-0.01	0.200	0.191	0.01
	more than 15 years	0.315	0.303	0.01	0.309	0.306	0.00
Spouse/partner:		0.666	0.666	0.00	0.663	0.673	-0.01

*Note: T- treatment group; C - control group; Diff - differences in means; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1*

The overlap of common support condition was verified by visual inspection of the propensity scores' distribution. We graph the propensity scores for treatment and control groups before and after matching. Based on Figure 5.1 - Figure 5.2 we conclude that matching was successful as the distribution of propensity scores after matching is similar for the treatment and control groups and there is a clear overlap.

Figure 5.1: PSM - Panel dataset: PS distribution before matching

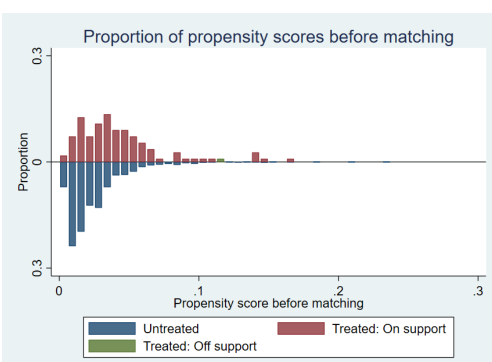
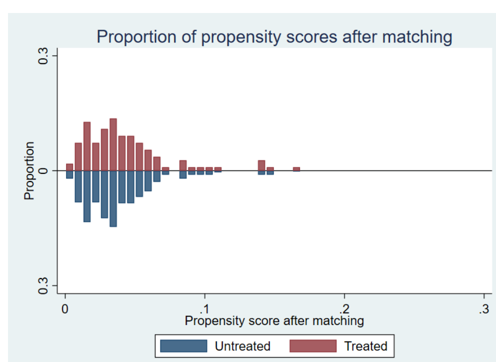


Figure 5.2: PSM - Panel dataset: PS distribution after matching



5.2 Propensity score matching - Cross-sectional dataset

Subsequently, we analyzed wave 8 only (cross-sectional dataset). In this case, we are interested in the difference between retirees who have an additional income from dependent employment, self-employment, or work for a family business, besides retirement pension (treatment group) and retirees who receive retirement as their only income (control group). The treatment and control groups include 1,776 and 20,626 retirees, respectively. We proceed the same way as explained in Section 5.1. However, in this case, our dependent variables are not related to changes in foods consumption but to the frequency of consumption of specific foods per week.

5.2.1 Characterizing the propensity scores

The results of the logit model which was used to estimate the propensity scores can be seen in Table A.4 in the Appendix. The dependent variable is the treatment variable describing whether a retiree is working or not. Based on the results of the logit model we conclude that the probability of working after retirement decreases with age. On average, men have a higher probability by 4 pp of working after retirement than women. Regarding region, compared to retirees from Western Europe, retirees from Northern and Central+Eastern Europe are more likely to be working. On the other hand, the probability of working is lower for retirees from Southern Europe. Regarding years of education, compared to having 11-15 years of education, having 5-10 years of education decreases the probability and having more than 15 years of education increases the probability of working after retirement. Thus we conclude that more educated retirees are more likely to work after retirement. Living with a spouse or partner decreases the probability of the treatment (working after retirement). Based on the propensity scores, the predicted probabilities were calculated.

5.2.2 Results of matching

As in Section 5.1, four matching methods were used to match the propensity scores of treatment and control groups. Different specifications of each method were tested and the results regarding individual matching methods were robust. Radius matching is our main model, the other matching alternatives serve as a robustness check. Results with bootstrapped standard errors are provided in Table 5.3. We can see that significant negative estimates regarding meat consumption are supported by all four models, therefore, we consider them robust. Specifically, the expected probability of retirees eating meat every day is lower by 4 pp for those who are working after retirement compared to those who are not working after retirement. Based on the main matching algorithm (radius matching) no other estimates are significant at 5% significance level. Regarding the alternative methods which serve as a robustness check, there is a positive significant effect of the treatment (working after retirement) on the consumption of dairy and the consumption of fruits & vegetables under stratification matching and NN matching, respectively. However, the estimates are no longer significant if we choose any other matching method. Further, none of the matching methods finds a significant impact on the consumption of legumes & eggs, or protein.

Table 5.3: PSM - Cross-sectional dataset: Results

Variable of interest: Working	Meat	Dairy	Legumes & Eggs	Fruits & Vegetables	Protein	Obs.
Radius matching:	-0.04** (0.01)	0.01 (0.02)	0.00 (0.01)	0.00 (0.01)	-0.03· (0.01)	22,402
NN matching:	-0.05*** (0.01)	-0.01 (0.02)	0.01 (0.02)	0.02* (0.01)	-0.02 (0.01)	22,402
Kernel matching:	-0.04** (0.01)	0.02 (0.01)	0.00 (0.01)	0.00 (0.01)	-0.02 (0.01)	22,402
Stratification matching:	-0.02* (0.01)	0.03** (0.01)	-0.01 (0.01)	0.00 (0.01)	-0.02 (0.01)	22,402

*Note: Marginal effects; Bootstrapped standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1; Meat - every day, Dairy - every day, Legumes & Eggs - 3 times a week or more, Fruits & Vegetables - every day, Protein - more often than the sample average*

The means of the predicted propensity scores of the treatment and control groups are compared in Table 5.4. Before matching, significant differences in means were observed especially for variables describing the region. Moreover, almost half of the differences in means would be significant under 10% significance level. After matching, the differences in means of the predicted PS are no longer statistically significant for any of the variables.

Visual inspection of the distribution of propensity scores (Figure 5.3 - Figure 5.4) supports the successful matching assumption and contributes to the conclusion that the common support condition is satisfied.

Table 5.4: PSM - Cross-sectional dataset: Differences in means before and after matching

		BEFORE MATCHING			AFTER MATCHING		
		T	C	Diff	T	C	Diff
Age:	70-75 years	0.302	0.282	0.02	0.302	0.299	0.00
	75 years or more	0.246	0.272	-0.03·	0.246	0.250	-0.00
Gender - male:		0.560	0.552	0.01	0.560	0.570	-0.01
Region:	Northern	0.304	0.234	0.07***	0.304	0.305	-0.00
	Southern	0.108	0.220	-0.11***	0.108	0.108	-0.00
	Central+Eastern	0.266	0.242	0.02	0.266	0.262	0.00
Education:	less than 5 years	0.044	0.031	0.01·	0.044	0.038	0.01
	5-10 years	0.163	0.184	-0.02	0.163	0.151	0.01
	more than 15 years	0.293	0.266	0.03·	0.293	0.299	-0.01
Partnership:		0.681	0.682	-0.00	0.681	0.697	-0.02

*Note: T- treatment group; C - control group; Diff - differences in means; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1*

