Developmental Trajectories of Body Mass Index: Evidence from the National Population Health Survey (1994-2011)

by

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Abstract

The body mass index (BMI) trajectory analysis can capture the developmental patterns of BMI over time. Knowledge on the long-term development of obesity throughout adulthood/later years and its determinants and health consequences (including death) is lacking for the Canadian population. The primary aim of this research is to examine whether there are distinct patterns of BMI change among Canadian adults and seniors through a longitudinal study. We analyzed data from the National Population Health Survey (NPHS, 1994-2011) to identify the BMI trajectories separately for young to middle-aged adults (20-39 years at baseline), middle-aged to older adults (40-55 years at baseline), and seniors (65-79 years at baseline). Additionally, we examined the impact of individual characteristics on BMI trajectories and whether morbidity and mortality risks differ between the identified BMI trajectories.

Our results showed that there were different patterns of BMI changes over time existing in the Canadian population. We also found a gender difference in the associated factors of BMI trajectories, while food insecurity and decreased years of smoking were associated with raising the BMI trajectories in both women and men. People who were continually severely obese in their midlife were at greater risk of developing numerous adverse health conditions compared with normal weight counterparts. Further, constantly obese men had the highest risk of all-cause mortality in the elderly population. An awareness of different BMI trajectories may allow clinicians and policy professionals to tailor programs to specific groups, who are at the highest risk of poorer health outcomes due to obesity, and to intervene at an earlier stage thus altering the path of risky trajectories.

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Candidates' Contribution to the Work

The candidate conducted literature review and data analysis from secondary data from the Statistics Canada. And the candidate was responsible for the first version of the manuscript and the subsequent presentation and interpretation of findings from this thesis. Dr. Yanqing Yi designed the study and provided advices on statistical modeling and interpretation of the results.

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Abbreviations

BMI	Body Mass Index
LCGM	Latent Class Growth Modeling
CGM	Conventional Growth Modeling
LFS	Labour Force Survey
ESS	Enquête sociale et de santé
RDC	Research Data Centre
SES	Socioeconomic Status
PA	Physical Activity
NLSY79	1979 National Longitudinal Survey of Youth
HRS	Health and Retirement Study
TVC	Time-Varying Covariates
ALD	Accelerated longitudinal design
GMP	Group Membership Probability
PMP	Posterior Membership Probability
AvePP	Average Posterior Probability of Group Membership
WHO	World Health Organizations
CI	Confidence Interval
N-S	Normal-Stable
N-OV	Normal-Overweight
OV-OB	Overweight-Obese
OB-UP	Obese-Up
SRH	Self-Reported Health
HR	Hazard Ratio
N-S	Normal weight-Stable
OV-S	Overweight Stable
OB I-S	Obese class I-Stable
OB II-S	Obese class II-Stable
N-D	Normal weight-Down
OV-D	Overweight-Down
OB I-D	Obese I-Down

OB II-D	Obese II-Down
OV-S	Overweight-Stable
OB-S	Obesity-Stable

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Chapter 1 Introduction

In this chapter, the importance of studying the development of obesity is presented. Latent Class Growth Modeling (LCGM) for Body Mass Index (BMI) trajectory analysis is introduced and is compared with the other alternative techniques. Additionally, previous studies on the applications of LCGM for adults and seniors are discussed and limitations are assessed. The data source and variables used in this thesis are also described. Finally, the research objectives and organization of the thesis are presented.

1.1 Background

The prevalence of obesity has greatly increased in Canada since 1985 [1]. In 2014, 61.8% of men and 46.2% of women were classified as overweight or obese based on self-reported height and weight [2]. Previous research has found that excess body weight was associated with numerous chronic health conditions and premature death [3, 4].

Studying obesity trajectory is important when examining the associated factors of obesity and evaluating adverse health outcomes due to excess weight from a developmental perspective [5]. The majority of previous studies assessed weight status based on a limited number of measurements, which failed to detect the development of obesity consistently. Obesity is usually defined based on body mass index (BMI) which has been widely accepted for its simplicity [6]. It has been documented that the duration of obesity rather than obesity at one time point is more predictive of adverse health outcomes, including death [7]. However, existing cross-sectional studies defined body weight status based on a one-time measurement; this cannot capture the dynamics of body mass over time or establish the trajectory of BMI changes across time at the individual level [5, 8]. The static assessment in cross-sectional studies also results in a lack of examination of obesity-related factors and consequences from a developmental perspective [5]. Furthermore, most longitudinal studies have used short follow-up periods and/or assessed BMI change based on limited time points or intervals [8-11]. As a result, most existing studies on obesity can neither capture weight fluctuations well nor detect the trajectory of weight change.

BMI trajectory analyses can better capture body weight change over time and offer new insights on factors determining obesity and adverse health outcomes due to excess weight. A trajectory is defined as “the evolution of an outcome over age or time” [12]. Regarding BMI trajectory analysis, most studies adopted conventional growth modeling (CGM). CGM uses one average pattern for the underlying population and estimates individual variability by random effects about this mean trend [12]. Therefore, CGM may only be suited for a process in which population members follow a common developmental pattern [12]. However, there may be meaningful subgroups within a population: some people’s BMI will never be high, some others’ will always be high, and others’ will increase and/or decrease over time.

In contrast to CGM, LCGM is a powerful statistical approach to quantify multiple BMI trajectories within a population [12, 13]. This technique can also assess if risk factors predict group membership probability and if time-varying covariates (TVCs) modify the BMI trajectory within each group [12]. To date, a limited number of longitudinal studies have identified developmental trajectories of BMI using LCGM for adulthood and/or old age over a substantial period of time [5, 7, 14, 15]. A recent study by Ostbye *et al.* investigated four distinct upward-sloping trajectories of BMI in adults (18-49 years) [14]. Likewise, Finkelstein *et al.* identified four different BMI trajectory groups with increasing trends for adults with class I obesity (age 25-33 years), but not for the general population [15]. Botoseneanu *et al.* also identified five different BMI trajectory subgroups with moderately increasing trends in older adults (51-61 years) [5]. The study by Botoseneanu *et al.* only depicted the development of BMI over time for a specific age group [5], but it did not reveal the direct impact of age on BMI evolution. Zheng *et al.* found six latent obesity trajectories for older adults (51 to 77 years), which showed either a minor increase or a minor decline [9]. None of these studies researched the Canadian population, and there is minimal research on the development of BMI from middle-age onward.

Importantly, previous evidence reveals that the characteristics and aspects of BMI trajectories usually change with different age groups. Young to middle-aged adults usually have a higher rate of BMI increase over time and four BMI trajectory patterns have been constantly identified [14, 16], whereas the progress of BMI in older adults generally shows decline, stability, or minor increase with aging. Five or six BMI trajectory groups have been detected and identified in the article authored by Botoseneanu *et al.* and Zheng *et al.*[5, 7]. This thesis aims to identify BMI trajectories for three age groups separately: young to middle-aged adults (20-39 years at baseline), middle-aged to older adults (40-55 years at baseline), and seniors (65-79 years at baseline).

Within BMI trajectory analysis, the majority of the previous studies focused on the associations between socio-demographic characteristics (e.g., sex, race, cohort, and educational attainment) and BMI trajectories. Few studies have examined whether behavior factors (e.g., smoking, drinking, or physical activity) alter BMI trajectories [5, 14-18]. It is generally believed that factors associated with body mass change as people age. For instance, these three age groups (20-39 years, 40-55 years, and 65-79 years at baseline) usually have different biological, psychosocial, and behavioral characteristics; they differ not only in physical development. These different age groups may also experience different life events including completion of education, and change of employment status as well as marital status [19]. Therefore, this study aims to examine factors, including socio-demographic characteristics (e.g., gender, race/ethnicity, and educational attainment), behavior factors (e.g., years of smoking, drinking, and being physically active), and other factors (e.g., food insecurity and rural living) associated with the BMI trajectories for different age groups.

The relationship between excess weight and adverse health consequences often varies with age. For instance, the association between obesity and diabetes (or hypertension) is stronger among middle-aged adults than among the elderly [20]. The association between obesity and mortality among seniors is controversial. Although there is clear evidence that excess weight is associated with an increased risk of all-cause mortality in young to middle-aged adults [21], previous studies reported conflicting evidence on the association between BMI and mortality in the elderly population [22, 23]. Accordingly, this thesis aims to examine whether the obesity trajectory groups in midlife affect the risk of adverse health outcomes (e.g., chronic conditions and cognitive problems) and to evaluate the association of BMI trajectory and mortality risk among Canadian seniors.

1.2 Trajectory Modeling Methods

LCGM was used in this study to capture the developmental patterns of BMI for individuals with increasing age. Besides LCGM, there are two other trajectory modeling methods available for modeling the developmental process: Conventional Growth Modeling (CGM) and Growth Mixture Modeling (GMM) [24]. CGM is an umbrella term for multilevel (hierarchical) modeling [25] and latent curve analysis [26]. All three approaches model individual developmental trajectory with a polynomial relationship, which links age to the outcome variable of interest. These models have the same objective of characterizing the developmental course of interest at the individual level within a population [12]. However, the three approaches differ in their modeling strategy for incorporating population heterogeneity in the growth curve parameters and they are suited to different types of research questions [12, 27, 28].

