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Does unemployment make you less healthy?

A longitudinal analysis from the Netherlands

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Abstract

Employment is often more than just a way to make a living and a job loss might be one of life's most stressful experiences. Aside from the financial hardship it causes, it may also affect individuals' behaviors. This study examines the impact of unemployment on different health behaviors, namely alcohol and cigarette consumption, total physical activity and dietary patterns. This is done by using individual-level panel data from the Dutch Longitudinal Internet Studies for the Social Sciences, LISS. The time period stretches from 2008 to 2018 and unlike other research carried out in this area, we are including data from more recent years. In order to estimate the effects of unemployment on different health behaviors, the paper uses fixed effects methods. The results reflect that following a job loss, both women and men experience a decline in minutes of strenuous physical activity per week. Additionally, experiencing a job loss results in a decrease in smoking among male smokers. A change in employment status does by contrast not seem to have a significant impact on neither alcohol consumption nor dietary patterns. Thus, the results suggest that it might not be the change in employment status per se that can be considered as the main health risk factor.

Keywords: unemployment, health behavior, panel data, Netherlands

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1. Introduction

Job loss might be one of life's most stressful experiences. It will not only cause financial hardship, but it may also result in deterioration in physical and mental health. One factor that is often researched, and that is extended in this thesis, is how unemployment affects an individual's health behaviors.

A job loss is associated with shifts in time and income constraints which in turn might affect the individual's demand for both health-promoting behaviors (such as physical activity and a healthy diet) but also health-compromising behaviors (such as smoking and alcohol consumption). The frequent financial constraints that unemployment creates can in turn force the individual to reduce the demand for some goods. For example, due to less income the unemployed may simply forgo alcohol consumption or choose to smoke less. Healthier diet patterns (including fruits, vegetables, fish and nuts) may be replaced with more unhealthy diets (including processed food and refined grains), since unhealthy diets in general are less expensive (Rao, Afshin, Singh & Mozaffarian, 2013). Due to an increase in leisure time, some individuals may engage in health-promoting behaviors, such as physical activity or preparing home-cooked meals. In addition, the psychological distress emerging from the job loss is an important factor that needs to be taken into consideration when we want to understand the relationship between unemployment and health behaviors. For example, if smoking is a way to cope with stress, an increased consumption of cigarettes might be a coping strategy to deal with the higher tensions and anxieties that the job loss causes. To summarize, the relationship of how unemployment affects the individual's health behaviors is far from being clear-cut and the expected directionality is ambiguous.

Prior studies that have examined the effect of unemployment on different health behaviors can be divided into two fields: studies focusing on the macroeconomic conditions of unemployment and studies focusing on the individual's own employment status. When examining the effects of macroeconomic conditions on health behaviors, previous findings have been decidedly mixed. Some studies have found that higher unemployment rates are associated with improved health behaviors, such as increased physical activity, improved diet, declined cigarette smoking and reduced obesity (Ruhm, 2000; Ruhm, 2003). Other studies have come to opposite conclusions where higher unemployment rates result in declined total physical exertion and

increased body mass index (Colman & Dave, 2013; Böckerman, Johansson, Helakorpi, Prättälä, Vartiainen & Uutela, 2007).

The effects of the individual's own employment status on health behaviors have not been researched to the same extent as the macroeconomic conditions of unemployment on health behaviors. Most of these studies differ in which health behaviors are examined. Nonetheless, whether individual unemployment is associated with improved or worsened health behaviors is also within this field disputed. Some studies have shown that health behaviors improve during a period of unemployment (Leino-Arjas, Liira, Mutanen, Malmivaara & Matikainen, 1999). By contrast, other studies have shown that health-compromising behaviors, such as alcohol and tobacco consumption, increase during a period of unemployment (Compton, Gfroerer, Conway & Finger, 2014; Smed, Tetens, Bøker Lund, Holm & Ljungdalh, 2018). Other research has shown varied results (Colman & Dave, 2014). However, most of these studies have been conducted in the U.S, or focused on a narrow sample of the population (e.g., young men, as in Björklund, Söderlund, Nyström & Häggström, 2015; or middle-aged construction workers as in Leino-Arjas et al. 1999), or only studied a short time interval consisting of a couple of years, or simply examined the correlation between unemployed and different health behaviors using cross-sectional data.

This thesis will contribute to the existing European literature by studying how unemployment affects the individual's health behaviors in the Netherlands. The Netherlands has during the last decades experienced one of Europe's lowest unemployment rates and has also been considered having one of the most comprehensive social security systems on the continent (Eurostat, 2021; Expatica, 2021). It is consequently interesting to study if a change in employment status will affect health behaviors in this type of welfare state and, if so, to what extent.

This study uses a nationally representative longitudinal survey, the Dutch Longitudinal Internet Studies for the Social Sciences (henceforth: LISS), to determine whether a change in employment status affects health behaviors. The longitudinal setting of the LISS data allows us to better reveal the relationship between unemployment and changed health behaviors compared to cross-sectional data. In addition, the time period stretches from 2008 to 2018, which means that we are extending upon previous studies by including data from more recent years. Our main focus is to examine four different health behaviors, namely alcohol and cigarette consumption, total physical activity and dietary patterns. These behavior-linked health determinants are the most important and well-known factors that affect the individual's overall

health (WHO, 2020b), which motivates our choice of dependent variables. Fixed effects models will be used in order to investigate these relationships, comprising linear, logistic and Poisson regression analyses respectively. We will estimate the effects for both the overall population but also separately for women and men.

To summarize, the overall aim of this study is to examine whether, or to what degree, a change in the individual's own employment status has an effect on health behaviors in the Netherlands, focusing on alcohol and cigarette consumption, total physical activity and dietary patterns. Throughout this paper we will use the terms “unemployment” and “job loss” interchangeably.

The remainder of this paper is organized as follows. Related literature will be presented in section two. In section three there will be a short presentation of the dismissal laws and the social security system for unemployed in the Netherlands. The fourth section includes the theoretical framework on which the study is based on. The fifth section presents the data and methodology. The sixth section includes the results. Empirical and theoretical analyses are found in section seven and the discussion in section eight. The last section concludes the paper.

2. Literature Review

Prior studies that have examined the effect of unemployment on different health behaviors can be divided into two fields: studies focusing on the macroeconomic conditions of unemployment and studies focusing on the individuals own employment status. Under this section, we will present the main effects found in the two groups of studies.

2.1 The Effect of Macroeconomic Conditions of Unemployment on Health Behaviors

Previous research focusing on the macroeconomic conditions of unemployment on health behaviors have shown varied results. In a pioneering microdata study, Ruhm (2000) showed by applying fixed effects methods, that higher unemployment rates affect both health-promoting behaviors (such as increased physical activity and improved diet) along with health-compromising behaviors (such as decreased smoking and obesity). Ruhm and Black (2002) have also examined the effect of macroeconomic conditions on drinking behaviors using microdata. Ruhm and Black (2002) found that there is a procyclical variation in overall

drinking, meaning that drinking behaviors fluctuate positively with the business cycle. However, the decrease in drinking is mostly among heavy consumers whereas light drinking, on the contrary, increases. Both studies mentioned above are based on data from the U.S (Ruhm, 2000; Ruhm & Black, 2002).

A more recent study examining the effect of unemployment rates on health behaviors was conducted in Iceland. The fixed effects regression results showed that health-compromising behaviors (such as smoking and heavy drinking) declined during the Great Recession in the late 2000's (Ásgeirsdóttir, Corman, Noonan, Ólafsdóttir & Reichman, 2014). Toffolutti and Suhrcke (2014) did however not find any association between unemployment and alcohol consumption during the Great Recession, when using cross-country panel data from 23 European Union countries.

The relationship between economic downturns and physical activity is also disputed. Ruhm (2000) showed that physical activity increases during recessions. Charles and DeCicca (2008), on the contrary, found that physical activity is independent of the business cycles, when using data from the U.S. Studies examining the relationship between economic downturns and smoking habits have also shown varied results. Ruhm (2005) and Xu (2013) found, by using data from the U.S, that an increase in employment rate leads to an increase in smoking. Similar results were obtained by the above-mentioned study in Iceland during the Great recession (Ásgeirsdóttir et al. 2014). However, a study from Sweden showed that an increase in the unemployment rate is associated with a higher probability of smoking (Öhlander, Vikström, Lindström & Sundquist, 2006).

A study examining the effect of unemployment on dietary behavior, using data from the U.S, found that an economic downturn is associated with fewer purchases of fruit and vegetables (Dave & Kelly, 2012). Ásgeirsdóttir et al. (2014) reached the same conclusion.

2.2 The Effect of Individuals Own Employment Status on Health Behaviors

The effect of an individual's own employment status on health behaviors have not been studied as vigorously as the effect of macroeconomic conditions of unemployment on health behaviors. Nonetheless, there have been several studies conducted in the late 1990's and in the very beginning of the 2010's. Compton et al. (2014) examined, by applying fixed effects methods, the relationship between individuals' employment status and substance use during the Great

Recession. By using data from the U.S, Compton et al. (2014) found that unemployment is associated with an increase in tobacco use and heavy alcohol consumption.

Another study from the U.S examined the effect of unemployment on health behaviors using microdata spanning from 1968 to 2009 (Colman & Dave, 2014). Colman and Dave (2014) found that becoming unemployed is associated with changes in both health-promoting behaviors (such as increased leisure time exercise but decreased total physical activity) along with health-compromising behaviors (such as decreased purchases of fast food and increased probability of smoking).

Similar to the findings on the effect of economic downturns on physical activity, a study from Finland has shown that being unemployed is associated with an increase in physical activity (Leino-Arjas et al. 1999). The study also showed that being unemployed results in decreased alcohol consumption (Leino-Arjas et al. 1999). By contrast, an American study examining the impact of unemployment compensation on health behaviors found that those individuals who do not receive any unemployment benefit increase their daily alcohol consumption (Bolton & Rodriguez, 2009). A cross-sectional study from Italy showed that being unemployed increases the probability of being a smoker (De Vogli & Santinello, 2005). Similarly, in a study using German data spanning from 2002 to 2010, Marcus (2014) found that the increase in smoking is mainly due to non-smokers starting to smoke.

Another study which examined the effect of unemployment on dietary behavior in Denmark, using data from 2008 to 2012, found that becoming unemployed is associated with fewer purchases of fruit (Smed et al. 2018). This result follows the findings on the effect of economic downturns on fruit purchases.