Figure 5.3: PSM - Cross-sectional dataset: PS distribution before matching

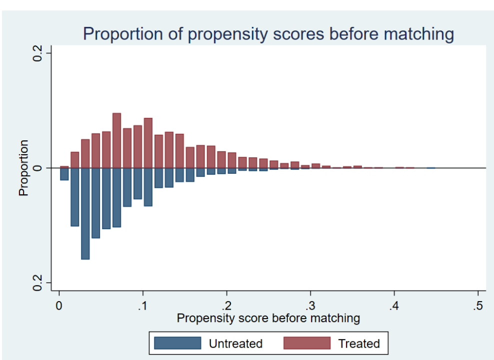
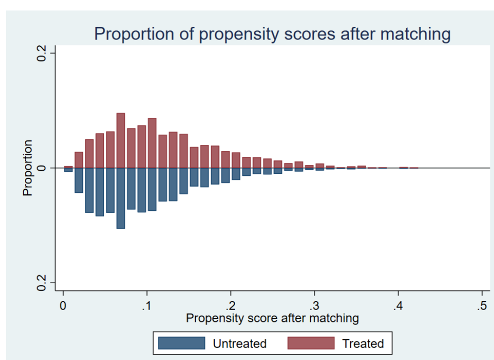


Figure 5.4: PSM - Cross-sectional dataset: PS distribution after matching



5.3 Logit - Cross-sectional dataset (Robustness check)

Data from the cross-sectional dataset are subsequently analyzed using logistic regression. Compared to the PSM approach, in this section, we include and analyze additional variable and moreover, we are able to comment on the effect of other independent variables that might explain the consumption of foods, not only on the working status.

First, in order to compare the logit results with PSM results, we estimated the logit model with the same variables as in Section 5.2. Table 5.5 shows the marginal effects obtained from the PSM model and the logit model for the variable of interest describing whether a retiree is working. The full results of the logit model are reported in Table A.6 in the Appendix. We see that the effect of working after retirement on meat consumption is robust since the results are highly significant in both models and the direction and magnitude of the estimate are the same. However, the same does not hold for dairy products consumption. While we could conclude based on the logit model that the probability of consuming dairy products every day increases by 3 pp for retirees who are working after retirement, compared to non-working retirees, the estimate in PSM model is not significant. None of the other estimates is significant at 5% significance. Nevertheless, the direction of the estimates is robust regardless method used.

Table 5.5: PSM & Logit - Cross-sectional dataset: Results

Variable of interest: Working					
	Meat	Dairy	Legumes & Eggs	Fruits & Vegetables	Protein
PSM	-0.04*** (0.01)	0.01 (0.02)	0.00 (0.01)	0.00 (0.01)	-0.03· (0.01)
LOGIT	-0.04*** (0.01)	0.03* (0.01)	0.00 (0.01)	0.01 (0.01)	-0.01 (0.01)

*Note: Marginal effects; Bootstrapped/Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1; Meat - every day, Dairy - every day, Legumes & Eggs - 3 times a week or more, Fruits & Vegetables - every day, Protein - more often than the sample average*

Next, we estimated the logit model which includes additional variable describing the household's ability to make ends meet. The new variable turns out as significant, therefore, we present the full results of this logit model in Table 5.6. Regarding our variable of interest - the working status of retirees - only estimates for meat consumption are significant at 5% significance level. We conclude that on average, the expected probability of eating meat every day is 4 pp lower for working retirees, compared to non-working retirees. There is no significant impact of working after retirement on the frequency of consumption of dairy products, legumes & eggs, fruits & vegetables, and protein. However, all the parameters, except for dairy products, are negative and do not exceed 0.02.

As for the control variables, each of them turns out as significant in at least one model. The likelihood of consuming fruits & vegetables and dairy products every day increases with increasing age. Retirees aged 75 years or older have a higher probability to consume dairy products and fruits and vegetables by 6 pp and 4 pp, respectively, compared to retirees younger than 70 years. Speaking about gender, compared to women, men have a higher probability by 4 pp to eat meat every day. But on the other hand, they have a lower probability of consuming dairy products (by 5 pp) and fruits & vegetables (by 10 pp) every day. The estimates of the variable region are significant for all categories, in all 5 models. Compared to retirees from Western Europe, retirees from other parts of Europe have a lower probability to eat fruits & vegetables every day (the biggest difference is observed for retirees from Central+Eastern Europe - 16 pp difference). Overall, all the estimates regarding Central+Eastern Europe are negative indicating less frequent consumption of all food types. The biggest difference in magnitude can be seen for dairy products, we conclude that, compared to retirees from Western Europe, retirees living in Central+Eastern Europe have a lower probability of eating dairy products every day by 25 pp. On the other hand, compared to retirees from Western Europe, retirees in Northern Europe are more likely to eat meat and dairy products every day, eat legumes & eggs 3 times per week or more, and consume protein more often than the sample average. Regarding Southern Europe, all the estimates are negative except for legumes & eggs, where the expected probability of consuming legumes & eggs 3 times per week or more is 10 pp higher for retirees from Southern Europe, compared to retirees living in Western Europe. Regarding education, compared to having 11-15 years of education, having less than 5 years of education is associated with a lower probability of eating protein more often than the sample average (by 4 pp) and a lower probability of eating meat and fruits & vegetables everyday (by 12 pp and 3 pp, respectively). On the other hand, having more than 15 years of education increases the probability of eating dairy products and fruits & vegetables every day by 4 pp. Thus, we conclude that years of education are positively correlated with the frequency of consumption of specific food products. All the estimates of the variable 'Spouse/partner' are positive, suggesting more frequent consumption. We conclude that by living in a household with a spouse or partner, the probability of eating meat, dairy products, and fruits & vegetables daily increases, so does the probability of eating legumes & eggs 3 times per week or more, and the probability of consuming protein more often than the sample average. The differences in probability range from 2 pp (dairy products) to 6 pp (protein). The household's ability to make ends meet (variable 'Hh gets by financially') also plays a significant role. With the decreasing ability to make ends meet, the probability of eating meat, dairy products, and fruits & vegetables every day decreases, and so does the probability of consumption of protein more often than the sample average. There is no significant impact of the household's ability to get along financially on the consumption of legumes & eggs.