CGM uses an average pattern to measure the developmental trajectory for a population, with the assumption that all individuals follow a similar pattern. Specifically, CGM assumes that all individuals come from a single population and the patterns of change for all individuals can be adequately described based on a single estimate of growth parameters [27]. In addition, it assumes that covariates associated with growth patterns have a similar impact for every individual. Statistically, June *et al.* states "CGM gives a single average growth estimate, and a single estimation of variance of the growth parameters, and assumes a uniform influence of covariates on the variance and growth parameters" [29]. In summary, this approach characterizes population differences in terms of variation about the population mean and identifies factors that account for this variation about the mean of developmental patterns [27].

GMM is an application of finite mixture modeling to CGM, modeling population variability in developmental trajectories based on two or more CGMs [30]. Although CGM assumes that all individuals come from a single population with common parameters, GMM relaxes this assumption and allows for differences in growth parameters across different groups of people by using latent trajectory classes. In GMM, people in different growth trajectories vary around different average patterns. The model results of GMM are separate CGMs for each latent class, each with its unique estimates of variances and impacts of covariates [30]. In summary, GMM uses multiple CGMs to model population variability in developmental trajectories by modeling each subpopulation using different growth curves based on CGMs [30].

The goal of LCGM is to approximate distinctive trajectories in a population. The model assumes that there may be several different trajectory groups among population members [12, 27, 30]. Trajectory groups are defined as "clusters of individuals following similar trajectories on an outcome over time" [30]. Nagin and Odgers described trajectory groups as "contour lines on a topographic map", measuring and revealing different regions (both regular and irregular characteristics) on the surface. LCGM captures the heterogeneity of individual differences by using different trajectories, each trajectory with a different polynomial [12]. For each trajectory, the magnitude and direction of change can be different from others in terms of the model parameters (e.g., different intercepts and/or slopes) [12]. With the trajectory group as a statistical structure, LCGM identifies factors which are associated with group membership differences and which alter group trajectories [12, 30].

The three models differ in important respects. In CGM, the growth trajectory parameters are generally assumed to be distributed according to the multivariate normal distribution. Thus, CGM models population variability in development with multivariate continuous distribution functions. By contrast, LCGM uses a multinomial modeling strategy and aims to identify heterogeneity in developmental trajectories in a population [12, 27]. CGM usually aims to identify factors that are associated with individual variability about the population's mean pattern [12]. LCGM focuses on the identification and examination of different developmental patterns. The underlying factors associated with population differences in developmental trajectories will also be assessed [12]. Though GMM and LCGM are both designed to identify different trajectory groups, GMM assumes that the population is composed of discrete groups, similar to how a plant genus is composed of different types of species [30]. LCGM conversely makes no assumption about population distribution. LCGM uses "trajectory groups as a statistical device" to measure and approximate unknown developmental trajectories in a population [30].

The choice of approach concerns the objectives of the analysis. CGM is well suited for modelling a process in which population members follow a common process of growth or decline. LCGM is suited for research questions about developmental trajectories: if different developmental trajectories predicted by the theory would actually present in the population, what factors distinguish group membership and whether and/or how much a factor alters a trajectory? [27]. Given that there is prior evidence that there may be a group of individuals whose BMI developmental trajectories are significantly different from the overall estimate (i.e., mean pattern) [14, 16, 31], LCGM should be adopted rather than CGM. Further, GMM has the assumption that the population is composed of discrete groups [30], whereas population differences in BMI trajectory development are unlikely to "reflect such bright-line differences". Thus, LCGM was adopted in this research rather than GMM.

1.3 Statistical Methods and Data

LCGM was applied to the National Population Health Survey (NPHS) data to identify BMI trajectories for Canadian populations in this research. LCGM allows for multiple BMI trajectories, and it assigns each individual to a specific BMI trajectory class based on the maximum probability of belonging to this class according to his/her BMI evolvement history [12]. LCGM can handle time- and age-based data and it is a data-drive method used to test whether the anticipated latent trajectories emerge from the data itself [12].

The generalization of LCGM allows for the examination of the impact of individual-level characteristics on distinct trajectory groups. Specifically, LCGM tests whether such individual-level characteristics predict the group membership of the trajectories or modify the change of the trajectories. Importantly, predictors (risk factors) of the trajectory should be constant and built at the start of trajectories. The estimates related to risk factors are obtained by using a multinomial logit model within the LCGM. Coefficients of risk factors indicate the change of relative odds of following a trajectory group as opposed to the reference group with one unit change in the risk factor. This statistically links group membership probability to individual characteristics so as to examine whether, and by how much, these factors impact the group membership probability. The Time-Varying Covariates (TVCs, e.g., behavior factors or life events) can raise or lower BMI trajectories. Coefficients of TVCs measure the changes in the BMI trajectory associated with changes in the TVCs at the trajectory level [12]. The estimates related to TVCs are trajectory group-specific, thus the impact of TVCs can vary across trajectories, which is one of the most important strengths of LCGM. The generalized model can also be used to test if there are differences across cohorts in their developmental trajectories (i.e., cohort effects) when multiple cohorts are combined in order to construct an overall trajectory model [12].

The NPHS provides nationally representative longitudinal health survey data on economic, social, demographic, occupational, and environmental correlates of health. It was conducted by Statistics Canada beginning in 1994/1995, and the data was collected biennially thereafter until the most recent survey in 2010/2011. The NPHS consists of 17,276 respondents from all ages in 1994/1995 and is a multi-stage complex longitudinal survey dataset. The Household component of NPHS has nine cycles: Cycle 1 (1994/1995), Cycle 2 (1996/1997), Cycle 3 (1998/1999), Cycle 4 (2000/2001), Cycle 5 (2002/2003), Cycle 6 (2004/2005), Cycle 7 (2006/2007), Cycle 8 (2008/2009), and Cycle 9 (2010/2011). All analyses of this study are based on one longitudinal dataset that includes nine cycles (1994-2011) of the NPHS data which has been linked by the Statistics Canada.

The NPHS intended to represent all household residents in the 10 provinces of Canada at baseline, except for persons on reserves and Crown Lands, residents of health institutions, full-time members of the Canadian Forces Bases, and some of those who live in remote areas in Ontario and Québec [32]. The sample design of the NPHS was based on the Labour Force Survey (LFS) in all provinces except Québec, where the NPHS sample was based on Santé Québec's design for the 1992/1993 Enquête sociale et de santé (ESS). There are more details on the NPHS sampling design elsewhere [32]. In the first cycle of the NPHS, the sample was created by first selecting households and then randomly selecting one household member to be the longitudinal respondent. Data collection was conducted using a computer-assisted interview system by employees hired and trained by Statistics Canada. The interviews lasted around one hour. Interviews in the first cycle were mainly conducted in person, and subsequent interviews in cycles 2 to 9 were mainly conducted by telephone. The overall response rate in cycle 1 was 83.6%. Longitudinal response rates in subsequent cycles were 92.8%, 88.3%, 84.9%, 80.8%, 77.6%, 77.0%, 70.7%, and 69.7% for cycles 2 to 9, respectively. Data is stored by Statistics Canada's Research Data Centres (RDC). Data is accessible within the RDC after projects get approved by the Social Scientists and Humanities Research Council. All results based on the NPHS in this study have been vetted for confidentiality prior to use after recommendation from Statistics Canada. The current study was conducted at the Research Data Centre at Memorial University of Newfoundland.

BMI was used as the trajectory variable. The NPHS provides up to nine serial measures of BMI based on self-reported weight and height over a span of 18 years. BMI was derived in the NPHS by calculating weight in kilograms divided by the square of height in meters, excluding pregnant women. Height and weight were self-reported in the NPHS. Respondents were excluded if they were pregnant during the observational period or if they had less than four BMI records. The covariates associated with obesity include time-constant covariates (i.e., risk factors) and TVCs. In this thesis, sex, race/ethnicity and educational attainment were risk factors for group membership. The TVCs included food insecurity, cohort effects, years of being physically active, of smoking, of drinking, of living with a low-income, of being employed (unemployed), of being married, and of rural living during the observational years (1994-2011). These TVCs were evaluated at the trajectory level. In addition, the health outcomes considered in this study included asthma, arthritis or rheumatism (excluding fibromyalgia), back problems (excluding fibromyalgia and arthritis), high blood pressure, chronic bronchitis or emphysema, diabetes, heart disease, cognitive problems, emotional problems, and health description index-self-rated health (SRH).