Most of the previous studies have been conducted in the U.S, or focused on a narrow sample of the population, or studied a short period of time, or simply examined the correlation between unemployment and different health behaviors using cross-sectional data. We will therefore address several gaps in the literature in which we will make contributions.

Firstly, to our knowledge, the relationship between unemployment and health behaviors has not been investigated so far in the Netherlands. The Netherlands has one of Europe's most comprehensive social security systems and has also experienced one of the lowest rates of unemployment on the continent during the last decade (Expatica, 2021; Eurostat, 2021). An extensive unemployment benefit system, such as the Dutch one, could reduce the impact of an

individual's changed employment status on health behaviors. The low unemployment rates in the Netherlands will additionally help us to better isolate the effects of the individual's changed employment status on health behaviors. This makes the Netherlands an interesting field of study and the question is further if a change in employment status will affect health behaviors in this type of welfare state, and to what extent. Additionally, most of the previous studies have used data from the U.S and there is a limited number of studies conducted using European data. The U.S and Europe differ in many ways, both observed (such as social welfare systems) and unobserved (such as culture). These differences may in turn affect various behaviors, including behavior-linked health determinants.

Secondly, no research in this topic has, as far as we know, been carried out during the recent years. Most studies which examine the relationship between the individual's own employment status and health behaviors were conducted in the late 1990's and in the very beginning of the 2010's. Society has changed drastically during the last decade (such as technology, globalization etc.), and it is therefore of value to investigate if previous findings are still relevant or if changes in society have led unemployment to affect individuals differently now compared to a decade ago.

Thirdly, most studies which examine the effect of unemployment on health behaviors have focused on macroeconomic conditions of unemployment and not the individuals own employment status. It is therefore imperative to extend the knowledge in this field, as it can provide insights into how unemployment directly affects an individual's health behaviors. Understanding if individual health behaviors are mostly affected by an individuals' own employment status or if it is mostly driven by macroeconomic conditions is therefore essential.

Fourthly, we are using longitudinal panel data spanning from 2008 to 2018, which records individuals' health behaviors over a long span of time. This makes our data stand out in comparison to the European studies and we will contribute with insightful knowledge of how the individual's health behaviors change in time of unemployment.

3. Employment in the Netherlands

In order to understand the context in which the study has been performed, this section will provide the reader with essential background information about the dismissal laws and the social security system for the unemployed in the Netherlands.

3.1 Dismissal Laws

Employees in the Netherlands are in some situations protected against dismissal and the employer must have a valid reason in order to dismiss employees. Examples of valid reasons could be "refusal to perform work, culpable conduct, excessive sickness absence, reorganisation or company closure" (Business.gov.nl, 2021). In addition, the employment contract needs to be terminated by a sub-district court (Business.gov.nl, 2021). If the dismissal is due to an employee being (long-term) incapable of working or due to economic reasons, it is necessary for the employer to request permission from the Employee Insurance Agency (Dutch: Uitvoeringsinstituut Werknemersverzekeringen, UWV*)* (Business.gov.nl, 2021). The employer cannot dismiss the employee if there is no permission for dismissal. However, dismissal and termination with mutual consent do not need approval by the UWV, nor to be judged by a sub-district court (Business.gov.nl, 2021). These rules are restricted to permanent contracts and not for employees having a temporary employment.[1] During the probation period, both parties can terminate the contract without having to give a proper reason (Business.gov.nl, 2021).

3.2 The Social Security System for Unemployed

The Dutch social security system is one of the most comprehensive in Europe (Expatica, 2021). If you become involuntarily unemployed in the Netherlands, you can be entitled to unemployment benefits under the Unemployment Insurance Act (Dutch: Werkloosheidswet, WW) (European Commission, n.d.). There are several rights as well as obligations that need to be fulfilled in order to receive unemployment benefits.[2] The amount of social security benefits the individual receives depends on the financial circumstances of the unemployed (Expatica, 2021). An individual that is qualified for the unemployment insurance benefits is eligible to receive 75 percent of his previous salary and a maximum of 219.28 euros per day during the first two months (European Commission, n.d.). Thereafter, the benefits amount to 70 percent of the last pay earned. The maximum duration of the unemployment benefits is three months but can be prolonged up to 24 months depending on the total duration of the working career (European Commission, n.d.).

[1] Most of the employment contracts in the Netherlands are of the permanent type (Business.gov.nl, n.d.).
[2] For more details, see e.g., European Commission (n.d.).

4. Theoretical Framework

This section will provide a foundation for the study by presenting the theoretical framework of the thesis. The two main models that will be introduced are the Grossman-model of human capital and the Becker–Murphy model of rational addiction.

4.1 Grossman's Human Capital Model

One of the first formal economic models of the determinants of health was developed by Grossman (1972) and is built on Becker's theories of human capital (Becker, 1965). In the Grossman's model, health (or good health) is assumed to be a desirable commodity, even though it is not valued above all else[3] (Wagstaff, 1986). Individuals produce health using their time and market good inputs, by choosing diet, lifestyle and health care (Morris, Devlin, Parkin & Spencer, 2012). According to the model, health is not only a direct source of utility, it is also demanded since it affects an individual's ability to work and therefore also the total time available to produce an income. The model views health as a durable capital stock. Stated differently, an individual inherits an initial amount of health that will depreciate with age and decrease when it is used in consumption and production of other commodities (Morris et al. 2012). The stock of health can increase if an individual invests time, effort and knowledge in health-promoting activities. The individual's skills and knowledge determine how efficiently the individual produces health (Morris et al. 2012). This demand-for-health model assumes that individuals invest in health production until the marginal cost of health production is equal to the marginal benefits of improved health status (Gerdtham, Johannesson, Lundberg & Isacson, 1999). The version of this framework can be applied to specifically health behaviors, e.g., smoking behavior, physical activity, alcohol consumption, dietary patterns etc. Our analysis below is based on the Grossman model's demand for health behaviors (in this example exercising) as described by Colman and Dave (2013).

The demand for exercise within the Grossman model

The Grossman model of health production, with focus on exercise, can be illustrated algebraically. Individual *i*'s intertemporal utility function can be modelled in the following way:

[3] The reason for this argument is as follows: if individuals value their health above all else, they would not smoke, consume alcohol, take drugs etc. (Wagstaff, 1986).

$$U_i = U(H_i, EX_i, OA_i, G) \quad (1)$$

where H_i is the individual's health, EX_i represents the amount of exercise, OA_i includes other activities and G is household goods. In general, exercise is assumed to reduce the overall utility whereas commodities and other activities (for example sleeping, watching television, taking care of the children etc.) increase the individual's utility level (Colman & Dave, 2013). Exercise might certainly increase the utility for some individuals but in this example, it is assumed to be utility reducing for the average person.[4]

The health-production function can be illustrated in the following way:

$$H_i = H[EX_i, OA_i, M_i; S_i] \quad (2)$$

$$G = G[OA_i, OA_j, X; S] \quad (3)$$

where equation 2 demonstrates that the individual produces health by exercising, EX_i, and by doing other activities, OA_i. Consumption of health care services and medication, M_i, is also improving the health of the individual. The efficiency parameter, S_i, represents the individual's education level. This parameter is expected to improve the marginal product of health production. Equation 3 notes that the production function for household commodities, G, can be produced with the individual's own time, OA_i, and the cohabiting partner's time, OA_j. Example of non-medical market inputs, X, includes for example groceries, housing etc.

The production of health is also influenced by income, prices, and initial health endowments, among other factors that enter the budget constraint:

$$W * TW_i + W * TW_j = P_M * M + P_X * X \quad (4)$$

$$T_{tot} = TW_i + EX_i + OA_i + LT_i \quad (5)$$

Where W is the wage level and TW the total work time for the cohabiting couple. Equation 4 demonstrates that the household spends the total income on medical market inputs and non-medical commodities (P_M and P_X denote the price for medical and non-medical commodities respectively). Equation 5 notes the time constraint, T_{tot}, the individual is facing. It shows that

[4] The reason for this argument is that physical activity is well-known to be beneficial for the individual's overall health. Notwithstanding this fact, more than 80 % of the world's adolescent population is insufficiently physically active (WHO, 2020a).

the time is exhausted between work, exercise, other activities and lost time due to sickness or injuries, LT_i.

It is assumed that the individual will attempt to attain the highest possible welfare contour, as arguments subject to budget and time constraints. In other words, the marginal cost of health production needs to be equaled the marginal benefits of improved health status.

The maximization problem results in the following conditional input demand functions for exercise and other activities:

$$EX_i = EX(TW_i, TW_j, H_i, G, W, P_M, P_X; S_i) \quad (6)$$

$$OA_i = OA(TW_i, TW_j, H_i, G, W, P_M, P_X; S_i) \quad (7)$$

Equation 6 and 7 can be rewritten in reduced-form input demand functions by substituting the determinants of health and other commodities (equation 2 and 3) into the two equations:

$$EX_i = EX(W, TW_i, TW_j, P_M, P_X; S_i) \quad (8)$$

$$OA_i = OA(W, TW_i, TW_j, P_M, P_X; S_i) \quad (9)$$

Equation 8 highlights that the demand for exercise depends on wage, the household's total work time, prices (both for medical and non-medical commodities) and the individual's level of education.

The question is further how a change in employment status will affect the demand of exercise. A job loss is associated with shifts in the individual's income and time constraints. In economic theory, decreased income is expected to decrease the demand for all but inferior goods, assuming all else equal. This implies that exercises which cost money (such as a gym membership) will decline in consumption when income decreases. By contrast, a job loss may also affect the individual's time constraint. The opportunity cost to undertake health-promoting activities that are time-intensive will decrease with more leisure time available and the demand for exercise might therefore increase. In sum, the impact of changes in income and time constraints depends on the individual's preferences and the net effect of a job loss on the demand of exercise is therefore uncertain.

4.2 Becker–Murphy Model of Rational Addiction

According to consumer choice theory, individuals are assumed to be rational utility maximisers. However, addictions such as consumption of cigarettes, alcohol and overeating seem to be antithesis of rational behavior. To understand these habits, Becker and Murphy (1988; henceforth B-M) developed a theory of rational addiction whereas rationality is defined as a consistent plan to maximize utility over time.