Table 5.6: Logit - Cross-sectional dataset: Results

		Meat	Dairy	Legumes & Eggs	Fruits & Vegetables	Protein
Working:		-0.04***	0.02	-0.00	-0.00	-0.02·
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age:	70-75 years	-0.01·	0.02**	-0.01	0.02**	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	75 years or more	-0.00	0.06***	-0.01	0.04***	0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gender - male:		0.04***	-0.05***	-0.01	-0.10***	-0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Region:	Northern	0.11***	0.02*	0.13***	-0.09***	0.11***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Southern	-0.15***	-0.16***	0.10***	-0.07***	-0.04***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Central+Eastern	-0.15***	-0.26***	-0.05***	-0.16***	-0.18***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education:	less than 5 years	-0.12***	-0.01	-0.01	-0.03*	-0.04**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	5-10 years	-0.02*	0.00	-0.02·	-0.03***	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	more than 15 years	-0.01·	0.04***	0.01	0.04***	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Spouse/partner:		0.03***	0.02***	0.03***	0.05***	0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hh gets by financially:	great difficulty	-0.12***	-0.19***	-0.01	-0.20***	-0.12***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	some difficulty	-0.02·	-0.13***	-0.00	-0.07***	-0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	fairly easily	-0.02·	-0.07***	0.01	-0.03**	-0.02*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	missing	-0.01	-0.02	0.01	-0.02	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations		22,402	22,402	22,402	22,402	22,402
Log Likelihood		-13,131	-13,697	-15,001	-11,855	-14,745
Pseudo R-squared		0.05	0.07	0.02	0.05	0.04

*Note: Marginal effects; Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1; Meat - every day, Dairy - every day, Legumes & Eggs - 3 times a week or more Fruits & Vegetables - every day, Protein - more often than the sample average*

Subsequently, we estimated the same logit models once more but with the variable of interest which described the number of hours a retiree works per week. Using this variable, we are able to observe whether it matters how many hours retirees work, and not only whether or not they work. The results for the explanatory variable ('Working hours') are provided in Table 5.7. Full results can be seen in Table A.5 in the Appendix. We conclude that the impact of working after retirement on the frequency of meat and protein consumption is present only for specific amounts of working hours. Compared to non-working retirees (working 0 hours), retirees who are working 1-5 or 6-10 hours per week have a significantly lower probability of consuming meat every day (by 10% and 6%, respectively). The effect of working is no longer significant for working hours over 11 hours per week. The similar holds also for the consumption of protein where retirees working 6-10 hours per week (compared to retirees working 0 hours) are less likely to consume protein more frequently than the sample average.

Table 5.7: Logit - Cross-sectional dataset: Results - Working hours (1/2)

		Meat	Dairy	Legumes & Eggs	Fruits & Vegetables	Protein
Hours worked:	1-5	-0.10***	0.01	-0.03	0.01	-0.03
		(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
	6-10	-0.06*	0.03	-0.02	0.01	-0.07*
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	11-20	0.01	0.05·	-0.02	-0.01	0.01
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	more than 20	0.01	0.00	0.03	-0.02	0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	missing	-0.03	0.02	-0.00	0.02	-0.02
		(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Complete results are shown in Table A.5 in Appendix						
Observations		22,402	22,402	22,402	22,402	22,402
Log Likelihood		-13,121	-13,696	-14,997	-11,855	-14,743
Pseudo R-squared		0.05	0.07	0.02	0.05	0.04

*Note: Marginal effects; Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1; Meat - every day, Dairy - every day, Legumes & Eggs - 3 times a week or more Fruits & Vegetables - every day, Protein - more often than the sample average*

6 Discussion and Limitations

In this section, we discuss the results obtained in Section 5. Further, we describe the major drawbacks and limitations of our study and provide suggestions for further research.

Based on (Section 5.1) we conclude that retirees who start working anew after being already retired and unemployed for some time have a higher probability (by 9 pp) to increase their consumption of meat and fruits & vegetables in comparison to retirees who do not start working. Increased meat consumption can have a diverse effects on health, mainly depending on the choice of meat products. While meat products with a low number of saturated fatty acids such as fish are beneficial for the organism, red meat and in general highly processed meat products might cause health problems (Aykan 2015). On the other hand, no negative effects of increased fruits & vegetable consumption have been reported and higher intakes are associated with reduced risk of health problems (especially cardiovascular disease and cancer) and all-cause mortality (Willett and Stampfer 2013; Aune et al. 2017). Thus, we confirm the hypothesis that starting to work might have a beneficial impact on the health of retirees through increased consumption of fruits & vegetables.

When we do not focus on the change in work status, but only on the fact of whether the retiree works or not, just the results of the frequency of meat consumption turn out significant using the PSM (Section 5.2). The magnitude and direction of the estimate are identical when using the PSM and the logit model. Thus, we conclude that working after retirement decreases the probability of consuming meat every day. The estimate of variable describing ’working after retirement’ is opposite to the estimate of ’started working anew in retirement’ variable. We hypothesize that this opposite effects might be explained by the unobserved characteristics between the group of individuals who continue to work directly after retirement and the individuals who do stop working at the time of retirement but later decide to re-join the labor market. We expect above all, that individuals who are facing financial problems are more likely to continue working right after retirement, but due to their poor financial situation (despite working), they cannot afford to consume meat as frequently as their counterparts who are not working after retirement.

Further, based on our logistic estimation including the number of working hours per week, we conclude that the effect of working after retirement on the frequency of consumption changes with a different number of working hours per week. For example, the negative impact of post-retirement work on the probability of daily intake of meat is significant only for retirees who are working 1-10 hours per week. Heterogeneity in the effects might arise from the different characteristics of the variables describing the working status. When we record our outcome variables only as binary variables, the type of work and the level of salary received from the post-retirement work are not reflected in our models. Further research could focus on analysing specific job characteristics and more complete data.

Due to the data restrictions, are not able to include in our models not only the specific working hours of retirees but also other variables. Most likely, there is a selection of unobservables (such as motivation, or work environment) that also influence working status - our treatment variable in the PSM analyses (Bratun and Zurc 2020; Sewdas et al. 2017; Zwaan et al. 2019). If we do not account for all relevant variables, our estimates would be biased. Further, there might be other indicators of the frequency of consumption of specific foods. In our models, we do not control for the knowledge of the balanced diet principles, the individual preferences and tastes, or the dietary habits, attitudes, and motivations (Chance, Gorlin, and Dhar 2014). However, we believe that some of the unobserved variables might be at least partially explained by other observed variables. For example, the motivation/need to work, the salary, or the type of job can be explained by the level of education or the financial situation of the household. Similarly, the knowledge of balanced diet principles could be correlated with the level of education. Further, we focus only on the retirement pension, public pension, private pension, or private occupational pension. Nevertheless, there might be other sources of income that could have an impact on the diet of retirees.

Another limitation relates to the dependent variables describing the diet of retirees. The consumption behaviors are self-reported, so there might be self-report bias (the deviation between the self-reported and true values). Livingstone and Black (2003) in their study identify that usually, individuals under-report consumption, but the bias is heterogeneous and based on individual characteristics. The categorization of frequency of foods consumption is also restrictive because in the case of some foods (e.g.: fruits & vegetables), the vast majority of the observations fell under one category only. More detailed information about the frequency of consumption including the number of foods or products consumed per day/week/month would be interesting for further research. In addition, the type of product should be also differentiated since not all products that fall into the same food category have the same health benefits due to their different nutritional value.

Last, the effect of different interaction terms between the explanatory variable describing the working status and some of the control variables remains open for future research.

7 Conclusion

Consuming an unhealthy or unbalanced diet has far-reaching negative consequences on the society as a whole by increasing the probability of health problems and thereby rising healthcare expenditures. Especially elderly are at risk of malnutrition and therefore, numerous studies try to explain the changes in diet caused by a decrease in income after the transition to retirement. However, to our knowledge, no study has analyzed the effect of additional post-retirement income (resulting from working after retirement) on diet.