1.4 Research Objectives

Previous research reveals that characteristics of BMI trajectories vary with the different age groups considered. Thus, based on LCGM, this thesis aims to model the patterns of BMI trajectories separately for young to middle-aged adults (20-39 years), middle-aged to older adults (40-55 years), as well as in seniors (65-79 years). This thesis is comprised of three distinct but interrelated studies designed to expand the understanding of the development of body mass in Canadian adults and seniors based on the NPHS (1994-2011), as well as to explore whether the individual characteristics and health consequences (including death) are associated with BMI trajectories. Specifically, this thesis aims to:

1. Identify and describe different BMI trajectory groups in young to middle-aged adults and assess how individual characteristics (risk factors and TVCs) predict/modify the identified BMI trajectories.
2. Capture distinct BMI trajectories in middle-aged to older adults, examine the associations between covariates and BMI trajectories, and evaluate the associations between trajectory classes and midlife health.
3. Characterize BMI trajectories in seniors and examine their associations with mortality, while controlling for a range of potential confounders.

This thesis has six chapters. Chapter 1 introduces the rationale of this research, the trajectory modeling method and the data sources. Chapter 2 reviews previous studies on BMI trajectories and summarizes factors and outcomes (including mortality) associated with obesity. Chapter 3, Chapter 4, and Chapter 5 present the results for the research objectives 1, 2, and 3 respectively, each including its own Introductions, Methods, Results, and Discussion sections. Specifically, Chapter 3 identifies different BMI trajectory groups for young to middle-aged adults and their associated factors. Chapter 4 mainly captures the BMI trajectories in middle-aged to older adults and their associated health outcomes. Chapter 5 characterizes BMI trajectories in seniors and examines their association with mortality. Chapter 6 summarizes the key findings, and discusses the implications and limitations of the research findings, and finally makes suggestions for further research directions.

Chapter 2 Literature Review

This chapter reviews studies on BMI trajectories which adopted LCGM, GMM, or CGM, and summarizes factors and outcomes (including mortality) associated with obesity.

2.1 BMI Trajectory Analysis

The application of LCGM for evaluating the heterogeneity in BMI change patterns has gained popularity amongst researchers in recent years. However, the majority of studies on BMI trajectory analyses used CGM [18, 33-35]. Additionally, a limited number of studies utilized GMM to model BMI trajectories for adults/seniors [17, 36, 37], and reported similar results as studies which adopted LCGM [5, 7, 14-16].

2.1.1 BMI Trajectory Analysis using LCGM

This section reviews the following articles in order to have a fuller picture of previous studies on BMI trajectory analysis using LCGM by covering all ages: children and youth [16, 31], adults [14], and seniors [5, 7]. Previous studies have analyzed populations ages 9-16 [31], 12-23 [16], 18–49 [14], 51-61 [5], 51-77 [7].

The study by Mustillo *et al.* found that there was heterogeneity in the development of obesity among children. They found four different obesity trajectories: a) no obesity (never obese), b) chronic obesity (always obese during observation), c) childhood obesity (obese during childhood and decreased in weight over time), and d) adolescent obesity (children with normal weight at the start and who become obese over time) for children (9-16 years) from a sample of rural white children (N=991) with an 8 year follow-up period [31]. Several other studies found similar results for children/youth [38, 39], though a different age group were considered: 4-10 years (n=1,566) [38] and 2-12 years (n=1,739) [39].

Using data from the 1979 National Longitudinal Survey of Youth (NLSY79) in the US, Nonnemaker *et al.* examined the heterogeneity of BMI trajectory classes among youth (12-23 years). They identified four distinct trajectories: a) high risk with 90% of members being obese at 23, b) moderate-to-high risk with 68% of members of being obese at 23, c) low-to-moderate risk with 27% of members of being obese at 23, and d) low risk with around 27% being overweight at aged 23. Nonnemaker *et al.* found that boys were more likely to be in the middle two groups, and less likely to be in the high risk group compared with boys in the low risk group. Additionally, Black and Hispanic ethnicity were important risk factor of being in the higher BMI trajectories [16]. Other studies on youth and young adults reported comparable BMI trajectory groups, although a different age group was considered: 12-28 years (n=4119) [40].

A recent study by Ostbye *et al.* also used data from the NLSY79 and investigated the obesity trajectories in adults (18-49 years). Four distinct BMI trajectories were detected: a) the normal weight group with most members remaining under/normal weight, b) the overweight group with most members reaching and staying overweight after 30 years, c) the later-adulthood obese group, with the weighted prevalence of obesity being 50% by age 31, and d) the early adulthood obese group, with the weighted prevalence of obesity being greater than 50% around age 20 [14]. In addition, Ostbye *et al.* found that males, blacks, and younger cohorts had higher odds of being in the higher BMI trajectories, and those with higher educational attainment and increased years married were associated with lower BMI trajectory within each group. Moreover, they demonstrated that the prevalence of most adverse health outcomes differed with the identified BMI trajectory classes, with the highest prevalent in the early-adulthood obese group [14]. Likewise, Finkelstein *et al.* identified four different BMI trajectory groups with increasing trends for adults with class I obesity (aged 25-33 years) and reported that adverse health conditions were more prevalent in trajectories representing a higher rate of BMI increase [15].

Additionally, two studies have adopted LCGM to examine the heterogeneity in the change patterns of the BMI in older adults. Botoseneanu *et al.* examined the evolution of BMI over time in the age group 51-61 years at baseline from the Health and Retirement Study (HRS). They suggested five distinct BMI trajectory groups that were best fit the data: a) normal weight at baseline with increasing rate of BMI, b) overweight at baseline with increasing rate, c) borderline-obese with increasing rate, with an average BMI of around 30 at baseline, d) obese with increasing rate, with an average BMI of around 35 at baseline, and e) morbidly obese with decreasing rate, with an average BMI greater than 40 at baseline. Furthermore, they reported that Blacks and Hispanics had higher odds of being in the higher BMI trajectory groups, and that compared to women, men were less likely to follow the risky groups [5].

In comparison, Zheng *et al.* found six latent obesity trajectories for older adults (51 to 77 years): a) normal weight downward, with decreasing BMI with age and an average BMI of < 25 at age 51; b) normal weight upward, with increasing BMI with age and an average BMI < 25 at age 51; c) overweight stable characterized by remaining in the overweight range all through the study; d) overweight obesity which started with a

BMI of > 25 at baseline and progressed to be in the obese class I; e) class I obese upward with a BMI of > 30 at age 51; and f) class II/III obese upward with a BMI of > 40 at age 51. Additionally, Zheng *et al.* found that people in the overweight stable group had the highest survival rate than other trajectory groups [7].

2.1.2 BMI Trajectory Analysis using CGM and GMM

The majority of studies on BMI trajectory analysis have used CGM, which has an assumption that one average pattern can describe the BMI change pattern for the whole population [33]. For example, Kahng *et al.* used a CGM and found that the trajectories of BMI for aged 65 and older adults decreased with time. Additionally, Kahng *et al.* reported that high educational level and smoking were associated with lower BMI in seniors; on the other hand, no association was found between gender and BMI or marital status and BMI [33]. Clark *et al.* utilized CGM and identified a curvilinear increasing rate of BMI change over adulthood (18–45 years). They further found that women, younger cohorts, black individuals, and those with low SES were more likely to be overweight or obese [34]. Botoseneanu *et al.* in comparison used CGM and found an increased linear BMI trajectory in middle-aged and older adults. They also reported that people younger at baseline were more likely to have lower BMI, whereas gender was not associated with BMI trajectory [18]. Regarding the trajectory of BMI in a Canadian context, previous studies reported that Aboriginals had a higher BMI trajectory compared with non-Aboriginal Canadians over time based on CGM [35].

A limited number of studies utilized GMM in identifying BMI trajectories for adults/seniors, and the studies reported similar results as those adopted LCGM [17, 36, 37]. For instance, Kuchibhatla and colleagues adopted GMM and modeled three different

BMI trajectories (normal weight, overweight, and obese) for seniors aged 65–105 years from a community sample. They found that females, black individuals, or those with lower educational levels had higher odds of being in higher obese trajectories. The prevalence of cognitive impairment, hypertension, and diabetes varied among the different BMI trajectories, with strongest adverse effects observed in the obese group [17]. However, although their analysis is informative, it is based on a community sample, which is hard to generalize to the whole population. Likewise, Clarke *et al.* captured two different BMI trajectories over early adulthood (19-35 years): one normal weight group with moderate growth in BMI, and the other one characterized by constantly being overweight. They found that women in the second group were more likely to develop any chronic health condition (hypertension, diabetes, asthma, chronic lung disease, heart disease, and cancer) by the age of 40 [36]. Similar results on different trajectory groups were also reported in other studies based on GMM [37].

Previous BMI trajectory analyses reveal that there is heterogeneity in the development of obesity among children, adults, and seniors based on LCGM or GMM for the US population [5, 14, 17, 31]. In addition, the characteristics of BMI trajectories depend on age. Younger populations usually have a higher increasing rate of BMI change over time, whereas the progress of BMI in older adults shows decline, stable, or only minor increase with aging. Moreover, within BMI trajectory analysis, the majority of studies focused on the associations between socio-demographic characteristics (e.g., sex, race, cohort, and educational attainment) and BMI trajectories. Few studies have examined whether behavior factors (e.g., smoking, drinking, or physical activity) alter BMI trajectories.