The basic model of rational addiction is based on the idea that an individual's utility, at any point in time *t*, depends on the consumption of two goods: *x* and *y*. These goods are distinguished by the assumption that *x* is addictive whereas *y* is not. Current utility depends on past consumption of *x*, but not *y*. This utility function can be expressed in a more formal way:

$$U(t) = U[x(t), y(t), s(t)] \tag{10}$$

The utility function is assumed to be a concave function of *x*, *y* and *s* (Becker & Murphy, 1988). Past consumption of *x* affects current utility through a process of "learning by doing", as summarized by the stock of consumption capital, *s*. If an increase of current consumption of *x* leads to an increase of future consumption of *x*, the individual is assumed to be addicted to *x* (Morris et al. 2012).

Addictions can be both harmful to the individual's health (such as consuming alcohol and cigarettes) but also beneficial (such as going to the gym or performing other physical activity) (Becker & Murphy, 1988). The distress and uncertainty associated with a job loss, divorce or other events, might affect the demand for addictive goods (Becker & Murphy, 1988). If these tension-raising events lower the individual's utility level, the marginal utility of addictive goods may increase (Becker & Murphy, 1988). Thus, if smoking is a way of coping with the daily grind and handling stressful moments in life, the demand for addictive goods is expected to increase in order to compensate for the decreased utility level that a stressful event has imposed. In addition, temporary stressful events can also cause rational individuals to become obsessed with addictive goods (Becker & Murphy, 1988).

4.3 Predictions from the Theory

The Grossman model and the B-M model can be considered as separate entities for theoretical and empirical analyses. However, to make accurate predictions and to better understand unemployment's effect on diverse health behaviors, it is interesting to do a simultaneous

evaluation of both the dynamics of the B-M's theory of addictions but also the human capital model of health investment.

In the framework of Grossman's human capital model, a decrease in hours of work may increase the demand for time-intensive health-promoting behaviors, such as physical activity or preparing home-cooked meals (and indirect the consumption of fruits and vegetables). More leisure time might also have a positive effect on health-depreciating behaviors, such as smoking or drinking, simply because there are more opportunities to do so. The reduced income due to a job loss can on the other hand impose a reversed effect on these behaviors. In order to cut the household's expenses, a decline in consumption of normal goods is expected. This includes for example both fruits and vegetables as well as exercise which cost money (such as a gym membership). Similarly, some smokers may need to reduce their cigarette consumption or even quit smoking altogether to be able to cut expenses. However, according to the B-M's theory of addictions, some individuals may instead draw on potentially health-damaging behaviors to reduce the psychological distress emerging from the job loss. If this is the case, an increased consumption of addictive goods (such as alcohol or cigarettes) is expected. Exercise addiction can in a similar fashion become more severe and enhance an unhealthy obsession.

Another aspect to take into consideration is the social security system for the unemployed since it might affect the potential outcomes mentioned above. A more generous unemployment insurance benefit, as the one in the Netherlands, will dampen the economic hardship that a job loss creates for the individual. Consequently, the unemployed may not be forced to change consumption habits to the same extent in order to cut expenses as in the absence of unemployment benefits or if the benefits were less generous. An extensive unemployment benefit system could in addition help mitigate the psychological distress emerging from a job loss.

In sum, there are various mechanisms at play when we want to investigate the impact of unemployment on different health behaviors. The net impact of job loss on health behaviors is therefore indeterminate and remains as an open empirical issue. Not least will individual preferences affect the outcomes and we expect that the effects are heterogeneous across individuals. We will consequently investigate these effects separately for men and women.

5. Data and Methodology

This section will cover information about the data and how the dataset was constructed. We will also present the dependent variables and baseline characteristics that are included in the analyses. Furthermore, the methodological strategies that have been used in order to study the relationship between unemployment and health behaviors will be introduced.

5.1 Data and Restrictions

This study uses data from the Dutch Longitudinal Internet Studies for the Social Sciences, LISS, from CentERdata in Tilburg. The LISS panel is a representative sample of Dutch individuals who participate in monthly internet surveys. The panel is based on a true probability sample of households drawn from the population register by Statistics Netherlands, CBS (LISS, n.d.a). The LISS panel consists of about 5 000 households, comprising 7 500 individuals. Panel members are asked to fill out a questionnaire every month and the topics of the surveys vary. Among them are core questionnaires on e.g., income, health, housing and employment repeated annually. The panel members complete the surveys online and households that could not otherwise participate are provided with a computer and internet connection. The LISS panel has been conducted every year since 2007 and all data is available through the LISS Data archive that can be found on their website.

The longitudinal setting of the LISS data allows us to better reveal unemployment's effect on health behaviors compared to cross-sectional data since we can control for time-invariant unobserved heterogeneity across individuals. The study covers the time period 2008-2018 and includes a total of ten[5] waves. We are restricted to this specific time interval because of limitations in the data available.[6]

In this thesis, we use a sample which is restricted to individuals that have participated in the LISS panel during at least two waves between 2008-2018. To isolate individuals in the labor force, our analysis sample is restricted to LISS participants who met any of the following criteria at the data collection year: (1) are working for pay; (2) works or assists in family

[5] The health-survey of 2014 did for some inexplicable reason never take place and can consequently not be included in the analyses.
[6] Due to changes in the questionnaires regarding the respondents' health, we have decided not to include the survey of 2019 and onwards in our study.

business; (3) autonomous professional, freelancer, or, self-employed; (4) job seeker following job loss. In this way we avoid selection bias due to factors affecting selection into the labor force instead of e.g., education and selection out of the labor force due to e.g., retirement. Voluntary work or individuals with (partial) work disability are eliminated from the sample. As there are panel members that do not participate in every wave and there are some missing observations in reported health behaviors, the data set is essentially unbalanced.

The fourth criteria above represent our indicator variable, i.e., whether the individual is unemployed or not. It is represented by a binary variable that records employment change between survey waves.

5.1.1 Dependent Variables

We investigate the relationship between changed employment status and health behaviors by using four different categories as dependent variables: physical activity, dietary patterns and consumption of alcohol and cigarettes. These behavior-linked health determinants are the most important and well-known factors that affect an individual's overall health (WHO, 2020b), which motivates our choice of dependent variables. They can furthermore be divided into two different groups: health-promoting behaviors (such as physical activity and healthy diet) and health-compromising behaviors (such as consumption of alcohol and cigarettes).

Physical activity

Regarding physical activity, LISS asks mainly three questions that are of interest for our study: "If you look back on the last 7 days, on how many of those days did you perform a strenuous physical activity such as lifting heavy loads, digging, aerobics or cycling?", "If you think of the past 7 days, on how many of those days did you perform a moderately intensive physical activity such as carrying light loads, cycling at a normal pace or cleaning windows?" and "If you look back on the last 7 days, on how many of those days did you spend at least 10 minutes walking? Think of walking on the job and at home, walking to get from one place to another, and all the walking you did as part of recreation, sports or leisure time activities". Besides reporting the number of days spent on each activity, the respondent also needs to write down the number of hours and minutes spent each time on the three activities above. Previous studies have expressed physical activity in minutes of exercise per week.[7] Consequently, physical activity is left as

[7] See for example Colman and Dave (2014).

continuous variables and are expressed as three measures: minutes of strenuous physical activity per week, minutes of moderate physical activity per week and minutes of walking per week.

Dietary patterns

In LISS, the respondents are asked about their consumption of a variety of foods. In this study we are focusing on fruits and vegetables since these commodities are well-known to be important components of a healthy diet (WHO, 2003). Our measures of dietary patterns are based on two questions: ‘‘Do you eat raw or cooked vegetables?’’ and “Do you eat fruits?”. The six possible response categories are: every day, five to six times per week, two to four times per week, one time per week, one to three times per month and never. We have merged these six categories into two classifications to create a dummy variable: low compared to high consumption of fruits and vegetables respectively (low consumption = 0; high consumption = 1). Low levels of fruits/vegetables include consumption of fruits/vegetables one time per week, one to three times per month or no consumption at all. High consumption corresponds to a consumption of fruits/vegetables every day, five to six times per week and two to four times per week.

Cigarette consumption

The cigarette use is based on two questions: “Do you smoke now?” and “How many cigarettes (including rolling tobacco) do you smoke on average per day?”. We have constructed three measures based on the responses. The first one is a binary measure and indicates whether the respondent is a current smoker or not (non-smoker = 0; smoker = 1). The second is a continuous measure of cigarette use per day among smokers. The third variable is another continuous measure of the daily number of cigarettes smoked among heavy smokers[8] at entry in the panel data. By creating two subgroups among smokers, we can examine whether unemployment has a bigger impact on smoking among initially heavy smokers than among average smokers. The two latter variables are expressed on a logarithmic scale, as mostly done in previous research.[9] Non-smokers are assigned as missing values for the two continuous variables.

[8] According to a study in WHO FCTC Global Studies Series, a heavy smoker consumes 20 or more cigarettes per day (Zafeiridou, Hopkinson & Voulvoulis, 2018).
[9] See for example Colman and Dave (2014).

Alcohol consumption

Drinking behavior is based on responses to the following survey question: "On how many of the past 7 days did you have a drink containing alcohol?". Alcohol consumption is consequently a count variable that can take values between 0 and 7.

5.1.2 Baseline Characteristics

Time-variant variables

The LISS Panel data includes a set of demographic and job-related variables. Along the main independent variable of interest, i.e., unemployment, a set of other time-variant covariates will be included in the analyses. These are chosen in line with earlier empirical findings.[10]

The time-variant covariates include the individual's marital status, income, age and whether the respondent has at least one child living at home or not. Marital status consists of a dummy, (separated/divorced/widow(er)/never been married = 0; married = 1). As described in the theoretical part of this study, it is the household's total income that is expected to influence an individual's health behaviors and not only the personal net income. Income is therefore measured as the net household income in euros and is expressed on a logarithmic scale. Age is left as a continuous variable. The variable indicating if the respondent has at least one child living at home is a dummy variable (no living-at-home children = 0; has at least one living-at-home child = 1). Finally, year dummies will also be included in the analyses in order to control for general trends in the dataset, using 2008 as a baseline.

Time-invariant variables

Time-invariant covariates will not be included in the regression analyses since we are using fixed effects models. They will however be presented in the descriptive statistics and a short presentation of these variables is therefore needed.

The time-invariant covariates consist of gender, origin and level of education. Dummy variables have been created for gender (male = 0; female = 1) and origin (Dutch background = 0; birthplace outside of the Netherlands = 1). Education is expected to be a time-invariant variable because of the four selection criteria mentioned in section 5.1. However, we cannot exclude the

[10] See for example Compton et al. (2014), Ásgeirsdóttir et al. (2014), Dave & Kelly (2012) etc.

possibility that some individuals attend school later in life and education will therefore be included in the analyses. The educational level is categorized as primary school, secondary school and academic education (coded as 1, 2 and 3 respectively).