Therefore, this thesis aims to identify the impact of working after retirement on the consumption of different food groups by analyzing data derived from the Survey of Health, Ageing and Retirement in Europe (SHARE).

We conclude that starting to work after retirement increases the consumption of meat, fruits & vegetables. Specifically, retirees who start working anew after being already retired for some time, have by 99 pp higher probability to increase their consumption of meat, fruits & vegetables, compared to their counterparts who do not start working. This impact is significant at 5% significance level and supports our hypothesis that consumption of meat, fruits & vegetables increases when retirees re-enter the labor market in retirement. We do not find any significant effect of starting to work after retirement on the consumption of dairy products, legumes & eggs, and protein. Similarly, starting to work after retirement does not explain the decrease in the consumption of any of the analyzed food groups. Even though we were not able to confirm our hypotheses about higher consumption of dairy products, legumes & eggs, and protein, neither the opposite - decrease in consumption - was explained by starting to work in retirement. We suggest that although increased meat consumption might have a diverse impact on health, higher consumption of fruits & vegetables caused by re-entering the labor market after retirement brings clear health benefits (Aykan 2015; Aune et al. 2017).

We further find that the probability of retirees eating meat every day is lower by 4 pp for those who are working after retirement compared to those who are not working after retirement. No significant impacts of working after retirement on the consumption of dairy products, legumes & eggs, fruits & vegetables, and protein were shown. We suggest that the different directions of the estimates describing the impact of 'starting to work anew after retirement' and 'working after retirement' on meat consumption might be explained by different unobserved characteristics of individuals who continued to work directly after retirement without any period of unemployment, and individuals who stopped working at the time of retirement but then decided to re-join the labor market later. To get a complete picture of how the diet changes based on working after retirement, it would be great to analyze also the data regarding diet prior to retirement or control for additional variables.

One of the limitations of this thesis is the possibility of missing variables which would cause biased estimates. Variables describing dietary habits, motivations to eat healthily, and different tastes most likely also influence dietary habits. Nevertheless, we think that some of the unobserved variables might be at least partially explained by our observed variables. Since we use questionnaires as a source of our data, self-reported bias might be also present in our results. Future research could focus on the inclusion of variables describing working status in more detail, not just as a binary variable. The variable could be based on the level of obtained income or on the number of working hours. In addition, more detailed information regarding the dependent variables describing foods consumption, for example by product or by nutritional value, could be used.

Although participation in the labor market might bring significant benefits to retirees through increased consumption of fruits & vegetables and thus improved health outcomes, employers still do not regularly employ the elderly (Wainwright et al. 2019). The willingness to hire older workers is limited and the reasons for not hiring elderly are stereotypes including lower productivity, slow adaptability, worse learning abilities, or declining job performance (Magd 2003; Fouarge and Montizaan 2015). However, older workers can often be an asset to the organizations. There is empirical evidence that older workers bring experience and discipline, are more loyal and dependent and their level of organizational trust is higher, compared to younger workers (Dordoni and Argentero 2015; Magd 2003).

Therefore, it is important to find ways how to enable the work participation of older workers. Governments could promote flexible retirement strategies or try to remove barriers to labor market entry for older workers to ensure their healthy, graceful, and decent aging.

Bibliography

Aaron, Henry J and Jean Marie Callan (2011). “Who retires early?” In: *Boston College Center for Retirement Research Working Paper* 2011-10.

Ali-Kovero, Kirsi et al. (2020). “Changes in fruit, vegetable and fish consumption after statutory retirement: a prospective cohort study”. In: *British Journal of Nutrition* 123.12, pp. 1390–1395.

Allais, Olivier, Pascal Leroy, and Julia Mink (2020). “Changes in food purchases at retirement in France”. In: *Food Policy* 90, p. 101806.

Alvarez-León, Eva-Elisa, Blanca Román-Vinas, and Lluis Serra-Majem (2006). “Dairy products and health: a review of the epidemiological evidence”. In: *British Journal of Nutrition* 96.S1, S94–S99.

Anekwe, Tobenna D and Ilya Rahkovsky (2013). “Economic costs and benefits of healthy eating”. In: *Current Obesity Reports* 2.3, pp. 225–234.

Angelino, Donato et al. (2019). “Fruit and vegetable consumption and health outcomes: An umbrella review of observational studies”. In: *International Journal of Food Sciences and Nutrition* 70.6, pp. 652–667.

Anxo, Dominique, Thomas Ericson, and Anna Herbert (2019). “Beyond retirement: who stays at work after the standard age of retirement?” In: *International Journal of Manpower*.

Armstrong-Stassen, Marjorie (2008). “Organisational practices and the post-retirement employment experience of older workers”. In: *Human Resource Management Journal* 18.1, pp. 36–53.

Aune, Dagfinn et al. (2017). “Fruit and vegetable intake and the risk of cardiovascular disease, total cancer and all-cause mortality—a systematic review and dose-response meta-analysis of prospective studies”. In: *International journal of epidemiology* 46.3, pp. 1029–1056.

Axelrad, Hila (2018). “Early retirement and late retirement: Comparative analysis of 20 European countries”. In: *International Journal of Sociology* 48.3, pp. 231–250.

Aykan, Nuri Faruk (2015). “Red meat and colorectal cancer”. In: *Oncology reviews* 9.1.

Bal, P Matthijs et al. (2012). “Motivating employees to work beyond retirement: A multi-level study of the role of I-deals and unit climate”. In: *Journal of Management Studies* 49.2, pp. 306–331.

Beehr, Terry A and Misty M Bennett (2015). “Working after retirement: Features of bridge employment and research directions”. In: *Work, Aging and Retirement* 1.1, pp. 112–128.

Bennett, Jenny and Katja Moehring (2015). "Cumulative (dis) advantage? The impact of labour market policies on late career employment from a life course perspective". In: *Journal of Social Policy* 44.2, pp. 213–233.

Beutell, Nicholas J and Joy A Schneer (2021). "Working beyond retirement: are there gender differences in bridge employment?" In: *Ageing International* 46.1, pp. 1–16.

Beydoun, A, A May, and Y Wang (2008). "How do socio-economic status, perceived economic barriers and nutritional benefits affect quality of dietary intake among US adults?" In: *European journal of clinical nutrition* 62.3, pp. 303–313.

Bloom, David E et al. (2007). "Demographic change, social security systems, and savings". In: *Journal of Monetary Economics* 54.1, pp. 92–114.

Bogue, Joe, Therese Coleman, and Douglas Sorenson (2005). "Determinants of consumers' dietary behaviour for health-enhancing foods". In: *British Food Journal*.

Boylan, Sinéad et al. (2011). "Socio-economic circumstances and food habits in Eastern, Central and Western European populations". In: *Public health nutrition* 14.4, pp. 678–687.

Bratun, Urša and Joca Zurc (2020). "The motives of people who delay retirement: An occupational perspective". In: *Scandinavian Journal of Occupational Therapy*, pp. 1–13.