2.2 Factors Associated with Obesity

Previous studies reported that obesity-related factors included age [41], sex [42], race [35, 43], socioeconomic status (SES) [34, 44], behaviour factors (e.g., smoking, alcohol usage, and leisure physical activity) [45-47], marital status [48], food insecurity [49], and place of residence [50].

2.2.1 Age, Sex and Race

Age plays a very important role in the development of obesity. BMI trajectory studies show that increasing BMI trajectories are typically found throughout childhood [31] and adulthood [14]. By contrast, decreasing BMI trajectories are generally observed for seniors [7, 17, 33]. In addition, the mean BMI and the prevalence of obesity have increased across all age groups among adults [41, 51-54]. There is also evidence that BMI peaks around people's 60s and then declines after [41, 54]. The majority of studies have reported that largest weight changes takes place in the younger age groups [41, 52, 53].

Previous studies reported that obesity was more prevalent among minority racial/ethnic groups [34, 44]. For instance, obesity was more prevalent among Aboriginal Canadians from previous studies [35, 43]. By contrast, the association between gender and obesity is inconsistent. Some studies reported that men were more likely to be overweight than women [42] and some suggested an inverse association [55], while others presented no gender differences [18].

2.2.2 Socioeconomic Status (SES)

The impact of SES on body weight may also vary with age. The negative association between socioeconomic status (SES) and obesity is well documented among adults, specifically for women in developed countries [56]. Previous studies reported that obesity was more prevalent among individuals of lower SES [34, 44]. For instance, an inverse association between obesity and educational attainment was identified among adults [57]. Previous research also reported that low-income was consistently associated with an increased obesity risk among women but not men [56]. On the other hand, the evidence of the effect of SES on BMI trajectories over the transition period from midlife to old age in late adulthood is mixed, with some [58] but not all [59] studies showing that lower SES groups have a greater risk of gaining weight.

Work-related activities are one of the main sources of daily physical activity; thus employment may play an important role in maintaining a healthy weight. Having a job may be helpful for losing weight because of work-related activities and burning energy by fulfilling work-related duties [60]. Nonetheless, Kouvonen *et al.* found that the strain of a job was associated with a higher BMI, and they explained that it probably explained by that stress leads to unpleasant healthy behaviors, including physical inactivity and overeating [61]. Also recent studies reported that there was a close relationship between long work hours (compared with standard work hours) and obesity [62]. Additionally, the impact of working status on BMI may vary with different occupations. For instance, lower occupational levels were associated with a higher BMI [61].

Retirement typically leads to a significant lifestyle change which contributes to weight changes. For instance, older people generally have more leisure time and reduced income after retirement, which may influence exercise and diet [63]. One study reported that people may gain weight after their retirement, and that the influence of retirement on weight gain may depend on an individual's initial weight and SES [64]. Specifically, the association of weight gain with retirement was stronger among overweight or obese people as compared to normal weight counterparts. Further, people who were retired from physically demanding jobs or who had limited financial resources were more susceptible to weight gain than their counterparts [64].

2.2.3 Behavior Factors

Smoking: most studies suggested that smoking was associated with a decreased weight on average for both men and women [45, 65], though a positive association was also reported [66]. It is generally believed that people usually reach their maximum weight around 45-64 years, which is also the time smoking cessation occurs [67]. Smoking may be considered as a way to maintain or lose weight for adolescents and adults, especially for white women [68].

The evidence on the association between smoking and obesity remains controversial by the age groups considered, the definition of smoking status, and confounders adjusted for in different studies [45, 66]. Although smoking may be helpful to reduce the risk of being overweight or obese among elders, no evidence has showed that smoking protect young adults from weight gain [69]. By contrast, some studies suggested that smoking increased the risk of gaining weight in older adults [70]. Epidemiological studies demonstrated that heavy smokers and former smokers had the greatest risk of being obese [69, 70]. Additionally, men, individuals between the ages of 18-44 years, and individuals with a lower level of education and/or income were more likely to smoke [71]. Moreover, most existing studies only assessed individuals' smoking statues once; albeit smoking status often change during the observational period, which may bias their results.

Alcohol Usage: Evidence on the association between alcohol consumption and obesity is quite mixed in the literature [46]. Drinking is supposed to contribute to weight gain because of additional calories intake. However, the findings on the association between alcohol intake and excess weight are inconsistent. The majority of studies found that alcohol consumption was associated with a high BMI, especially for heavy drinkers [46, 72]. On the other hand, moderate alcohol intake was shown to protect against gaining weight [72] or lack association with weight gain [73]. Additionally, some studies indicated that alcohol consumption was not associated with weight gain among women and older adults [74]. Moreover, the relationship between alcohol intake and body weight may also change with gender and type of alcoholic beverage [46]. Furthermore, it is important to investigate the impact of alcohol use on body weight at different stages of people's lives, as metabolic functions generally decline with age. Thus, drinking may have a varying impact on body weight depending on age, considering the positive association between alcohol intake and body weight may increase with age [74].

Physical Activity: Physical activity (PA) is one of the most proximate determinates of obesity and it may decrease over age [47]. Activities during leisure time and occupational time both contribute to overall activity level. This thesis refers to leisure time only when referring to PA thereafter. It is well documented that physically inactive increases the risk of gaining weight in both men and women [75-77], either from cross-sectional studies [78] or longitudinal studies [76]. For instance, people with lower levels of physical activity were more likely to gain weight than people with higher levels of physical activity in young and middle-aged adults [76]. Additionally, Riebe *et al.* indicated that obesity, rather than just overweight, was associated with lower levels of physical activity in older people [47]. Furthermore, some experts also suggested that compared with socio-demographic factors (e.g., race/ethnicity, income, age, or gender), PA played a more important role in maintaining a healthy weight in older adults [79].

2.2.4 Other Factors

Marital Status: Marriage is associated with a decreased mortality risk but an increased risk of weight gain. People with a partner may contribute to lower morbidity and mortality risk as opposed to people without a partner [80]. On the other hand, previous studies found that married people were more likely to have higher BMIs than those not married [48]. Importantly, some studies pointed out that the change of marital status was a better predictor of gaining or losing weight than current marital status [81]. Moreover, Dinour reported that people recently married were more likely to gain weight; whereas people who experienced marriage dissolution tended to lose weight [82]. Previous studies also reported that people with weight problems were less likely to get married than individuals with normal BMIs [83]. Thus, the association between obesity and marital status may be bidirectional.

Furthermore, age also plays a vital role in the relationship between obesity and marital status. People with different ages tend to experience different life events socially, economically, and physiologically [84]. For instance, older adults are more likely to suffer from marital changes such as widowhood than younger adults. Also, older adults are less likely to have the motivation to lose weight in order to be seen as attractive [84]. It is necessary to study the impact on obesity of marital statuses with a long-time follow-up for different age groups as it allows for better understanding of the effects of living in different marital status on weight changes over the course of one's life.

Food insecurity and rural living: previous findings suggested that the connection between food insecurity and excess body weight only existed in women [49, 85]. However, these studies are based on either cross-sectional design [49] or short period cohort data [85]. Additionally, most studies reported that obesity was more prevalent in rural areas compared with urban areas in developed countries [50].

2.3 Health Outcomes Associated with Obesity

There is consistent evidence that obesity is associated with chronic conditions including asthma [86], arthritis [87, 88], high blood pressure [89, 90], diabetes [91-93], and heart disease [94, 95]. Although most experts have indicated that the prevalence of obesity may contribute to a great increase in back pain [96], there are limited longitudinal studies on the association between being overweight or obese and having back pain [97]. In addition, the majority of studies found that low BMIs were associated with increased risk of developing chronic obstructive pulmonary disease (COPD) [98]. Chronic bronchitis and emphysema are two of the main conditions related to COPD. However, evidence from national data on the relationship between obesity and COPD is limited [99].

Previous research reported that being overweight or obese was associated with cognitive problems [100], emotional problems [101], and reduced self-reported health levels or Self-Rated Health (SRH) [102]. Previous research from cross-sectional and longitudinal studies suggested that people with higher BMIs in midlife were more likely to have lower cognitive scores later in life [100, 103]. A long period of observation is needed to demonstrate lower cognitive scores in later life since the negative impact of excess weight on cognitive ability can be subtle [104]. Moreover, the association between obesity and cognitive function may depend on the duration of obesity [100]. We found only a few studies that considered the long-term effects of BMI on cognitive function in midlife. Most investigators reported that the association between obesity and emotional health was less evident than it was for physical health [101, 105], but high BMIs tend to have a detrimental impact on emotional well-being [101]. Self-Rated Health (SRH) is generally regarded as an important outcome in a clinical setting, which serves as a useful indicator for people's overall well-being, and can reflect a person's physical and mental health [106]. The majority of studies reported that being underweight, overweight, or obese was associated with reduced SRH [102].