To summarize, the reference group consists of Dutch-born single males with no living-at-home-children and who only attended primary school.

5.2 Limitations and Critical Discussion of the Data

As with any empirical study there are limitations to the data which may affect the overall significance of the results. Although we will consider the limitations in section 8, we have chosen to discuss some of the most important aspects below.

The longitudinal setting of the LISS data allows us to better reveal how unemployment affects health behaviors since we can control for time-invariant unobserved heterogeneity across individuals. The most potentially damaging threat to the value of panel data is however the presence of biasing attrition (Baltagi, 2012). Attrition is to some extent unavoidable (e.g., because of death), but households may also leave the panel for various other reasons. If the attrition (or non-responses) in the data over time is non-random, the results will suffer from selection bias (Dahmström, 2011). Considering the LISS panel, the respondent attrition is about 12 % per year and the household attrition is about 10 % per year (LISS, n.d.b). In 2019, the average individual response to at least one survey per month was 80.42 % and the average household response was 83,92 % (LISS, n.d.b). If the attrition (or non-responses) is non-random, sample weights can be applied.

Because of the complexity, the LISS panel does not include sample weights that correct for non-responses and attrition (LISS, n.d.b).[11] Since the LISS panel is based on a true probability sample and is regularly recruited with refreshment samples, the representativity of the panel should (at least to some degree) be assured (LISS, n.d.c). In addition, various studies have been conducted in order to examine the representativeness of the LISS panel and to explore which demographic groups have a higher probability of becoming inactive or even leaving the panel. De Vos (2009) did not find significant differences in attrition when differentiating by

[11] There are mainly two reasons why LISS does not provide weights. Firstly, in panel data there are several possible target populations to weight (for example: the population at the present, the population at the time of the start of the panel, or weights to compensate for attrition or nonresponse). Secondly, due to the way the LISS panel is constructed, there are different possible variables to take into the weights (LISS, n.d.c).

characteristics such as gender, household size, type of tenure, education level, the presence or absence of students, self-employed, unemployed and homemakers. One exception was age where De Vos (2009) found significant differences between the youngest (age below 25) and the oldest (age above 75) in the panel. Scherpenzeel and Bethlehem (2011) showed that the representativeness of the LISS panel was similar to those from the traditional surveys.

According to Fitzgerald, Gottschalak and Moffitt (1998), the simplest way of testing for attrition is to estimate a probit model in which the dependent variable takes the value one if the individual attrit from the sample after one wave to the next and zero otherwise. This has consequently been done on our sample and the results are shown in table 3 in Appendix. The baseline characteristics that are used as explanatory variables are age, gender, marriage, income, living-at-home children, birthplace and education level. One year is compared to the next and the results are presented in each column (i.e., column one compares 2008 with 2009, column two compares 2009 with 2010 etc.). The table shows the probability of attrition given the different baseline characteristics. As can be seen from the results, the coefficient for age tends to be significant during some years but the other coefficients do not seem to follow any specific pattern. One important thing to mention is that using this probit estimation method might not be the most accurate approach to investigate the attrition in the LISS panel but it will at least shed light if non-random attrition seems to be a severe problem. Due to the time-limitation of this study, any more in-depth analysis of the attrition in the LISS panel has not been performed. However, it is essential in order to detect and correct for potential attrition bias.

Another limitation and critical aspect with the LISS panel is the lack of information on the panel members. For example, the reason for the job loss is not stated in the surveys. This means that the individual could have been laid-off because of personal reasons which in turn might bias our results (more about this in section 8). Furthermore, it is a major weakness that the information about the duration of unemployment is missing since we cannot rule out the fact that the panel member may have become unemployed the same day as the survey took place (or a couple of days before). In such a case, we cannot expect to reveal any changes in reported behaviors. Knowledge about the time-duration could give additional information about changed behaviors across long-term and short-term unemployment, respectively. Moreover, these two groups of unemployed might also differ in characteristics and behaviors which consequently can affect the outcomes in different ways.

Misreporting among the panel members might also be a limitation in this study. Respondents may deliberately misreport certain answers when asked more sensitive questions (for example about alcohol consumption or smoking habits) or misreport simply because they fail to remember accurately. Individuals might also make typing errors in the questionnaires. All these types of misreporting can lead to an over- and/or underestimation of the dependent variables.

5.3 Descriptive Statistics

As a final step, observations for which certain values for different variables are missing have to be excluded from the dataset and as a result, a total of 5 699 respondents are fulfilling the four criteria mentioned in section 5.1 regarding employment status. Table 1 below shows the summary statistics and comparisons in means for the two categories of employment status; unemployed and employed. Note that it is possible for the same individual to shift between the two groups and consequently be present in both categories below.

Table 1. Summary Statistics by Employment Status.

	Unemployed			Employed			
Dependent variables	**Mean**	**N**	**n**	**Mean**	**N**	**n**	**Sig.**
Health-promoting behaviors							
Fruit consumption	0.74	1277	618	0.80	27199	5614	***
Vegetable consumption	0.85	1277	618	0.89	27199	5614	***
Minutes strenuous physical activity per week	145.49	1278	620	259.35	27206	5615	***
Minutes moderate physical activity per week	374.26	1272	618	486.62	27158	5614	**
Minutes walking per week	565.38	1276	619	602.59	27137	5610	
Health-compromising behaviors							
Number of days consumed alcohol last 7 days	2.59	1086	554	2.32	24483	5271	***
Whether smokes	0.31	1280	620	0.19	27269	5615	***
Cigarettes per day among smokers	15.23	345	177	13.17	4482	1333	**
Heavy smoker at entry	0.13	1285	621	0.08	27352	5615	***
Cigarettes per day among heavy smokers at entry	22.20	127	62	20.36	1465	375	***
Baseline characteristics							
Time-varying covariates							
Age	48.42	1285	621	44.97	27352	5615	***
Married	0.49	1285	621	0.58	27352	5615	***
Net household income in euros	2351.78	1178	568	3332.01	24964	5270	***
Having living-at-home children in the household	0.42	1285	621	0.51	27352	5615	***
Time-invariant covariates							
Birthplace outside of the Netherlands	0.15	1226	586	0.07	26237	5130	***
Female	0.53	1285	621	0.50	27352	5615	**
Education level	2.25	1285	621	2.38	27336	5609	***
Primary school (percent)	5.91	76	39	3.82	1043	278	
Secondary school (percent)	63.58	817	387	54.33	14852	3093	
Academic education (percent)	30.51	392	201	41.85	11441	2457	

Notes: Sig. describes p-values from t-tests for differences in means between the two subgroups.
N represents the number of observations; n represents the number of individuals.
*** p<.01. ** p<.05. * p<.10.

As can be seen in table 1, there appears to be differences between the means in the majority of the health behaviors and the baseline characteristics. Regarding the health behaviors, unemployed seem to engage less in health-promoting behaviors (such as total physical activity and consumption of fruits and vegetables) and engage more in health-compromising behaviors (such as smoking and drinking alcohol). Regarding the baseline characteristics, unemployed are in general slightly older, are more often women, have lower income and education level and

are more often born outside of the Netherlands. Additionally, there seem to be fewer marriages and living-at-home children among unemployed compared to employed.

As mentioned above, there appears to be significant differences in the baseline characteristics between unemployed and employed. There is consequently a potential threat of endogeneity bias (more about this in section 8). Unemployment is sometimes argued to be more exogenous during a crisis (see for example Dave & Kelly, 2012; Ásgeirsdóttir et al. 2014), which in turn means that the differences in characteristics between unemployed and employed should be non-existent. We have consequently checked the baseline characteristics between the two categories of employment status during the Great Recession, spanning from 2008 to 2012. The result can be found in table 4 in Appendix. The test shows that the baseline characteristics are still significantly different even during an external shock. This implies that our variable "job seeker following a job loss" does not seem to be more exogenous during the Great Recession.

5.4 Methodology

In order to control for unobservable characteristics between employed and unemployed individuals, a fixed effects model will be used.[12] Since the objective of this study is to investigate the effect of unemployment on different health behaviors, we specify the following model where the dependent variable, $HealthBeh_{it}$, is the health behavior for individual *i* at time *t*:

$$HealthBeh_{it} = X_{it}\beta + \theta_i + \alpha E_{it} + \pi_t + \varepsilon_{it} \qquad (11)$$

where X_{it} is a vector of individual characteristics that vary over time (marital status, income, age and living-at-home children), θ_i is unobserved individual effects that do not vary over time, E_{it} indicates the individual's employment status at time *t* (coded as 1 if the individual is unemployed), π_t is the year specific effects and ε_{it} represents all time-varying unobserved factors that affect the outcome. Strict exogeneity with respect to the error term is required in order to obtain consistent results.

Using a fixed effects model within this field of study is in line with previous research (see Compton et al. 2014; Smed et al. 2018; Ruhm, 2000 etc.). One of the advantages with this

[12] A Durbin–Wu-Hausman test can be conducted in order to differentiate between fixed effects and random effects models in panel analysis (Verbeek, 2004). Our result obtained from the Hausman-test is in favor of a fixed effects model.

model is that it eliminates the variation in all unobserved time-invariant characteristics. This means that omitted time-invariant characteristics will not bias the estimated coefficients (Dahmström, 2011). One limitation of the fixed effects model is that time-varying omitted variables are still present, although the omitted variable bias becomes smaller compared to cross sectional data (Lundborg, 2021). Another drawback is that it is inapplicable to the investigation of observed time-invariant causes of the dependent variables (Verbeek, 2004). In our case, this means that the individuals who do not change their employment status will not contribute to the estimates since the model relies on within-individual variation. Thus, the power of the model will decrease considerably as well as the standard errors of the coefficient estimates (Dahmström, 2011). We argue that the advantages do however outweigh the disadvantages in this particular case.

As mentioned earlier, we are going to investigate four different categories of health behaviors, comprising nine dependent variables. Different estimation techniques and tests need to be applied depending on the measurement of the dependent variable. These techniques will be presented here below.