Caliendo, Marco and Sabine Kopeinig (2008). "Some practical guidance for the implementation of propensity score matching". In: *Journal of economic surveys* 22.1, pp. 31–72.

Chakrabarty, Kaveri, and Chakrabarty (2019). "Food groups, balanced diet, and food composition". In.

Chambers, Stephanie et al. (2008). "The influence of age and gender on food choice: a focus group exploration". In: *International journal of consumer studies* 32.4, pp. 356–365.

Chan, Ruth SM and Jean Woo (2010). "Prevention of overweight and obesity: how effective is the current public health approach". In: *International journal of environmental research and public health* 7.3, pp. 765–783.

Chance, Zoe, Margarita Gorlin, and Ravi Dhar (2014). "Why choosing healthy foods is hard, and how to help: presenting the 4Ps framework for behavior change". In: *Customer needs and solutions* 1.4, pp. 253–262.

Chida, Yoichi and Andrew Steptoe (2008). "Positive psychological well-being and mortality: a quantitative review of prospective observational studies". In: *Psychosomatic medicine* 70.7, pp. 741–756.

Choi, Namkee G (2001). "Relationship between life satisfaction and postretirement employment among older women". In: *The International Journal of Aging and Human Development* 52.1, pp. 45–70.

Cochran, William G and S Paul Chambers (1965). “The planning of observational studies of human populations”. In: *Journal of the Royal Statistical Society. Series A (General)* 128.2, pp. 234–266.

Damman, Marleen, Kène Henkens, and Matthijs Kalmijn (2011). “The impact of midlife educational, work, health, and family experiences on men’s early retirement”. In: *Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 66.5, pp. 617–627.

Darmon, Nicole and Adam Drewnowski (2015). “Contribution of food prices and diet cost to socioeconomic disparities in diet quality and health: a systematic review and analysis”. In: *Nutrition reviews* 73.10, pp. 643–660.

Dave, Dhaval, Inas Rashad, and Jasmina Spasojevic (2008). “The effects of retirement on physical and mental health outcomes”. In: *Southern Economic Journal* 75.2, pp. 497–523.

Demou, Evangelia et al. (2017). “Health, lifestyle and employment beyond state-pension age”. In: *BMC Public Health* 17.1, pp. 1–13.

Depolo, M, JA León Moriano, JF Domınguez Morales, et al. (2009). “Bridge employment and retirees’ personal well-being. A structural equation model with a European probabilistic sample”. In: *Psicothema* 21.2, pp. 280–287.

Di Bonaventura, Marco et al. (2018). “Obesity in Germany and Italy: prevalence, comorbidities, and associations with patient outcomes”. In: *ClinicoEconomics and outcomes research: CEOR* 10, p. 457.

Dingemans, Ellen and Kène Henkens (2014). “Involuntary retirement, bridge employment, and satisfaction with life: A longitudinal investigation”. In: *Journal of organizational Behavior* 35.4, pp. 575–591.

Dingemans, Ellen and Katja Möhring (2019). “A life course perspective on working after retirement: What role does the work history play?” In: *Advances in Life Course Research* 39, pp. 23–33.

Dingemans, Ellen Anna Antonetta (2016). “Working after retirement: Determinants and consequences of bridge employment”. In.

Dordoni, Paola and Piergiorgio Argentero (2015). “When age stereotypes are employment barriers: a conceptual analysis and a literature review on older workers stereotypes”. In: *Ageing International* 40.4, pp. 393–412.

EC, European Commission (2022). *Food-Based Dietary Guidelines in Europe*. URL: `https://knowledge4policy.ec.europa.eu/health-promotion-knowledge-gateway/topic/food-based-dietary-guidelines-europe_en`.

Eurostat (2020). *Ageing Europe — looking at the lives of older people in the EU — 2020 edition*. URL: `https://ec.europa.eu/eurostat/en/web/products-statistical-books/-/ks-02-20-655`.

Fisher, Gwenith G, Dorey S Chaffee, and Amanda Sonnega (2016). "Retirement timing: A review and recommendations for future research". In: *Work, Aging and Retirement* 2.2, pp. 230–261.

Fisher, Gwenith G, Lindsay H Ryan, et al. (2016). "Job lock, work, and psychological well-being in the United States". In: *Work, Aging and Retirement* 2.3, pp. 345–358.

Fisher, Jonathan D et al. (2008). "The retirement consumption conundrum: Evidence from a consumption survey". In: *Economics Letters* 99.3, pp. 482–485.

Fortuna, Jeffrey L (2012). "The obesity epidemic and food addiction: clinical similarities to drug dependence". In: *Journal of psychoactive drugs* 44.1, pp. 56–63.

Fouarge, Didier and Raymond Montizaan (2015). "Hoe bereid zijn werkgevers om ouderen aan te nemen?" In: *Tijdschrift Voor Arbeidsvraagstukken* 31.3.

Fujiwara, Yoshinori et al. (2016). "Engagement in paid work as a protective predictor of basic activities of daily living disability in J apanese urban and rural community-dwelling elderly residents: An 8-year prospective study". In: *Geriatrics & gerontology international* 16.1, pp. 126–134.

Gehlich, Kerstin H et al. (2020). "Consumption of fruits and vegetables: improved physical health, mental health, physical functioning and cognitive health in older adults from 11 European countries". In: *Aging & Mental Health* 24.4, pp. 634–641.

Goll, Nicolas (2020). "Working Pensioners in Europe-Demographics, Health, Economic Situation and the Role of Pension Systems". In: *Health, Economic Situation and the Role of Pension Systems*.

Gustafsson, Kerstin and Birgitta Sidenvall (2002). "Food-related health perceptions and food habits among older women". In: *Journal of advanced nursing* 39.2, pp. 164–173.

Heide, Iris van der et al. (2013). "Is retirement good for your health? A systematic review of longitudinal studies". In: *BMC public health* 13.1, pp. 1–11.

Heinrich, Carolyn, Alessandro Maffioli, Gonzalo Vazquez, et al. (2010). "A primer for applying propensity-score matching". In: *Inter-American Development Bank*.

Helldan, Anni et al. (2012). "Changes in healthy food habits after transition to old age retirement". In: *The European Journal of Public Health* 22.4, pp. 582–586.

Heller-Sahlgren, Gabriel (2017). "Retirement blues". In: *Journal of health economics* 54, pp. 66–78.

Henkens, Kène and Hanna Solinge (2013). "Returning to work after retirement: Who, what and why?" In.

Hertzler, Steven R et al. (2020). “Plant proteins: Assessing their nutritional quality and effects on health and physical function”. In: *Nutrients* 12.12, p. 3704.

Herzog, A, James S House, and James N Morgan (1991). “Relation of work and retirement to health and well-being in older age.” In: *Psychology and aging* 6.2, p. 202.

Kim, Seongsu and Daniel C Feldman (2000). “Working in retirement: The antecedents of bridge employment and its consequences for quality of life in retirement”. In: *Academy of management Journal* 43.6, pp. 1195–1210.