2.4 Mortality and Obesity

Previous studies presented conflicting evidence on the association between BMI and mortality in elderly populations. Some studies reported J- or U-shaped associations between mortality and BMI [22, 23], while some others reported a positive linear relationship between BMI and mortality [107, 108]. Although there is clear evidence that excess weight is associated with an increased risk of all-cause mortality in young to middle-aged adults [21, 107], this may not be the case for seniors. Some researchers suggested that obesity was associated with increased mortality in older ages [109, 110], whereas other studies reported no association [111]. Previous findings implied that weight loss was as an important risk factor for mortality in all BMI levels [112]. Importantly, Mehta *et al.* demonstrated that old data collected before 1990 was more likely to show a deleterious impact of obesity on mortality; whereas the association was modest based on recent data [113]. Further, most studies found that weight change (weight loss/gain) had a greater impact on mortality risk when compared with initial weight at baseline [5]. Moreover, some studies found that there was no excess risk of death associated with the overweight categories [22, 114, 115], but the risk was reported in others [116, 117]. Further, the association between mortality and BMI may differ by sex [118].

2.5 Summary

Previous studies on the BMI trajectories reinforce the importance of considering heterogeneity in BMI growth among adults and seniors, whereas none of these studies have been researched in the Canadian population. To date, a limited number of longitudinal studies have identified developmental trajectories of BMI using LCGM for adulthood and/or old age over a substantial period of time [5, 7, 14, 15]. Previous BMI trajectory analyses reveal that there is heterogeneity in the development of obesity in children, adults, and seniors based on LCGM or GMM for the US population [5, 14, 17, 31]. However, there are few studies which have applied LCGM to identify BMI trajectories for the Canadian population.

In addition, age plays a very important role in the development of BMI. BMI trajectory studies show that increasing BMI trajectories are typically found throughout childhood [31] and adulthood [14]. By contrast, decreasing BMI trajectories are generally observed in seniors based on LCGM [7], GMM [17], or CGM [33].

Moreover, previous findings on factors which determine obesity including specific behaviour factors like smoking and drinking, have had mixed results. Although BMI trajectory analyses offer new insights in evaluating a range of potential factors, existing studies focus on the associations between socio-demographic characteristics (e.g., sex, race, cohort, and educational attainment) and BMI trajectories. Few studies have examined whether behavior factors (e.g., smoking, drinking, or physical activity) alter BMI trajectories. Also, factors associated with body mass may change over the course of one's life [14, 119].

Further, few studies have addressed the heterogeneity in BMI development and their associations with adverse health outcomes and mortality risks among adults and seniors. Previous studies on the association between obesity and mortality risk in seniors have mixed results. This may be a result of methodological differences as well as the length of study on mortality. Most studies did not consider the heterogeneity in the trajectory of BMI among a population and these findings defined weight changes based on limited measurements (typically one or two time points) [110, 112, 114]. A limited number of studies have identified distinct BMI trajectories and their associations with adverse health outcomes (including death). Specifically we could only find two studies that tested whether certain BMI trajectories were associated with selected adverse health outcomes based on LCGM [14, 15]. Only one study had examined the association between mortality risk and BMI trajectory groups [7]. In addition, all the studies we did find were for the US population.

Chapter 3

BMI Trajectories among Young to Middle-Aged Adults (20-39 years) and Associated Factors

3.1 Introduction

BMI trajectory analyses can better capture body weight change over time and offer new insights on factors determining obesity [120]. Although there is a general agreement that the obesity epidemic arises from changes in the environment and health behaviors rather than from changes in genes[121], there lacks a clear consensus on which of these changes contribute to the obesity epidemic [122]. In order to better understand the multiple factors of obesity, it is important to capture the actual change of BMI with age. However, the majority of previous studies assessed weight status based on limited times of measurements, which fail to detect the development of obesity well.

The BMI change patterns over time are generally linked to sex, race, socioeconomic status (SES), and birth cohort [34, 35, 123, 124]. In addition, food insecurity, place of residence, and lifestyles (physical activity, smoking, and alcohol use) are all potential predictors of body mass change [44, 124]. Although links between obesity and these indicators have been widely studied, many findings are mixed based on our literature review (section 2.2); this may be due to that most studies used cross-sectional design, limited time measurements of BMI in longitudinal studies or CGM within BMI trajectory analyses.

BMI trajectory analyses based on LCGM can capture the heterogeneity in BMI change patterns in a population and allow for examining the impact of obesity-related factors on distinct levels of BMI trajectories [5]. LCGM is a powerful approach describing the obesity development by different trajectories over time. However, only two studies have applied LCGM to analyze BMI trajectories and their associated individual characteristics based on a substantial period of adult life [14]. A recent study by Ostbye *et al.* investigated four distinct upward-sloping trajectories of BMI in adults (18-49 years) [14]. Likewise, Finkelstein *et al.* identified four different BMI trajectory groups with increasing trends for adults with class I obesity (aged 25-33 years) [15]. However, the two studies were for the US population and did not consider some important determinants of body mass, including food and physical activity [14]. Additionally, within BMI trajectory analysis, the majority of studies focused on the associations between socio-demographic characteristics (e.g., sex, race, cohort, and educational attainment) and BMI trajectories. Few studies have examined whether behavior factors (e.g., smoking, drinking, or physically inactive) alter BMI trajectories.

Therefore, this chapter applies LCGM to identify subgroups with distinct BMI trajectories for adults (20-39 years at baseline), who had at least four measures of BMI over an 18 year period based on the NPHS (1994-2011), and to examine individual characteristics (e.g., socio-demographic characteristics and behavior factors) that distinguish people in BMI trajectories representing a higher rate BMI increase.

3.2. Methods

In order to identify BMI trajectories for young to middle-aged adults, we limited our analysis to individuals within the age range of 20-39. There were 4790 individuals in this age range in the NPHS at baseline. In the following sections, the body weight categories followed the guidelines of World Health Organizations (WHO) for categorizing body weight status based on BMI as underweight to normal weight (BMI of less than 24.9), overweight (BMI of 25– 29.9), obese class I (BMI of 30–34.9), obese class II (BMI of 35–39.9), and obese class III (BMI greater than or equal to 40).

3.2.1 LCGM Model Selection

In order to select the optimal model that best fits the data, the statistical selection criteria used model fit statistics (Bayesian Information Criterion (BIC)), value of Group Membership Probability (GMP), and average posterior probability (AvePP) were used [12].

BIC is generally used as fit statistics to select the number of trajectory groups and the shape of trajectory groups that best fit the data. During the process of model selection, the log form of the Bayes factor (B_{10}) is used to quantify the evidence that favors the alternative model; the log form of B_{10} is a useful statistic to compare two models, which is estimated by the change in BIC [13]. For a given model, BIC is calculated as:

$$BIC=log(L)-0.5k\ log(N) \tag{3.1}$$

Where L is the value of the models' maximized likelihood. k is the number of parameters and is determined by the order of the polynomial used to model each trajectory and the number of groups. N is the sample size.

BIC log Bayes factor is approximated by

$$2log(B10) \approx 2(\Delta BIC) \tag{3.2}$$

ΔBIC is the difference in the *BIC* values between the simpler model (with smaller number of trajectory groups) and the alternative model (with greater number of trajectory groups). Log Bayes factor greater than 6 shows strong evidence in favor of the alternative model [13].

GMP estimated within LCGM quantifies the size of each trajectory group, that is, the proportion of the population that belongs to each group. Nagin suggested that the GMP of each trajectory should be equal or greater than 5% in a population ideally [12]. The Posterior Membership Probability (PMP) measures the probability that an individual with a set of characteristics belongs to a specific trajectory group. PMP can be used to assign each individual into the trajectory group to which he/she has the highest posterior membership probability (a maximum-probability assignment rule) [12].

Moreover, the AvePP of assignment is a diagnostic statistics used to assess the quality of the models fit to the data, which could be derived from the PMP. The AvePP of a trajectory can be obtained by averaging the PMP, which reveals the internal reliability for approximation of a trajectory. It is suggested that AvePP should be at least 0.7 for all trajectory groups [12].

3.2.2 Accelerated Longitudinal Design

An accelerated longitudinal design (ALD) is used to study age-related developmental trajectories over an extensive age span in a relative short follow-up period of study by pulling data from different overlapping age cohorts [125]. An age cohort is a group of people who were born within a defined period of time. Many longitudinal studies (including the current data from the NPHS) have various age cohorts. In a single cohort design, one age cohort is sampled at baseline and followed for a period of time, whereas multiple single age cohorts would be sampled and followed within an ALD. Each cohort begins with a set age and is finished with another set age at a different time [125, 126]. By design, ALD collects "each individuals' measurements which covers only part of the age range being studied", thus each individuals' measurements contribute to only part of the whole growth curve [125]. There is evidence that longitudinal data with ALD is more powerful than single cohort data in investigating the development of an outcome over time [126].