Physical activity and Cigarette consumption among smokers and heavy smokers

The continuous dependent variables, consisting of physical activity (measured as number of minutes spent on each activity per week) and the number of cigarettes consumed per day among smokers and heavy smokers respectively, will be estimated by using linear regression analysis within the fixed effects model. Since inferences will become unreliable if the data is heteroscedastic (i.e., when the variance is not constant), a test for the possible existence of heteroscedasticity needs to be conducted (Verbeek, 2004). To correct for heteroscedasticity, one should use robust standard errors. The Modified Wald statistics (Baum, 2001) for groupwise heteroskedasticity in the fixed effects model will therefore be performed in order to detect the problem with heteroscedasticity.

Smoker/Non-smoker and Consumption of fruits and vegetables

Binary dependent variables should by contrast be estimated using logit or probit models (Verbeek, 2004). The main difference between the two estimation techniques is that the probit model assumes standard normal distribution whereas the logit model is based on the standard logistic distribution (Lind, Marchal & Wathen, 2014). In practice, they generally generate similar estimations and there are no guidelines when one model is preferred over the other.

However, since logistic regressions have been mostly used in previous studies, we will apply the fixed effects logit model on our binary dependent variables (i.e., smoker/non-smoker and high/low consumption of fruits/vegetables). As an example, the logit model with fixed effects specifies the probability of being a smoker ($Smoker_{it} = 1$) conditionally on the regressors, X_{it}, the unemployment indicator, E_{it}, and the year specific effects, π_t:

$$Probability(Smoker_{it} = 1|X_{it}, E_{it}, \pi_t) = \frac{e^{-Z_{it}}}{1+e^{-Z_{it}}} \quad (12)$$

where

$$Z_{it} = X_{it}\beta + \alpha E_{it} + \pi_t \quad (13)$$

The logistic model is a cumulative distribution function, where $\mathbb{R} \rightarrow [0,1]$. Due to the non-linearity of the model, the fixed effects estimators are obtained by maximum likelihood methods (Verbeek, 2004). The same reasoning applies for high/low consumption of fruits and vegetables, respectively. Further, when dealing with binary variables within the fixed effects model, standard errors are obtained using bootstrapping methods which automatically correct for heteroscedasticity.

Alcohol consumption

The Poisson and negative binomial models (henceforth NegBin I) are the two most common models when dealing with count data (Verbeek, 2004). It is generally the amount of overdispersion in the data (i.e., when the conditional variance exceeds the conditional mean) that should determine whether the Poisson or the NegBin I model is the most appropriate model to apply. If the dispersion in the data is high, NegBin I is the preferred one.[13] However, studies have shown that the NegBin I model for panel data is not a true fixed effects method (Allison & Waterman, 2002). The Poisson estimator will therefore be considered as more suitable for this study and will be used for the empirical analysis of the count variable. It is nonetheless important to check the amount of dispersion in the data.[14] The reason for this is that if the data is overdispersed, robust standard errors should be used in the Poisson model (Kennedy, 2008). The Poisson model can be expressed in the following way:

[13] For Poisson models, variance increases with the mean and, therefore, variance usually (roughly) equals the mean value. If the variance is much higher, the data is said to be overdispersed and the NegBin I model is preferred.
[14] Overdispersion can be tested in most statistical software.

$$Probability(AlcoholCon_{it} = j|X_{it}, E_{it}, \pi_t) = \frac{\lambda_{it}^{j} e^{-\lambda_{it}}}{j!} \qquad j = 0,1,2 \dots 7 \qquad (14)$$

where

$$\lambda_{it} = \exp(X_{it}\beta + \alpha E_{it} + \pi_t) > 0 \qquad (15)$$

Similar to the logit model, the parameters of the Poisson model are estimated by maximum-likelihood methods. In our analysis, the count data consists of alcohol consumption.

Irrespective of which estimation technique that will be used, we need to test for multicollinearity (i.e., whether there exists a high internal correlation between the explanatory variables). A general rule is if the correlation between two independent variables is between -0.70 and 0.70, multicollinearity is not likely to be a problem (Lind et al. 2014).

Finally, we also need to test if year fixed effects should be included in each regression analysis. In order to be included in the regressions, the year fixed effects requires regressors' variation over units within each time period. To determine if year fixed effects are needed, the so-called Testparm[15] can be conducted. This is a joint test to see if the dummies for all years are equal to zero, and if they are, then no year fixed effects are needed in the regressions (Baum, 2014). The test needs to be performed on each regression that will be estimated.

6. Empirical Results

This section will present the results of the study. The first part will provide results from general diagnostic tests. The second part will include the main results from the regression analysis, comprising both the entire sample but also men and women separately.

6.1 General Diagnostic Tests

To yield accurate estimations, there are several tests that need to be performed before conducting our analysis (as previously mentioned in section 5.4). All the statistical analyses were performed with Stata version 16.1.

[15] There is no official name for this test. In the statistical software Stata it is called Testparm.

Firstly, a correlation matrix was used in order to determine if any of the independent variables have a high internal correlation. The results can be found in table 5 in Appendix. The table shows that our data does not suffer from multicollinearity and all of our independent variables are consequently kept in the analyses.

For the continuous variables, tests for heteroscedasticity are required. The modified Wald statistic was performed which confirmed that our data is heteroskedastic. To correct for the heteroscedasticity, robust standard errors are included in all of our regressions.

For the count variable, "Number of drinks containing alcohol during the last 7 days", a Poisson model will be used. As mentioned earlier, we need to test whether the data is overdispersed or not in order to determine whether robust standard errors should be used. The test showed that the conditional variance is greater than the conditional mean for this variable, which indicates that the data is overdispersed. Robust standard errors are therefore applied in the regressions to correct for the overdispersion.

As a final test, the so-called Testparm was conducted for each regression to determine if year fixed effects should be included in the analyses. The test showed varied results. For the following dependent variables, year fixed effects should be included in the analysis: "Whether smokes", "Minutes strenuous physical activity per week", "Number of days consumed alcohol last 7 days" and "Fruit consumption". By contrast, year fixed effects should not be used in the remaining regressions: "Log of cigarettes per day among smokers", "Log of cigarettes per day among heavy smokers", "Minutes moderate physical activity per week", "Minutes walking per week" and "Vegetable consumption". This applies for the entire sample but also for women and men, respectively.

6.2 Main Results

As can be seen below in table 2A, 2B and 2C, nine regressions have been estimated for each subgroup: the entire sample, men and women. The model specification is found beneath each of the regressions in table 2A, 2B and 2C and the full regressions can be found in Appendix (table 6A, 6B and 6C). The following time-variant control variables are included in all of the regressions: age, having living-at-home children in the household, log of net household income in euros, education and marriage. We have previously stated that education is assumed to be a time-invariant variable and should therefore be omitted when using a fixed effects model. In

contrast to our expectations, the education level is time-varying which shows that some individuals have studied later in life. The education variable is therefore included in our regressions.

Table 2A. Regressions on Panel A: Entire Sample.

VARIABLES	(1) Minutes strenuous physical activity per week	(2) Minutes moderate physical activity per week	(3) Minutes walking per week
Job-loss	-83.36***	-52.68	-98.50
	(19.35)	(83.12)	(95.79)
Observations	25,649	25,602	25,589
Number of individuals	5,259	5,260	5,258
	Robust standard errors in parentheses	Robust standard errors in parentheses	Robust standard errors in parentheses
	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1
Model	Linear regression	Linear regression	Linear regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	Yes	No	No

VARIABLES	(4) Fruit consumption (OR)	(5) Vegetable consumption (OR)	(6) Number of days consumed alcohol last week
Job-loss	0.0176	0.0888	0.00913
	(0.173)	(0.181)	(0.0258)
Observations	8,319	7,792	20,983
Number of individuals	1,414	1,317	4,158
	Bootstrap standard errors in parentheses	Bootstrap standard errors in parentheses	Bootstrap standard errors in parentheses
	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1
Model	Logistic regression	Logistic regression	Poisson regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	Yes	No	Yes

VARIABLES	(7) Log of cigarettes per day among smokers	(8) Log of cigarettes per day among heavy smokers	(9) Whether smokes (OR)
Job-loss	-0.0198	-0.0494	0.0384
	(0.0333)	(0.0622)	(0.266)
Observations	4,319	1,449	4,201
Number of individuals	1,234	360	702
	Robust standard errors in parentheses	Robust standard errors in parentheses	Robust standard errors in parentheses
	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1
Model	Linear regression	Linear regression	Logistic regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	No	No	Yes

Table 2B. Regressions on Panel B: Men.

VARIABLES	(1) Minutes strenuous physical activity per week	(2) Minutes moderate physical activity per week	(3) Minutes walking per week
Job-loss	-94.06***	-13.99	16.06
	(28.30)	(156.3)	(161.0)
Observations	12,856	12,834	12,833
Number of individuals	2,559	2,559	2,557
	Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Model	Linear regression	Linear regression	Linear regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	Yes	No	No

VARIABLES	(4) Fruit consumption (OR)	(5) Vegetable consumption (OR)	(6) Number of days consumed alcohol last week
Job-loss	-0.139	0.178	-0.0306
	(0.244)	(0.206)	(0.0357)
Observations	4,684	4,611	11,149
Number of individuals	785	759	2,161
	Bootstrap standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	Bootstrap standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	Bootstrap standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Model	Logistic regression	Logistic regression	Poisson regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	Yes	No	Yes

VARIABLES	(7) Log of cigarettes per day among smokers	(8) Log of cigarettes per day among heavy smokers	(9) Whether smokes (OR)
Job-loss	-0.113**	-0.0775	0.0257
	(0.0567)	(0.0944)	(0.354)
Observations	2,234	812	2,313
Number of individuals	625	205	368
	Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Model	Linear regression	Linear regression	Logistic regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	No	No	Yes

Table 2C. Regressions on Panel C: Women.