Kopp, Wolfgang (2019). “How western diet and lifestyle drive the pandemic of obesity and civilization diseases”. In: *Diabetes, metabolic syndrome and obesity: targets and therapy* 12, p. 2221.

Lauque, S et al. (1998). “A prospective study of changes on nutritional patterns 6 months before and 18 months after retirement.” In: *The journal of nutrition, health & aging* 2.2, pp. 88–91.

Leuven, Edwin and Barbara Sianesi (2003). “PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing”. In.

Livingstone, M Barbara E and Alison E Black (2003). “Markers of the validity of reported energy intake”. In: *The Journal of nutrition* 133.3, 895S–920S.

Macdiarmid, Jennie I et al. (2013). ““It was an education in portion size”. Experience of eating a healthy diet and barriers to long term dietary change”. In: *Appetite* 71, pp. 411–419.

Magd, Hesham (2003). “Management attitudes and perceptions of older employees in hospitality management”. In: *International Journal of Contemporary Hospitality Management.*

Maillot, Matthieu, Nicole Darmon, and Adam Drewnowski (2010). “Are the lowest-cost healthful food plans culturally and socially acceptable?” In: *Public Health Nutrition* 13.8, pp. 1178–1185.

Maimaris, Will, Helen Hogan, and Karen Lock (2010). “The impact of working beyond traditional retirement ages on mental health: implications for public health and welfare policy”. In: *Public Health Reviews* 32.2, pp. 532–548.

Manor, Shlomit and Roy Holland (2022). “Retiring in a white coat: Doctors working after retirement”. In: *Journal of Vocational Behavior* 133, p. 103678.

McFadden, Daniel (1974). “The measurement of urban travel demand”. In: *Journal of public economics* 3.4, pp. 303–328.

Mestral, Carlos de, Silvia Stringhini, and Pedro Marques-Vidal (2016). “Barriers to healthy eating in Switzerland: a nationwide study”. In: *Clinical nutrition* 35.6, pp. 1490–1498.

Müller-Riemenschneider, Falk et al. (2008). “Health-economic burden of obesity in Europe”. In: *European journal of epidemiology* 23.8, pp. 499–509.

Nemoto, Yuta et al. (2020). "Working for only financial reasons attenuates the health effects of working beyond retirement age: A 2-year longitudinal study". In: *Geriatrics & Gerontology International* 20.8, pp. 745–751.

Nutbeam, Don (2000). "Health literacy as a public health goal: a challenge for contemporary health education and communication strategies into the 21st century". In: *Health promotion international* 15.3, pp. 259–267.

OECD (2019). *Health for everyone?: social inequalities in health and health systems, OECD health policy studies.*

OECD: Labour force participation rate (2021). URL: `https://data.oecd.org/emp/labour-force-participation-rate.htm`.

Oude Mulders, J et al. (2016). "Organizations, managers, and the employment of older workers after retirement". PhD thesis. Utrecht University.

Picchio, Matteo and Jan C van Ours (2020). "Mental health effects of retirement". In: *De Economist* 168.3, pp. 419–452.

Pienta, Amy Mehraban and Mark D Hayward (2002). "Who expects to continue working after age 62? The retirement plans of couples". In: *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 57.4, S199–S208.

Pinho, MGM et al. (2018). "Exploring the relationship between perceived barriers to healthy eating and dietary behaviours in European adults". In: *European journal of nutrition* 57.5, pp. 1761–1770.

Pleau, Robin L (2010). "Gender differences in postretirement employment". In: *Research on Aging* 32.3, pp. 267–303.

Plouvier, Sandrine et al. (2011). "Low back pain around retirement age and physical occupational exposure during working life". In: *BMC Public Health* 11.1, pp. 1–6.

Price, Susan (2005). "Understanding the importance to health of a balanced diet." In: *Nursing times* 101.1, pp. 30–31.

Quandt, Sara A et al. (2000). "Nutritional self-management of elderly widows in rural communities." In: *The Gerontologist* 40.1, pp. 86–96.

Rao, Mayuree et al. (2013). "Do healthier foods and diet patterns cost more than less healthy options? A systematic review and meta-analysis". In: *BMJ open* 3.12, e004277.

Reynolds, Frances, Alexandra Farrow, and Alison Blank (2012). "“Otherwise it would be nothing but cruises”: exploring the subjective benefits of working beyond 65". In: *International Journal of Ageing and Later Life* 7.1, pp. 79–106.

Ricci, G et al. (2018). "Obesity in the European region: social aspects, epidemiology and preventive strategies". In: *Eur Rev Med Pharmacol Sci* 22.20, pp. 6930–6939.

Rosenbaum, Paul R and Donald B Rubin (1983). “The central role of the propensity score in observational studies for causal effects”. In: *Biometrika* 70.1, pp. 41–55.

Rubin, Donald B (2005). “Causal inference using potential outcomes: Design, modeling, decisions”. In: *Journal of the American Statistical Association* 100.469, pp. 322–331.

Schlosser, Francine, Deborah Zinni, and Marjorie Armstrong-Stassen (2012). “Intention to unretire: HR and the boomerang effect”. In: *Career Development International*.

Schoeppe, Stephanie et al. (2018). “Do singles or couples live healthier lifestyles? Trends in Queensland between 2005-2014”. In: *PloS one* 13.2, e0192584.

Sewdas, Ranu et al. (2017). “Why older workers work beyond the retirement age: a qualitative study”. In: *BMC public health* 17.1, pp. 1–9.

Si Hassen, Wendy et al. (2017). “Associations between transition to retirement and changes in dietary intakes in French adults (NutriNet-Santé cohort study)”. In: *International Journal of Behavioral Nutrition and Physical Activity* 14.1, pp. 1–10.

Skerrett, Patrick J and Walter C Willett (2010). “Essentials of healthy eating: a guide”. In: *Journal of midwifery & women’s health* 55.6, pp. 492–501.

Slavin, Joanne L (2000). “Mechanisms for the impact of whole grain foods on cancer risk”. In: *Journal of the American College of Nutrition* 19.sup3, 300S–307S.

Smed, Sinne, Helene Normann Rønnow, and Inge Tetens (2022). “The retirement (food)-consumption puzzle revisited-A panel data study from Denmark”. In: *Food Policy* 112, p. 102330.

Smith, Herbert L (1997). “6. matching with multiple controls to estimate treatment effects in observational studies”. In: *Sociological methodology* 27.1, pp. 325–353.

Staubli, Stefan and Josef Zweimüller (2013). “Does raising the early retirement age increase employment of older workers?” In: *Journal of public economics* 108, pp. 17–32.

Steen, B et al. (1988). “Age retirement in women. II. Dietary habits and body composition.” In: *Comprehensive gerontology. Section A, Clinical and laboratory sciences* 2.2, pp. 78–82.

Stephens, Jr Melvin and Desmond Toohey (2018). *Changes in nutrient intake at retirement*. Tech. rep. National Bureau of Economic Research.