The essential advantages of the using ALD include a shorter follow-up period, and a reduction of costs and potential attrition. One of the main disadvantages of ALD is that missing participant data is still assumed to be in line with available participant data; this may be vulnerable to age cohort interaction effect. That is, there are systematic differences for participants born at different times [125, 126]. Despite this, previous research has provided evidence that ALD can reasonably and adequately approximate age-related developmental change over time by linking different cohorts together [127].

3.2.3 Statistical Analysis

Age rather than the cycle years was used to define the time variable in this thesis. A longitudinal sample which consists of respondents aged 20-39 years at baseline (1994/95) was selected. Based on this sample, ALD allowed us to analyze the pattern of BMI change over a period of 36 years (ages 20-55), even though the data set only include 9 waves with 18 years of observation data (1994-2011) for each individual.

BMI was used as the trajectory variable. The NPHS provides up to nine measures of BMI over a span of 18 years. BMI was derived in the NPHS by calculating weight in kilograms divided by the square of height in meters, excluding pregnant women. Height and weight were self-reported in the NPHS. Respondents were excluded if they had less than four BMI values computed from their reported height and weight in the analyses.

LCGM was conducted to capture BMI trajectories and examine the associations between the identified trajectories and covariates. All analyses were conducted using SAS version 9.3 (SAS Institute). We used SAS PROC TRAJ package to estimate the LCGM model. LCGM uses maximum likelihood methods to estimate model parameters; maximization is performed using a general quasi-Newton procedure [27].

To determine the optimal number of trajectories, we followed the following selection criteria suggested in [12, 128]: BIC, GMP, AvePP, and significance of polynomial terms. Specifically, model selection started with one cubic group, and more groups were added if the model with the added groups has a better fit based on the above criteria; successive models with between 2 and 7 trajectories were tested. Within the model selection, we only kept the polynomial terms (quadratic or cubic pattern) with significant coefficients before adding additional groups, and linear terms were held no matter if they were significant or not [128]. For the purpose of representativeness and simplicity, the GMP of each group was set to be not smaller than 5%. Each participant was assigned to a trajectory group for which he/she had the highest posterior probability of membership. Within each trajectory group, the values of average posterior probability of group membership were ascertained [12]. Additionally, the trajectory analysis was conducted for men and women separately because of compelling evidence on gender difference in obesity [5, 14, 16, 17, 34, 36].

Moreover, the associations between covariates (i.e., risk factors and TVCs) and BMI trajectories were examined within LCGM. In this thesis, the covariates potentially associated with obesity include time-constant covariates (i.e., risk factors) and TVCs. Coefficients of risk factors indicate the change of relative odds of following a trajectory group as opposed to the reference group with one unit change in the risk factor. Similarly, coefficients of TVCs measure the changes in the BMI trajectory associated with changes in the TVCs at the trajectory level [12].

Time Constant Covariates (Risk Factors)

Race/ethnicity (Aboriginal vs. Non-Aboriginal) and educational attainment (whether or not graduated from high school) were included as risk factors with the assumption that they have a potential impact on group membership probabilities. Given that there were a number of people who were still at college/university for the sample (respondents 20-39 years at baseline), we selected 'if high school graduate' as the education indicator considering that risk factors need to be established before the initial period of the trajectory. Additionally, the NPHS asked the study population: "How would you best describe your race or colour?" "Did you graduate from high school?"

Time-Varying Covariates (TVCs)

The TVCs including food insecurity, cohort effects, and years of being physically active, smoking, drinking, living in low-income, being employed, and rural living during the observational years (1994-2011) were evaluated, as to examine whether and by how much they modify the change of trajectories. The NPHS had collected information on physical activity, types of smoker, types of drinker, household income, employment status, and place of residence at each wave; these variables were used to define the TVCs in our analyses. 'Years of being physically active' (since 1994) was defined based on the derived variable on physical activity index in the NPHS. This derived variable was categorized as three levels from activity to inactivity which were based on the average daily energy expended during leisure time activities in the past three months. An energy expenditure of 1.5 *kcal/kg/day* was classified as an active lifestyle pattern, which met the recommended 30 minutes of exercise per day [32]. We assigned a value of '1' if the respondents were physically active or moderately active in 1994/95, and '0' otherwise. Then, for each wave, we added '2' to the previous wave's value if the individual was assigned as physically moderate/active in the wave, or '0' was added otherwise. For waves with a missing value variable, the value of years of being physically active from the previous wave was carried through. This method was used to define all other TVCs, including 'years of living in low-income', 'years of being employed', 'years of rural living', 'years of smoking', and 'years as a regular drinker'.

'Years of smoking' (since 1994) was used to examine the accumulative impact of smoking on body weight. Three questions were asked in the NPHS to obtain information on respondents' current and former smoking habits: "At the present time do you smoke cigarettes daily, occasionally or not at all? "; " Have you ever smoked cigarettes at all?" ; "Have you ever smoked cigarettes daily?". Based on the questions above, a derived variable was provided by the NPHS for describing which category of smokers the participants belong to. This variable was categorized into daily smoker, occasional smoker but former daily smoker, always an occasional smoker, former daily smoker, former occasional smoker, and never smoked by the NPHS. We defined the first three categories as current smoker and the rest of categories as non-current smokers. Then years of smoking was defined as that introduced previously.

‘Years as a regular drinker’ (since 1994) was defined from the type of drinker the respondents self-reported to be. The NPHS asked questions such as “During the past 12 months, how often did you drink alcoholic beverages?” This variable was dichotomized to regular drinker (drink more than once a month to drink every day) and non-regular drinker, which combined the occasional drinker (drink less than once a month), former drinker and non-drinkers as non-regular drinkers. Then years as regular drinker was defined as that introduced before.

‘Years of living in low-income’ (since 1994) was defined based on the income adequacy variable derived by the NPHS. This variable classified the total household income into four categories (i.e., lowest, lower middle, upper middle, and highest income level) based on total household income adjusted for the number of people living in the household. Respondents who were in the lowest or low middle income were considered as living in low-income. Then we defined years of living in low-income as that introduced before.

‘Years in employment’ (since 1994) was defined based on the derived variable on working status by the NPHS, which collected the respondent’s working status in the past 12 months. In the first three cycles of the NPHS, this derived variable was categorized into the following four classes: currently working, not currently working but worked in past 12 months, did not work in past 12 months, worked in past 12 months but unknown if current; in addition, in the last five cycles, categories of this variable were recorded as: had a job-at work last week, had a job-absent from work last week, did not have a job last week, permanently unable to work by the NPHS. We dichotomized this derived variable: the first two categories of the variable were referred to as employment, while the rest of categories were referred to as unemployment for all nine cycles in our analysis. Then 'years in employment' were defined as that introduced previously.

The NPHS defined a variable on the geographical location of the postal code of a household based on population size groups according to the Census GeoSuite in nice cycles (1994-2011). Specifically, in the NPHS, the 1991 Census GeoSuite was used for cycles 1 and 2; 1996 Census GeoSuite was used for cycles 3 and 4; 2001 Census GeoSuite was used for cycles 5 and 6; and 2006 Census GeoSuite was used for cycles 7, 8 and 9. This variable has five categories: rural area, urban area population size less than 30,000, urban area population size less than 100,000, urban area population size less than 500,000, and urban area population size greater than 500,000. We divided this variable into two groups: rural area (reference group), and urban area (population size equal and greater than 30,000). Then we defined 'Years of rural living' as that introduced before.

'Food insecurity' was included in the model as a latent variable based on the trajectories of food insecurity flag variable asked in cycle 2, cycle 7, cycle 8, and cycle 9. The NPHS defined food insecurity as those who were worried about not having enough to eat, who did not have enough food to eat, or who did not eat the quality or variety of foods that they wanted to eat because of a lack of money. In the NPHS, the following questions were asked: "In the past 12 months, did you or anyone else in your household worry that there would not be enough to eat because of a lack of money? " ; "Did you or anyone else in your household not have enough food to eat because of a lack of money?; and "Did you or anyone else in your household not eat the quality or variety of foods that you wanted to eat because of a lack of money?". The NPHS recorded the respondents as having a food insecurity problem if they answered yes to at least one of the above questions. LCGM was used to identify different food insecurity patterns of the individuals included in this research, and then each individual was assigned to the most probable food insecurity trajectory.

The ‘Age cohort’ variable was defined based on respondents’ age at baseline: those aged 20–29 years in 1994/95 were coded as ‘1’, those aged 30–39 years in 1994/95 were coded as ‘0’. Because of the limitation of sample size, the impacts of birth cohorts by decades were examined rather than a single year cohort.

All descriptive analyses were weighted ones using the survey sampling weights and bootstrap weights, which were provided and suggested by Statistics Canada. Within LCGM, no sampling weights were used because most variables used in the calculation of sampling weights (e.g., race/ethnic group and rural living) were included as covariates in the LCGM model, and this makes un-weighted estimates less biased than weighted estimates according to previous research [129]. Differences with p-value <0.05 were considered to be statistically significant.