VARIABLES	(1) Minutes strenuous physical activity per week	(2) Minutes moderate physical activity per week	(3) Minutes walking per week
Job-loss	-77.61***	-105.2*	-198.8*
	(27.25)	(55.03)	(108.8)
Observations	12,793	12,768	12,756
Number of individuals	2,701	2,702	2,702
	Robust standard errors in parentheses	Robust standard errors in parentheses	Robust standard errors in parentheses
	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1
Model	Linear regression	Linear regression	Linear regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	Yes	No	No

VARIABLES	(4) Fruit consumption (OR)	(5) Vegetable consumption (OR)	(6) Number of days consumed alcohol last week
Job-loss	0.161	-0.0588	0.0586
	(0.261)	(0.278)	(0.0370)
Observations	3,635	3,181	9,834
Number of individuals	629	558	1,998
	Bootstrap standard errors in parentheses	Bootstrap standard errors in parentheses	Bootstrap standard errors in parentheses
	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1
Model	Logistic regression	Logistic regression	Poisson regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	Yes	No	Yes

VARIABLES	(7) Log of cigarettes per day among smokers	(8) Log of cigarettes per day among heavy smokers	(9) Whether smokes (OR)
Job-loss	0.0597	-0.00808	0.0274
	(0.0364)	(0.0740)	(0.285)
Observations	2,085	637	1,886
Number of individuals	610	155	334
	Robust standard errors in parentheses	Robust standard errors in parentheses	Robust standard errors in parentheses
	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1	*** p<0.01, ** p<0.05, * p<0.1
Model	Linear regression	Linear regression	Logistic regression
Fixed Effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Year dummies	No	No	Yes

6.2.1 Entire Sample

Physical Activity

As can be seen in regression 1 in table 2A, minutes of strenuous physical activity per week seems to be the only health behavior which shows to be significant when experiencing a job loss. The coefficient is significant at a 1 % significance level and experiencing a job loss seems to reduce the number of minutes spent on strenuous physical activity by around 83 minutes per week. In regression 2 and 3, moderate physical activity and walking also seem to reduce when experiencing a job loss. Although, since these coefficients are insignificant, we cannot rule out that there is no change in these variables.

Dietary Patterns

As can be seen in regression 4 and 5 in table 2A, the odds of having a high consumption of fruits and vegetables seem to increase when experiencing a job loss. However, these relationships are non-significant and we cannot rule out that there is no change in these variables.

Smoking

As can be seen in regression 9 in table 2A, there seems to be no relationship between being a smoker and experiencing a job loss. In regression 7 and 8, the number of cigarettes smoked per day among both smokers and heavy smokers at entry also show no significant relationship with unemployment.

Alcohol Consumption

As can be seen in regression 6 in table 2A, the number of days consumed alcohol also show no significant relationship with unemployment.

6.2.2 Men and Woman

Physical Activity

As can be seen in regression 1 in table 2B and table 2C, respectively, experiencing a job loss seems to reduce the number of minutes spent on strenuous physical activity by around 94 minutes per week for men and around 78 minutes per week for women. The coefficient is significant at a 1 % significance level for both men and women. In regression 2 and 3 in table

2B, neither the number of minutes spent on moderate physical activity nor walking seem to be significant for men. On the contrary, in regression 2 and 3 in table 2C, women seem to reduce the number of minutes spent on moderate physical activity by 105 minutes per week and walking by 199 minutes per week. Since these latter coefficients only are significant at a 10 % significance level, we cannot conclude that there is a change in the number of minutes spent on either moderate physical activity or walking when experiencing a job loss.

Dietary Patterns

As can be seen in regression 4 in table 2B and 2C, respectively, the health-promoting variables for consumption of fruits show no significant relationship with unemployment among neither men nor women. It is although interesting that the odds of having a high consumption of fruits seem to increase when experiencing a job loss among women but decrease among men. By contrast, in regression 5 in table 2B and 2C, the opposite is true for the consumption of vegetables, where the odds of having a high consumption of vegetables seem to increase when experiencing a job loss among men but decrease among women. However, as stated previously, since these coefficients are insignificant, we cannot rule out that there is no change in these variables.

Smoking

As can be seen in regression 7 and 8 in table 2B, experiencing a job loss seems to reduce the number of cigarettes smoked per day among male smokers with around 11.3 % with a significance level of 5 %. Although, this relationship seems to disappear when examining men who were heavy smokers at entry. In regression 7 and 8 in table 2C, consumption of cigarettes for both smokers and heavy smokers at entry seem to have no relationship with unemployment among women. As can be seen in regression 9 in table 2B and 2C, job loss also seems to have no impact on whether an individual starts, or quits, smoking among both men and women.

Alcohol Consumption

As can be seen in regression 6 in table 2B and 2C, the number of days consumed alcohol also show no significant relationship with unemployment among neither men nor women.

7. Empirical and Theoretical Analysis

In this section, we will discuss the findings of this paper and compare them with both the theoretical background but also previous literature.

7.1 Theoretical Analysis

Predicting in what, if any, direction the four health behaviors will change when experiencing a job loss is an arduous task. Since there are several factors affecting an individual's health behaviors, the additional impact a job loss might create on these behaviors is therefore far from being clear-cut. As discussed in section 4.3, the two main effects of experiencing a job loss are increased leisure time and decreased income, but a job loss can also cause psychological distress which in turn can change health behaviors.

As we can see in the results, there is a decrease in the amount of time spent on strenuous physical activity. This result does not follow the prediction that an increase in leisure time would increase the amount of time spent on physical activity. Since all three measures of physical activity refer to both work-related and leisure time activities, it is impossible to distinguish between them. A reduction in strenuous physical activity could therefore either be the effect of individuals who previously had a physically demanding job losing their jobs, or that individuals reduce their leisure time exercise. Most likely, it is a combination of both. The reduced income that a job loss creates, could also be the reason for why an individual would reduce the number of minutes spent on leisure time exercise, if they normally practice exercises which cost money (for example gym membership). An exception to this behavior is that some individuals could be addicted to exercise and a reduction in income would therefore not affect these individuals exercise habits.

There is no change in dietary patterns when experiencing a job loss among neither subgroup. Perhaps dietary patterns are not as sensitive to a change in job status as one would predict. How the variables for consumption of fruits and vegetables are measured could, however, also affect the outcome. Since we can only measure the consumption of fruits and vegetables as the number of days consumed, and not the amount of total intake, we lose a lot of variation. A variable measuring the number of fruits and vegetables per day could therefore give us more insight into whether an individual changes dietary patterns following a job loss.

The results show that neither men nor women seem to start or quit smoking following a job loss. A lower income could decrease the probability of starting to smoke, since the main priority is to make ends meet. Someone who already is a current smoker could, however, be less likely to quit when experiencing a job loss since the individual has more leisure time to smoke. When experiencing a job loss, cigarette consumption decreases by 11.3 % among male smokers. This could be explained by the lower income during unemployment, which forces the individual to make other priorities. This was on the other hand not true among women. The number of cigarettes smoked among heavy smokers at entry did not change either. This could be explained by the B-M theory of rational addiction, which would imply that an individual who is addicted to smoking might be less likely to reduce their cigarette consumption when experiencing a job loss.

Alcohol consumption shows to not be affected by a job loss. Neither an increase in leisure time nor a decrease in income seem to affect how many days an individual consumes alcohol. Similarly, as the variables for consumption of fruits and vegetables, alcohol consumption is only measured as the number of days consumed alcohol during the past 7 days and there is no measure of how many drinks were consumed in the same period. The outcome might have been different if another measure would have been used, as for example the number of drinks per week. Nonetheless, it is an interesting finding that individuals do not consume alcohol more often during unemployment.

7.2 Empirical Analysis

The results obtained in this thesis differ from what previous research has shown in several ways. We will mainly compare the results of our thesis to studies which have examined the effects of the individual's own employment status on different health behaviors.

Firstly, strenuous physical activity is in this study shown to decrease during unemployment. This follows the results obtained by Colman and Dave (2014), where they found that the total physical activity declines during unemployment. Some studies however found that leisure time exercise increases during unemployment (Colman & Dave 2014, Leino-Arjas et al. 1999). It could therefore in future research be interesting to examine whether the Netherlands follow the same pattern in their leisure time physical activity.

In a study examining dietary behaviors in Denmark, Smed et al. (2018) found that unemployment is associated with fewer purchases of fruit. On the contrary, our study showed that the consumption of fruits remains unchanged. On the other hand, Smed et al. (2018) used data which measured fruit consumption as the number of fruits the individual consumed, compared to our study which measured how often an individual eats fruit. It is therefore difficult to compare these two distinct results.

Several studies have found that unemployment is associated with an increased probability of being a smoker (Colman & Dave, 2014; Marcus, 2014; De Vogli & Santinello, 2005). By contrast, the results obtained in our study show that unemployment does not affect whether an individual smoke or not. Compton et al. (2014) also found that unemployment is associated with an increase in tobacco use. This is in contrast to the results obtained in our study among men.

Alcohol consumption shows to not be affected by unemployment in this paper. By contrast, Leino-Arjas et al. (1999) found that unemployment is associated with a decreased alcohol consumption, whereas another study shows that heavy alcohol use increases during unemployment (Compton et al. 2014). Both studies used the number of drinks consumed as their dependent variable. This may be the reason for why we did not find similar results, since our variable is measured solely on how many days the individual consumed alcohol the last 7 days. Nonetheless, it would be interesting to examine whether this relationship would hold if we had information about the number of drinks consumed as well.

8. Discussion

Possible reasons for our findings are multifold and in this part we will provide a discussion of these reasons. Limitations of the study will also be presented and suggestions for improvements and further research will be made.

As we noted in section 5.3, table 1, there are observed differences in health behaviors across the two categories of employment: employed and unemployed. Unemployed tend to engage less in health-promoting behaviors (such as total physical activity and healthy diets) and engage more in health-compromising behaviors (such as smoking and alcohol consumption). According to our results, these differences do not seem to stem mainly from the job loss per se.

Our results, however, may suffer from endogeneity bias. Certain personality characteristics might have a higher probability of being laid-off compared to others. Whether an individual experiences a job loss or not could therefore be correlated with the individual's observed and unobserved characteristics. This would make our variable for unemployment endogenous. During crises however, unemployment is more likely to be exogenous and examining the effect of unemployment on health behaviors during a crisis could therefore reduce the problem of endogeneity bias. In an attempt to test this assumption, we compared the baseline characteristics between employed and unemployed during the Great Recession and found that there were still significant differences between the two groups (see section 5.3). Thus, studying the effect of unemployment on health behaviors during a crisis (like the Great Recession), will probably not completely solve the possible problem of endogeneity bias.

Using an IV-estimator for unemployment could be an option to get around this problem. For example, using business closing as an indicator for job loss might have been a more exogenous variable compared to our indicator for unemployment; "job seeker after job loss". Business closing due to insufficient demand for the company's products or services is probably less likely to be correlated with the individual's characteristics. Using business closing as an IV-estimator for unemployment could therefore be of interest. Unfortunately, this method was not possible to perform since the reason for the job loss is not stated in the LISS surveys. On the other hand, even if the surveys contained information about the reason for job loss, the question remains how trustworthy this measure would have been. Misreporting could instead be a threat to the study.