Topa, Gabriela and Carlos-Marıa Alcover (2015). “Psychosocial factors in retirement intentions and adjustment: a multi-sample study”. In: *Career Development International*.

Topa, Gabriela, Juan Antonio Moriano, et al. (2009). “Antecedents and consequences of retirement planning and decision-making: A meta-analysis and model”. In: *Journal of Vocational Behavior* 75.1, pp. 38–55.

United Nations FAO, Food Agriculture Organization of the (2022). *Food-Based Dietary Guidelines*. URL: https://www.fao.org/nutrition/education/food-dietary-guidelines/regions/europe/en/.

Veth, Klaske N et al. (2018). "Bridge over an aging population: Examining longitudinal relations among human resource management, social support, and employee outcomes among bridge workers". In: *Frontiers in Psychology* 9, p. 574.

Wahrendorf, Morten et al. (2018). "Late life employment histories and their association with work and family formation during adulthood: A sequence analysis based on ELSA". In: *The Journals of Gerontology: Series B* 73.7, pp. 1263–1277.

Wainwright, David et al. (2019). "Extending working life and the management of change. Is the workplace ready for the ageing worker?" In: *Ageing & Society* 39.11, pp. 2397–2419.

Wang, Mo et al. (2008). "Antecedents of bridge employment: a longitudinal investigation." In: *Journal of applied Psychology* 93.4, p. 818.

Wardle, Jane et al. (2004). "Gender differences in food choice: the contribution of health beliefs and dieting". In: *Annals of behavioral medicine* 27.2, pp. 107–116.

Wertenbroch, Klaus (1998). "Consumption self-control by rationing purchase quantities of virtue and vice". In: *Marketing science* 17.4, pp. 317–337.

Westerlund, Hugo et al. (2010). "Effect of retirement on major chronic conditions and fatigue: French GAZEL occupational cohort study". In: *Bmj* 341.

Wheaton, Felicia and Eileen M Crimmins (2012). "The Demography of Aging and". In: *The Oxford handbook of retirement*, p. 22.

WHO et al. (2013). "Meeting to develop a global consensus on preconception care to reduce maternal and childhood mortality and morbidity: World Health Organization Headquarters, Geneva, 6–7 February 2012: meeting report". In.

WHO (2015). *World report on ageing and health*. World Health Organization.

WHO, World Health Organization (2022). *Healthy diet*. URL: https://www.who.int/news-room/fact-sheets/detail/healthy-diet.

Willett, Walter C (2002). "Balancing life-style and genomics research for disease prevention". In: *Science* 296.5568, pp. 695–698.

Willett, Walter C and Meir J Stampfer (2013). "Current evidence on healthy eating". In: *Annual review of public health* 34, pp. 77–95.

Wind, Astrid de et al. (2016). "A life course perspective on working beyond retirement—results from a longitudinal study in the Netherlands". In: *BMC Public Health* 16.1, pp. 1–12.

Wooldridge, Jeffrey M (2015). *Introductory econometrics: A modern approach*. Cengage learning.

Yin, Ruoyu et al. (2022). "Bridge Employment and Longevity: Evidence From a 10-Year Follow-Up Cohort Study in 0.16 Million Chinese". In: *The Journals of Gerontology: Series B* 77.4, pp. 750–758.

Zantinge, Else M et al. (2014). "Retirement and a healthy lifestyle: opportunity or pitfall? A narrative review of the literature". In: *The European Journal of Public Health* 24.3, pp. 433–439.

Zhan, Yujie et al. (2009). "Bridge employment and retirees' health: A longitudinal investigation." In: *Journal of occupational health psychology* 14.4, p. 374.

Zwaan, G Lennart van der et al. (2019). "The role of personal characteristics, work environment and context in working beyond retirement: a mixed-methods study". In: *International Archives of Occupational and Environmental Health* 92.4, pp. 535–549.

A Appendix

Full data acknowledgement

This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6, 7, 8.
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see Börsch-Supan et al. (2013) for methodological details.

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Data and descriptive statistics: Distribution of consumption

Table A.1: Original variables used for the creation of dummy dependent variables

		Panel dataset				Cross-sectional dataset	
		Wave 7 (4,431 obs.)		Wave 8 (4,431 obs.)		Wave 8 (22,402 obs.)	
Dependent variable		N	%	N	%	N	%
Meat:	*every day*	1,516	34%	1,439	32%	6,949	31%
	3-6 times a week	1,994	45%	2,006	45%	10,692	48%
	twice a week	661	15%	699	16%	3,285	15%
	once a week	213	5%	210	5%	1,055	5%
	less than once a week	47	1%	77	2%	421	2%
Dairy:	*every day*	2,980	67%	2,922	66%	14,139	63%
	3-6 times a week	826	19%	845	19%	4,701	21%
	twice a week	340	8%	402	9%	1,968	9%
	once a week	159	4%	166	4%	769	3%
	less than once a week	126	3%	96	2%	825	4%
Legumes & Eggs:	*every day*	438	10%	431	10%	2,235	10%
	3-6 times a week	1,366	31%	1,310	30%	7,298	33%
	twice a week	1,406	32%	1,449	33%	6,645	30%
	once a week	885	20%	904	20%	4,403	20%
	less than once a week	336	8%	337	8%	1,821	8%
Fruits & Vegetables:	*every day*	3,460	78%	3,455	78%	16,908	75%
	3-6 times a week	748	17%	758	17%	4,060	18%
	twice a week	149	3%	151	3%	935	4%
	once a week	48	1%	44	1%	327	1%
	less than once a week	26	1%	23	1%	172	1%

Note: The panel dataset consists of retirees who participated in both wave 7 and wave 8. The cross-sectional dataset consist of retirees who participated in wave 8.