3.3 Results

Four BMI trajectory groups, ‘Normal-Stable’ (N-S), ‘Normal-Overweight’ (N-OV), ‘Overweight-Obese’ (OV-OB), and ‘Obese-Up’ (OB-UP) were identified for both men and women. Aboriginal women were found to have higher odds of being in the three latter groups, relative to N-S (OR = 2.6, 7.1, and 12.2 for N-OV, OV-OB, and OB-UP respectively). Increased years of smoking, drinking, and being physically active were associated with lowering the trajectory in all groups for both women and men, with some exceptions in N-S for men. Additionally, increased years of living in low-income, employment, and rural living were associated with raising the trajectory in each group for women and in some groups for men. On the other hand, younger cohorts were found to be associated with raising the trajectory in each group for men rather for women. Further, food insecurity was associated with raising the trajectory in each group in both women and men.

3.3.1 Baseline characteristics

At baseline, the adults in the present cohort were approximately half females (49.9%) and half males (50.1%). They were predominantly white (88.8%), with 1.14% from an Aboriginal population. Further, 18.4% had not graduated from high school (Table 3.1). From 1994 to 2011, the weighted prevalence of overweight (25≤BMI<30 kg/m2), obese-class I (30≤BMI<35 kg/m2), obese-class II (35≤BMI<40 kg/m2), and obese-class III (BMI≥40 kg/m2) increased from 31.1% to 39.0%, 8.6% to 16.7%, 1.8% to 4.4%, 0.8% to 2.6%, respectively. By contrast, the weighted percent of underweight (BMI<18.5 kg/m2) and normal weight (18.5≤BMI<25 kg/m2) declined from 2.5% to 0.9% and 55.2% to 36.5%, respectively.

Table 3.1 Characteristics of subjects aged 20-39 at baseline from the NPHS (1994/95)

Characteristics	Sample size (n=4790) No. (%)
Sex	
Males	2390 (49.9)
Females	2400 (50.1)
Race	
White	4253 (88.8)
Aboriginal	54 (1.14)
Other races	484 (10.1)
High school graduate	
Yes	3909 (81.6)
No	881 (18.4)
BMI	
Underweight	120 (2.5)
Normal	2644 (55.2)
Overweight	1490 (31.1)
Obese class-I	412 (8.6)
Obese class-II	86 (1.8)
Obese class-III	38 (0.8)

3.3.2 BMI Trajectories

We identified four trajectory groups for both sexes in a nationally representative sample of those aged 20-39 years at baseline. The trajectory groups were a N-S group, a N-OV group, an OV-OB group, and an OB-UP group for both men and women (Figure 3.1 and Figure 3.2). Trajectory results, including estimated parameters, GMP, and AvePP are shown in Tables 3.2 and 3.3 for women and men, respectively. Figure 3.1 and Figure 3.2 show that the identified BMI trajectories differ in terms of a start value of BMI at age 20 and distinct increasing rates of BMI over time. And higher trajectory groups have higher BMI at each time point than the lower patterns. The AvePP of each trajectory group exceeds 0.85 for both women and men. We found that that BMI trajectories differed by sex in terms of the shape and the percent of subjects in trajectories. All the trajectories in men display significant curvature in terms of quadratic term, but the curvature was only observed in the OB-UP trajectory group in women. Thereby, BMI trajectories and their associations with covariates were estimated separately for each sex.

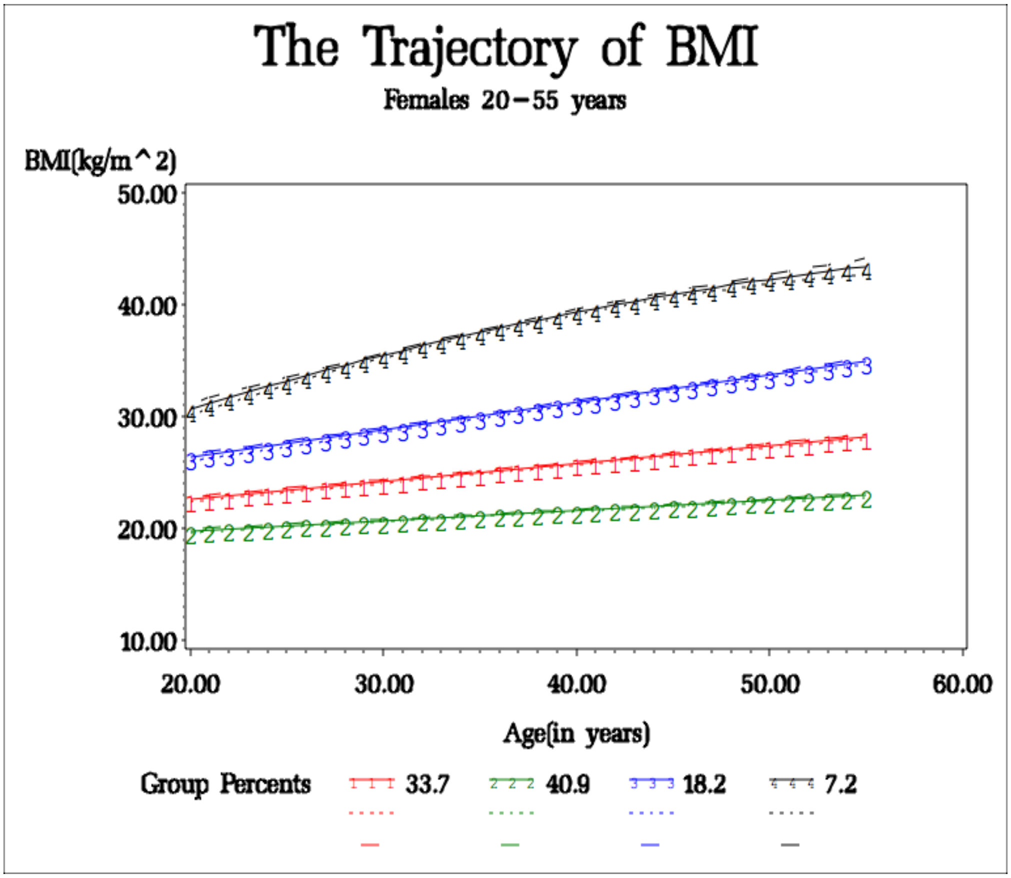

Figure 3.1 BMI trajectories for females (20-55 years), with 95% confidence intervals (four group model, no covariates included), NPHS, 1994-2011.

Table 3.2 The parameters estimated for BMI trajectories for females (20-55 years), NPHS (1994-2011).

The Trajectory of BMI	Intercept-BMI at age 20 (s.e)	Linear term (s.e)	Quadratic term (s.e)	GMP	AvePP
N-S	19.75(0.16)	0.09(0.004)	-	40.9%	0.88
N-OV	22.57(0.21)	0.16(0.005)	-	33.7%	0.87
OV-OB	26.38(0.29)	0.25(0.007)	-	18.2%	0.87
OB-UP	32.42(1.34)	0.71(0.075)	0.005(0.001)	7.2%	0.86

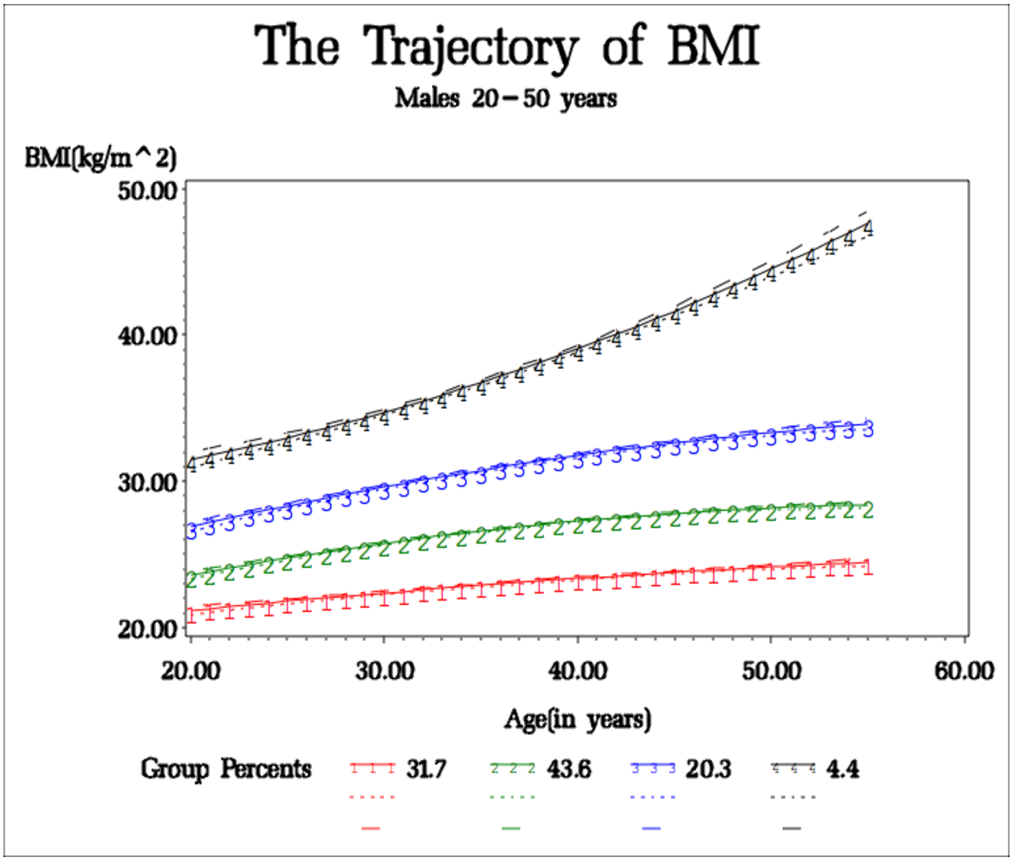

Figure 3.2 BMI trajectories for males (20-55 years), with 95% confidence intervals (four group model, no covariates included), NPHS, 1994-2011.