Misreporting is per se a major concern since it might lead to measurement errors. Even though misreporting may be more common in "sensitive" topics (such as alcohol consumption or smoking habits), it can appear in all forms of questions. Misreporting could therefore affect the data's trustworthiness and lead to either an over- or underestimation of the dependent variables, which in turn would bias our results. For example, when individuals are asked about their alcohol and cigarette consumption there might be a tendency of underreporting the consumption because of the stigma associated with smoking and drinking alcohol. This will in return lead to a downward bias of our results. The opposite might hold for health-promoting behaviors, such as physical activity and consumption of fruits and vegetables, where upward bias can be a threat to our estimations.

An additional weakness of our study is the lack of information about the duration of unemployment. This is an important factor that needs to be considered if we want to study the effects of unemployment on different health behaviors. Firstly, the individual might have been laid-off the same day as the survey took place and in that case we will probably not observe any changes in behaviors. In addition, expectations about the future might also play a crucial role. If a recent job loser expects to soon be re-employed, it might not result in any changed health behaviors. By contrast, if unemployment is expected to last, changed behaviors might be needed in order to adjust to a possibly prolonged decrease in income and increase in leisure time. The duration of unemployment can consequently be an important determinant of health behavior that is expected to be more pronounced with time.

Another limitation of the data is the lack of information about the number of working hours before experiencing a job loss. Information about the number of working hours before experiencing a job loss could give more insight into what degree unemployment affects health behaviors. An individual who worked full-time might be more affected by a job loss compared to an individual who worked part-time, due to a larger change in everyday life. In addition, information about what type of employment an individual had before experiencing a job loss could also affect the expectations of a job loss occurring in the near future. For example, an individual shifting between temporary contracts could become more accustomed to being unemployed for short periods of time and already having an expectation about losing their job before the actual job loss. Individuals with permanent employment might on the other hand not be equally prepared for a job loss and consequently have other expectations. It would therefore be of interest to investigate this relationship in future research.

Finally, our findings are presumably affected by the context in which the study has been performed. Compared to previous studies, there does not seem to be any association between unemployment and the majority of the health behaviors examined in this study. This may partly be explained by the generous unemployment benefit system in the Netherlands, considering the reduced economic impact of unemployment. Since the impact of job loss on health behaviors will depend on the generosity of the unemployment benefit system operating in the individual's country, this could affect the external validity of the study. Nonetheless, further research is required to determine whether, and to what extent, the Dutch unemployment benefits are impacting the unemployed and furthermore various health behaviors.

9. Conclusion

In this thesis we have studied the impact of unemployment on different health behaviors, comprising alcohol and cigarette consumption, total physical activity and dietary patterns. This is done by using individual-level panel data from the Dutch Longitudinal Internet Studies for the Social Sciences, LISS. The time period stretches from 2008 to 2018. Fixed effects methods were used in order to estimate the effects of unemployment on different health behaviors. In contrast to previous studies, most of our results were insignificant and we did not find any association between unemployment and the majority of our researched health behaviors. However, we did find a negative relationship between unemployment and the number of minutes of strenuous physical activity per week, which is in line with previous research. Among men, we also found a negative relationship between job loss and cigarette consumption. Taken together, our results suggest that it is not the change in employment status per se that can be considered as the main health risk factor. Nonetheless, further research including more details about the individual's employment type, unemployment duration and unemployment benefits, among other information, would give more insight into the effect of unemployment on health behaviors.

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Appendix

Table 3. Attrition test using Probit model.

	Time period								
Variables	**2008-2009**	**2009-2010**	**2010-2011**	**2011-2012**	**2012-2013**	**2013-2015**	**2015-2016**	**2016-2017**	**2017-2018**
Age	-0.00598	-0.167***	-0.0304	-0.0777***	-0.102	-0.129***	-0.00348	0.0152	-0.0321
	(0.0178)	(0.0268)	(0.0262)	(0.0206)	(0.0621)	(0.0365)	(0.0137)	(0.0640)	(0.0255)
Having living-at-home children in the household	-0.00718	0.0908	-0.0639	-0.111	-0.155	-0.679***	-0.310	-0.415	-0.170
	(0.330)	(0.657)	(0.626)	(0.503)	(0.378)	(0.263)	(0.293)	(0.379)	(0.671)
Secondary education	-0.406	-0.717	-0.312	0.127	-1.104	-2.121***	5.122***	-1.988***	-0.00777
	(0.544)	(1.312)	(1.253)	(1.293)	(0.940)	(0.789)	(0.753)	(0.502)	(1.739)
Academic education	-0.321	-1.090	-0.366	0.0845	-1.601	-1.611**	4.870***	-0.841	-0.189
	(0.592)	(1.351)	(1.277)	(1.310)	(1.104)	(0.690)	(0.723)	(0)	(1.753)
Log of net household income in euros	-0.181	-0.0112	0.194	0.207	0.215	-0.782**	0.0523	-0.339	-0.0103
	(0.322)	(0.666)	(0.646)	(0.522)	(0.311)	(0.332)	(0.276)	(0.739)	(0.592)
Gender	0.0193	0.171	0.0464	0.194	0.829**	0.375	-0.441	-0.612	0.0536
	(0.325)	(0.607)	(0.603)	(0.474)	(0.387)	(0.257)	(0.294)	(0.420)	(0.624)
Origin	11.26	1.541	0.0861	0.345	-0.591	3.560***	-0.638*	5.528	0.544
	(0)	(1.114)	(1.088)	(0.986)	(0.417)	(0.916)	(0.381)	(0)	(0.803)
Married		-0.789	-0.0807	-0.139	-0.928*	-1.270***	-0.0675	0.557	-0.153
		(0.725)	(0.666)	(0.544)	(0.560)	(0.483)	(0.295)	(0.443)	(0.721)
Constant	-7.938***	-11.46**	-5.848	-5.214	0.550	10.49***	0.195	-2.233	-4.448
	(2.713)	(5.324)	(5.283)	(4.333)	(3.054)	(3.738)	(2.293)	(8.203)	(4.933)
Observations	6,359	5,231	5,286	5,220	5,242	5,256	5,235	5,131	5,110
Number of individuals	4,026	2,862	3,086	3,225	3,028	3,366	3,095	3,275	2,982

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Comparison of baseline characteristics during 2008 – 2012.

	Employment status		
	Unemployed	Employed	Sig.
Time-varying covariates			
Age	46.65	44.38	***
Married	0.47	0.61	***
Net household income in euros	2303.91	3203.51	***
Having living-at-home children in the household	0.39	0.52	***
Time-invariant covariates			
Birthplace outside of the Netherlands	0.15	0.06	***
Female	0.50	0.50	
Education level	2.27	2.34	***

Notes: Sig. describes p-values from t-tests for differences in means between the two subgroups are significant
*** p<.01. ** p<.05. * p<.10.

Table 5. Matrix of correlations.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Unemployed	1.000							
(2) Age	0.066	1.000						
(3) Having living-at-home children in the household	-0.034	-0.116	1.000					
(4) Gender	0.017	-0.082	0.004	1.000				
(5) Log of net household income in euros	-0.128	0.012	0.261	-0.048	1.000			
(6) Education	-0.032	-0.124	0.000	0.006	0.237	1.000		
(7) Origin	0.034	-0.008	0.030	-0.026	-0.053	-0.021	1.000	
(8) Married	-0.019	0.288	0.263	-0.056	0.296	-0.059	0.018	1.000

Table 6A. Full regressions on Panel A: Entire Sample.

	Entire Sample								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Linear regression	Linear regression	Linear regression	Logistic regression	Logistic regression	Poisson regression	Linear regression	Linear regression	Logistic regression
VARIABLES	Minutes strenuous physical activity per week	Minutes moderate physical activity per week	Minutes walking per week	Fruit consumption (OR)	Vegetable consumption (OR)	Number of days consumed alcohol last 7 days	Log of cigarettes per day among smokers	Log of cigarettes per day among heavy smokers	Whether smokes (OR)
Job-loss	-83.36***	-52.68	-98.50	0.0176	0.0888	0.00913	-0.0198	-0.0494	0.0384
	(19.35)	(83.12)	(95.79)	(0.173)	(0.181)	(0.0258)	(0.0333)	(0.0622)	(0.266)
Age	-6.947	562.2	-7.179	0.0765	-0.00224	0.0277	-0.00976***	-0.0170***	0.0134
	(20.82)	(553.6)	(75.51)	(0.155)	(0.0108)	(0.0216)	(0.00282)	(0.00425)	(0.254)
Having living-at-home children in the household	10.18	-25.51	1.835	0.150	0.0216	-0.00433	-0.123**	-0.201**	0.182
	(8.474)	(28.30)	(6.387)	(0.163)	(0.164)	(0.0248)	(0.0571)	(0.0922)	(0.354)
Log of net household income in euros	-34.84*	35.06	49.14	0.335**	0.346**	-0.0162	0.000221	-0.0341	-0.346
	(20.43)	(78.62)	(68.92)	(0.161)	(0.144)	(0.0218)	(0.0348)	(0.0809)	(0.268)
Secondary education	34.19	-132.3	-35.45	-0.149	-0.621	0.159	0.0242	0.136	0.237
	(50.06)	(305.3)	(149.6)	(0.607)	(0.447)	(0.102)	(0.0395)	(0.0874)	(0.763)
Academic education	-69.84	-199.0	199.9	-0.340	-0.721	0.238**	0.0728	-0.181	0.519
	(62.80)	(423.6)	(180.9)	(0.706)	(0.524)	(0.0982)	(0.158)	(0.258)	(0.896)
Married	-18.67	-16.67	-246.1	0.0856	0.137	-0.0468	-0.0399	0.0126	-0.648**
	(21.02)	(63.58)	(159.0)	(0.168)	(0.196)	(0.0292)	(0.0374)	(0.0607)	(0.278)
2009.year	-29.32*			-0.179		0.00486			-0.406
	(15.43)			(0.178)		(0.0252)			(0.270)
2010.year	-40.19*			-0.668**		-0.0572			-0.651
	(22.97)			(0.313)		(0.0458)			(0.520)
2011.year	-39.98			-0.553		-0.0979			-0.939
	(37.45)			(0.454)		(0.0667)			(0.765)
2012.year	-89.60**			-0.614		-0.126			-1.154
	(37.10)			(0.606)		(0.0881)			(1.001)
2013.year	-121.3***			-0.633		-0.155			-1.627
	(43.81)			(0.745)		(0.110)			(1.266)
2015.year	-56.46			-0.543		-0.0812			-1.633
	(50.14)			(1.018)		(0.146)			(1.655)
2016.year	-117.2*			-0.561		-0.261			-2.168
	(70.96)			(1.240)		(0.174)			(1.973)

Continue table 6A. Full regressions on Panel A: Entire Sample.