Figure A.1: Distribution of meat consumption

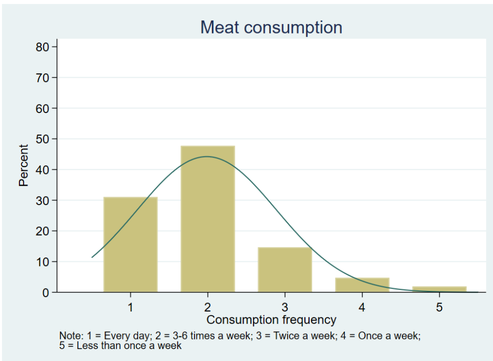


Figure A.2: Distribution of dairy consumption

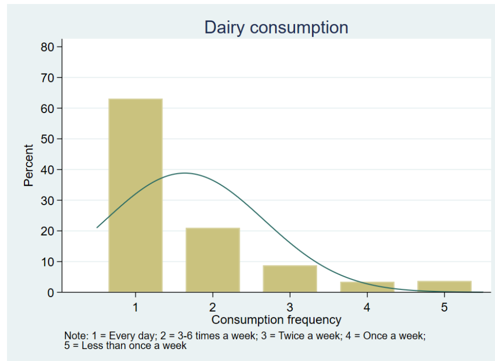


Figure A.3: Distribution of legumes & eggs consumption

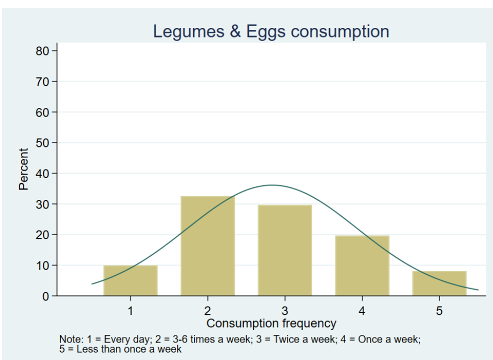
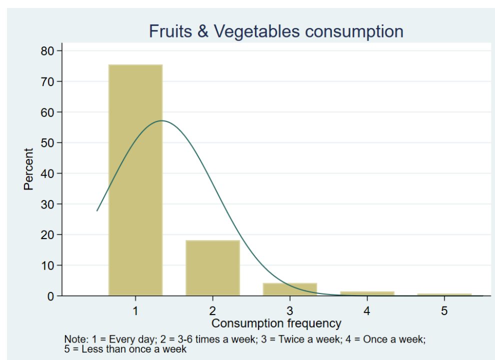


Figure A.4: Distribution of fruits & vegetables consumption



Data and descriptive statistics: Correlation matrix

Table A.2: Correlation matrix

	Paid work	*Age*	*Gender*	*Region*	*Education*	*Spouse/partner*	*Hh gets by financially*
Paid work	1.00						
Age	-0.13	1.00					
Gender	0.05	0.004	1.00				
Region	-0.01	-0.08	0.02	1.00			
Education	0.08	-0.12	0.03	-0.01	1.00		
Spouse/partner	0.01	-0.13	0.26	0.02	0.06	1.00	
Hh gets by financially	0.04	-0.02	0.16	0.09	0.10	0.33	1.00

Propensity score matching - Panel dataset

Table A.3: PSM - Panel dataset: Logit

		Started working
Age:	70-75 years	-0.02* (0.01)
	75 years or more	-0.03*** (0.01)
Gender - male:		0.01** (0.01)
Region:	Northern	0.03** (0.01)
	Southern	-0.01** (0.00)
	Central+Eastern	0.00 (0.01)
Education:	less than 5 years	0.01 (0.02)
	5-10 years	0.00 (0.01)
	more than 15 years	0.01 (0.01)
Spouse/partner:		-0.01 (0.01)
Observations		4,431
Log Likelihood		-492
Pseudo R-squared		0.06

*Note: Marginal effects; Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1*

Propensity score matching - Cross-sectional dataset

Table A.4: PSM - Cross-sectional dataset: Logit

		Working
Age:	70-75 years	-0.05***
		(0.01)
	75 years or more	-0.09***
		(0.00)
Gender - male:		0.04***
		(0.00)
Region:	Northern	0.04***
		(0.01)
	Southern	-0.03***
		(0.00)
	Central+Eastern	0.01*
		(0.00)
Education:	less than 5 years	0.00
		(0.01)
	5-10 years	-0.01**
		(0.00)
	more than 15 years	0.03***
		(0.01)
Spouse/partner:		-0.01*
		(0.00)
Observations		22,402
Log Likelihood		-5838
Pseudo R-squared		0.07

*Note: Marginal effects; Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1*

Logit - Cross-sectional dataset: Results

Table A.5: Logit - Cross-sectional dataset: Results - Working hours (2/2)

		Meat	Dairy	Legumes & Eggs	Fruits & Vegetables	Protein
Hours worked:	1-5	-0.10***	0.01	-0.03	0.01	-0.03
		(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
	6-10	-0.06*	0.03	-0.02	0.01	-0.07*
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	11-20	0.01	0.05·	-0.02	-0.01	0.01
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	more than 20	0.01	0.00	0.03	-0.02	0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	missing	-0.03	0.02	-0.00	0.02	-0.02
		(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Age:	70-75 years	-0.01	0.02**	-0.01	0.02*	-0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	75 years or more	-0.00	0.06***	-0.01	0.04***	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gender - male:		0.03***	-0.05***	-0.01	-0.10***	-0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Region:	Northern	0.11***	0.02*	0.13***	-0.09***	0.11***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Southern	-0.15***	-0.16***	0.10***	-0.07***	-0.04***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Central+Eastern	-0.16***	-0.26***	-0.05***	-0.16***	-0.18***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education:	less than 5 years	-0.12***	-0.01	-0.01	-0.03*	-0.04**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	5-10 years	-0.02*	0.00	-0.02·	-0.03***	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	more than 15 years	-0.01·	0.04***	0.01	0.04***	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Spouse/partner:		0.03***	0.03***	0.03***	0.05***	0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hh gets by financially:	great difficulty	-0.12***	-0.19***	-0.01	-0.20***	-0.12***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	some difficulty	-0.01	-0.13***	-0.00	-0.07***	-0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	fairly easily	-0.01	-0.07***	0.00	-0.03**	-0.02*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	missing	-0.01	-0.02	0.01	-0.02	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations		22,402	22,402	22,402	22,402	22,402
Log Likelihood		-13,121	-13,696	-14,997	-11,855	-14,743
Pseudo R-squared		0.05	0.07	0.02	0.05	0.04

*Note: Marginal effects; Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1; Meat - every day, Dairy - every day, Legumes & Eggs - 3 times a week or more Fruits & Vegetables - every day, Protein - more often than the sample average*

Table A.6: Logit - Cross-sectional dataset: Results for comparison with PSM

		Meat	Dairy	Legumes & Eggs	Fruits & Vegetables	Protein
Working:		-0.04***	0.03*	0.00	0.01	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age:	70-75 years	-0.01	0.03**	-0.01	0.02**	-0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	75 years or more	-0.00	0.06***	-0.01	0.05***	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gender - male:		0.04***	-0.04***	-0.01	-0.10***	-0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Region:	Northern	0.11***	-0.00	0.13***	-0.10***	0.11***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Southern	-0.16***	-0.20***	0.10***	-0.10***	-0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Central+Eastern	-0.16***	-0.28***	-0.05***	-0.18***	-0.19***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Education:	less than 5 years	-0.12***	-0.02	-0.01	-0.04**	-0.04**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	5-10 years	-0.02**	-0.01	-0.02*	-0.04***	-0.02*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	more than 15 years	-0.01	0.05***	0.01	0.05***	0.02·
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Spouse/partner:		0.03***	0.03***	0.04***	0.07***	0.07***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations		22,402	22,402	22,402	22,402	22,402
Log Likelihood		-13,163	-13,843	-15,029	-11,973	-14,807
Pseudo R-squared		0.05	0.06	0.02	0.04	0.04

*Note: Marginal effects; Robust standard errors provided in brackets; *** p<0.001, ** p<0.01, * p<0.05, · p<0.1; Meat - every day, Dairy - every day, Legumes & Eggs - 3 times a week or more Fruits & Vegetables - every day, Protein - more often than the sample average*