	Entire Sample								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Linear regression	Linear regression	Linear regression	Logistic regression	Logistic regression	Poisson regression	Linear regression	Linear regression	Logistic regression
VARIABLES	Minutes strenuous physical activity per week	Minutes moderate physical activity per week	Minutes walking per week	Fruit consumption (OR)	Vegetable consumption (OR)	Number of days consumed alcohol last 7 days	Log of cigarettes per day among smokers	Log of cigarettes per day among heavy smokers	Whether smokes (OR)
2017.year	-231.2**			-0.424		-0.286			-2.536
	(111.5)			(1.393)		(0.196)			(2.236)
2018.year	-58.04			-0.552		-0.334			-2.959
	(123.1)			(1.528)		(0.217)			(2.516)
Constant	176.5	1,246**	216.9				2.847***	3.958***	
	(372.9)	(605.4)	(541.3)				(0.294)	(0.700)	
Observations	25,649	25,602	25,589	8,319	7,792	20,983	4,319	1,449	4,201
Number of individuals	5,259	5,260	5,258	1,414	1,317	4,158	1,234	360	702
R-squared	0.001	0.000	0.000				0.013	0.041	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6B. Full regressions on Panel B: Men.

	Men								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Linear regression	Linear regression	Linear regression	Logistic regression	Logistic regression	Poisson regression	Linear regression	Linear regression	Logistic regression
VARIABLES	Minutes strenuous physical activity per week	Minutes moderate physical activity per week	Minutes walking per week	Fruit consumption (OR)	Vegetable consumption (OR)	Number of days consumed alcohol last 7 days	Log of cigarettes per day among smokers	Log of cigarettes per day among heavy smokers	Whether smokes (OR)
Job-loss	-94.06***	-13.99	16.06	-0.139	0.178	-0.0306	-0.113**	-0.0775	0.0257
	(28.30)	(156.3)	(161.0)	(0.244)	(0.206)	(0.0357)	(0.0567)	(0.0944)	(0.354)
Age	7.705	1,042	11.03	0.145	-0.0118	0.0719***	-0.00514	-0.0122**	-0.246
	(25.03)	(1,027)	(9.698)	(0.199)	(0.0156)	(0.0177)	(0.00409)	(0.00588)	(0.293)
Having living-at-home children in the household	20.88	-52.63	-12.30	0.363	0.0548	-0.0104	-0.0406	-0.0889	-0.480
	(17.86)	(54.52)	(132.3)	(0.227)	(0.236)	(0.0303)	(0.0673)	(0.0666)	(0.397)
Log of net household income in euros	-25.38	171.5	-5.068	0.423**	0.400**	-0.0364	-0.0750	-0.0803	-0.119
	(27.62)	(200.5)	(119.1)	(0.179)	(0.195)	(0.0275)	(0.0513)	(0.0733)	(0.435)
Secondary education	-66.02	-531.5	-15.74	-0.446	-1.095**	0.0920	0.0458	0.135***	0.0738
	(77.83)	(599.4)	(161.1)	(0.804)	(0.443)	(0.139)	(0.0427)	(0.00881)	(2.548)
Academic education	-9.147	-557.1	55.14	-0.756	-1.186**	0.221	0.313	0.0809	0.253
	(79.02)	(847.8)	(187.6)	(0.882)	(0.525)	(0.143)	(0.200)	(0.0638)	(2.757)
Married	-34.71	-134.4	-398.3	-0.0245	0.363	0.00752	-0.0340	0.0111	-0.584
	(29.40)	(138.1)	(292.6)	(0.278)	(0.257)	(0.0308)	(0.0409)	(0.0784)	(0.467)
2009.year	-68.30**			-0.129		-0.0380			-0.371
	(27.04)			(0.245)		(0.0248)			(0.383)
2010.year	-112.0***			-0.731*		-0.154***			-0.284
	(39.98)			(0.441)		(0.0402)			(0.616)
2011.year	-116.7*			-0.856		-0.221***			-0.383
	(60.50)			(0.643)		(0.0575)			(0.891)
2012.year	-163.9**			-0.947		-0.295***			-0.367
	(78.11)			(0.824)		(0.0734)			(1.204)
2013.year	-208.0**			-1.000		-0.367***			-0.518
	(90.41)			(1.018)		(0.0905)			(1.559)
2015.year	-122.7			-1.115		-0.386***			-0.0977
	(109.4)			(1.384)		(0.122)			(2.041)
2016.year	-267.1*			-1.163		-0.609***			-0.150
	(146.2)			(1.619)		(0.145)			(2.399)

Continue table 6B. Full regressions on Panel B: Men.

	Men								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Linear regression	Linear regression	Linear regression	Logistic regression	Logistic regression	Poisson regression	Linear regression	Linear regression	Logistic regression
VARIABLES	Minutes strenuous physical activity per week	Minutes moderate physical activity per week	Minutes walking per week	Fruit consumption (OR)	Vegetable consumption (OR)	Number of days consumed alcohol last 7 days	Log of cigarettes per day among smokers	Log of cigarettes per day among heavy smokers	Whether smokes (OR)
2017.year	-268.7			-1.043		-0.684***			-0.415
	(165.3)			(1.846)		(0.162)			(2.636)
2018.year	-292.5			-1.092		-0.749***			-0.590
				(2.054)		(0.180)			(2.914)
Constant	(183.3)	1,655**	340.1				3.188***	4.081***	
	-248.5	(832.1)	(895.9)				(0.437)	(0.711)	
	(749.0)								
Observations		12,834	12,833	4,684	4,611	11,149	2,234	812	2,313
Number of individuals	12,856	2,559	2,557	785	759	2,161	625	205	368
R-squared	2,559	0.001	0.001				0.015	0.020	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6C. Full regressions on Panel A: Woman.

	Woman								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Linear regression	Linear regression	Linear regression	Logistic regression	Logistic regression	Poisson regression	Linear regression	Linear regression	Logistic regression
VARIABLES	Minutes strenuous physical activity per week	Minutes moderate physical activity per week	Minutes walking per week	Fruit consumption (OR)	Vegetable consumption (OR)	Number of days consumed alcohol last 7 days	Log of cigarettes per day among smokers	Log of cigarettes per day among heavy smokers	Whether smokes (OR)
Job-loss	-77.61***	-105.2*	-198.8*	0.161	-0.0588	-0.0306	0.0597	-0.00808	0.0274
	(27.25)	(55.03)	(108.8)	(0.261)	(0.278)	(0.0357)	(0.0364)	(0.0740)	(0.285)
Age	-24.27	6.633	-7.655	0.0597	0.0135	0.0719***	-0.0149***	-0.0237***	0.0654
	(34.73)	(62.58)	(8.270)	(0.240)	(0.0205)	(0.0177)	(0.00381)	(0.00627)	(0.396)
Having living-at-home children in the household	-4.130	3.984	12.37	-0.136	-0.0818	-0.0104	-0.227***	-0.367*	1.050**
	(7.969)	(5.645)	(58.29)	(0.250)	(0.266)	(0.0303)	(0.0831)	(0.203)	(0.423)
Log of net household income in euros	-42.70	-49.68	77.68	0.257	0.319	-0.0364	0.0597	-0.00712	-0.608**
	(29.74)	(54.06)	(74.56)	(0.199)	(0.263)	(0.0275)	(0.0445)	(0.142)	(0.291)
Secondary education	181.5**	255.3	-121.5	0.482	0.0616	0.0920	0.0196	0.139	0.596
	(85.51)	(300.1)	(257.0)	(2.848)	(0.818)	(0.139)	(0.0812)	(0.107)	(5.564)
Academic education	-108.3	96.01	306.5	0.417	-0.315	0.221	-0.199	-1.160***	0.974
	(89.46)	(381.5)	(276.3)	(2.924)	(1.200)	(0.143)	(0.204)	(0.160)	(5.762)
Married	-2.979	80.09	-76.25	0.219	-0.259	0.00752	-0.0512	-0.00214	-0.681*
	(30.25)	(57.24)	(84.25)	(0.270)	(0.286)	(0.0308)	(0.0639)	(0.0950)	(0.349)
2009.year	12.81			-0.309		-0.0380			-0.239
	(17.72)			(0.263)		(0.0248)			(0.475)
2010.year	39.68			-0.718		-0.154***			-0.615
	(30.68)			(0.478)		(0.0402)			(0.844)
2011.year	48.28			-0.363		-0.221***			-0.868
	(54.73)			(0.711)		(0.0575)			(1.262)
2012.year	0.206			-0.454		-0.295***			-1.096
	(29.46)			(0.959)		(0.0734)			(1.655)
2013.year	-16.03			-0.500		-0.367***			-1.713
	(43.55)			(1.206)		(0.0905)			(2.054)
2015.year	35.29			-0.268		-0.386***			-1.796
	(54.15)			(1.617)		(0.122)			(2.677)
2016.year	64.38			-0.346		-0.609***			-2.570
	(70.38)			(1.917)		(0.145)			(3.218)

Continue table 6C. Full regressions on Panel A: Woman.

	Woman								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	Linear regression	Linear regression	Linear regression	Logistic regression	Logistic regression	Poisson regression	Linear regression	Linear regression	Logistic regression
VARIABLES	Minutes strenuous physical activity per week	Minutes moderate physical activity per week	Minutes walking per week	Fruit consumption (OR)	Vegetable consumption (OR)	Number of days consumed alcohol last 7 days	Log of cigarettes per day among smokers	Log of cigarettes per day among heavy smokers	Whether smokes (OR)
2017.year	-157.8			-0.257		-0.684***			-2.819
	(178.7)			(2.177)		(0.162)			(3.604)
2018.year	210.9			-0.551		-0.749***			-3.289
	(179.8)			(2.401)		(0.180)			(3.989)
Constant	676.0*	451.3	340.8				2.660***	4.246***	
	(409.8)	(541.2)	(617.7)				(0.386)	(1.267)	
Observations	12,793	12,768	12,756	3,635	3,181	11,149	2,085	637	1,886
Number of individuals	2,701	2,702	2,702	629	558	2,161	610	155	334
R-squared	0.001	0.000	0.001				0.031	0.117	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1