Table 3.3 The parameters estimated for BMI trajectories for males (20-55 years), NPHS (1994-2011).

The Trajectory of BMI	Intercept-BMI at age 20 (s.e)	Linear term (s.e)	Quadratic term (s.e)	GMP	AvePP
N-S	21.20(0.66)	0.17(0.03)	-0.001(0.0005)	31.7%	0.87
N-OV	23.77(0.52)	0.38(0.03)	-0.003(0.0004)	43.6%	0.87
OV-OB	26.78(0.77)	0.41(0.04)	-0.003(0.0006)	20.3%	0.87
OB-UP	31.61(1.43)	0.04(0.08)	0.006(0.001)	4.4%	0.88

The GMP of N-S group is 40.9% in women (marked by number “2” in Figure 3.1), and 31.7% in men (marked by number “1” in Figure 3.2). This group remains in the normal weight through age 20-55 years. Although the proportion of under/normal weight individuals in this trajectory group decreases over age, most members assigned to this group remains under/normal weight from 20 to 55 years for both women and men.

The N-OV group (GMP: 33.7% of women, marked by number “1” in Figure 3.1; 43.6% of men, marked by number “2” in Figure 3.2) starts at a normal weight at the age of 20 (average BMI = 22.6 for women, 23.8 for men), then crosses the overweight range and remains overweight till the age of 55. Within the N-OV group, around 85% or more of women had a BMI of <25 until around 30 years, but only 18% of men. The majority of women and men in this group were overweight after age 40. The proportion of obese individuals in this group increased steadily after age 40, but this proportion did not exceed 25% at any age for both sexes.

The OV-OB group marked by number “3” in Figure 1 and 2 has GMPs of 18.2% in women and 20.3% in men. This trajectory starts with an overweight status at age 20 (average BMI = 26.4 in women; average BMI = 26.8 in men), increases to reach the obese class I, and keeps increasing but remains in obese class I. This trajectory has an average BMI of 34.9 and 33.9 at age 55 in women and men, respectively. Additionally, the majority (around 65% of women and 75% of men) of individuals in this group were overweight at age 20, but the prevalence of overweight was negligible by age 55 years. The prevalence of obesity in this group exceeded 70% and 85% after age 45 for both sexes, respectively.

The GMP of the OB-UP trajectory group (marked by number "4" in Figure 1 and 2) is 7.2% and 4.4% for women and men. The OB-UP group starts with an obese status at age 20 (average BMI = 32.4 in women, 31.6 in men), and remains in the obese status until age 55 years. The proportion of obese subjects in the OB-UP group was greater than 70% around age 20, and the prevalence of under/normal weight in OB-UP was negligible after age 40 for both sexes.

3.3.3 Associated Factors

The impacts of risk factors and TVCs on BMI trajectories were examined with the LCGM model including all risk factors and TVCs. As shown in Table 3.4, compared with non-Aboriginal women, Aboriginal women had higher odds of being in the N-OV, OV-OB, and OB-UP groups, relative to N-S (OR = 2.6, 7.1, and 12.2 for N-OV, OV-OB, and OB-UP, respectively). However, this association was not significant in men. On the other hand, whether graduating from high school was found to be insignificant in changing trajectory membership in either women or men (Table 3.4).

It was found that lifestyle factors and SES were significantly related to the shift of BMI trajectories in most groups and gender difference was observed in these associations. Increased years of smoking was associated with lowering the BMI trajectory in each group for both women and men, with the biggest increase observed in the OB-UP group. Increased years of being physically active and drinking were associated with lowering the BMI trajectory in all groups for both women and men, except for N-S in men. The impacts of persistent employment, low income, and rural living on BMI trajectories were found to differ between women and men. Increased years of living in low-income was associated with raising the trajectory in each group for women, whereas this association was only found in the OV-OB and OB-UP groups of men. By contrast, more years of living in low-income was associated with lowering the BMI trajectory in N-S in men. In addition, increased years in employment was associated with raising the BMI trajectory in all groups in women and in the N-S, N-OV, and OV-OB groups in men. On the other hand, increased years of being employed was associated with lowering the trajectory in OB-UP in men. Furthermore, increased years of rural living was associated with raising the trajectory in each group in women and only in N-S in men. On the other hand, in men, longer rural living was associated with lowering the trajectory in OV-OB and OB-UP, and this association was insignificant in N-OV.

In addition, a younger age cohort was associated with raising the BMI trajectory in all the groups for men. By contrast, in women, a younger cohort was associated with raising the trajectory in N-OV and lowering the trajectory in OB-UP, whereas this association lost significance in the N-S and OV-OB groups. Furthermore, food insecurity was associated with raising the trajectory in each group in both women and men (Table 3.4).

Table 3.4 Risk factors for BMI trajectory group membership, and TVCs influencing trajectory level within each group: multivariable analysis, NPHS (1994-2011).

Predictors	Female Odds1	P-value	Male Odds[1]	P-value
Aboriginal				
N-S	1	-	1.0	-
N-OV	2.6	.047	1.4	0.43
OV-OB	7.1	<.0001	1.2	0.67
OB-UP	12.2	<.0001	0.9	0.89
Not graduate from High school				
N-S	1	-	1.0	-
N-OV	1.03	0.84	0.9	0.43
OV-OB	1.05	0.74	1.2	0.15
OB-UP	0.93	0.77	0.9	0.72
	Females		**Males**	
TVCs	Alter in BMI traj per unit change in TVCs	**P-value**	Alter in BMI traj per unit change in TVCs	**P-value**
Years of PA				
N-S	-0.03	.003	0.04	<.001
N-OV	-0.06	<.001	-0.03	.008
OV-OB	-0.05	.005	-0.10	<.001
OB-UP	-0.09	.003	-0.36	<.001
Years of smoking				
N-S	-0.05	<.001	-0.05	<.001
N-OV	-0.04	.001	-0.04	<.001
OV-OB	-0.03	.045	-0.05	<.001
OB-UP	-0.09	<.001	-0.20	<.001
Years of regular drink				
N-S	-0.02	.029	0.02	.053
N-OV	-0.10	<.001	-0.03	.003
OV-OB	-0.16	<.001	-0.12	<.001
OB-UP	-0.30	<.001	-0.10	<.001
Years of living in low-income				

N-S	0.05	<.001	-0.07	<.001
N-OV	0.07	<.001	0.02	.064
OV-OB	0.10	<.001	0.10	<.001
OB-UP	0.26	<.001	0.16	<.001
Years in employment				
N-S	0.08	<.001	0.04	.003
N-OV	0.10	<.001	0.07	<.001
OV-OB	0.17	<.001	0.11	<.001
OB-UP	0.18	<.001	-0.20	<.001
Years of rural living				
N-S	0.08	<.001	0.03	.002
N-OV	0.10	<.001	-0.01	.354
OV-OB	0.17	<.001	-0.07	<.001
OB-UP	0.18	<.001	-0.20	<.001
Food insecurity[2]				
N-S	0.85	<.001	0.26	.002
N-OV	2.09	<.001	0.78	<.001
OV-OB	3.18	<.001	1.37	<.001
OB-UP	4.23	<.001	0.61	.019
Age cohort[3]				
N-S	0.17	.129	0.23	.039
N-OV	0.78	<.001	0.96	<.001
OV-OB	0.10	.620	1.57	<.001
OB-UP	-1.74	<.001	5.91	<.001

[1]: relative adjusted odds ratios for membership in each trajectory using the N-S group as the reference class.
[2]: latent variable which record the most probability food insecurity group of individuals (Appendix A3-1)
[3]: Age cohorts: 20-29 years at baseline vs. 30-39 years at baseline (ref.)

3.4 Discussion

Our study provides evidence on the heterogeneity of BMI trajectories among the population of Canadian adults. The identified BMI trajectory groups of N-S, N-OV, OV-OB, and OB-UP are well coherent with the findings in the previous studies for the US population of adults [14, 15]. In addition, we investigated the accumulation and incremental impacts of behavior factors (e.g., years of smoking, drinking, and being physically active) and SES (e.g., years of living in low-income and in employment) on the BMI trajectories. Thus, this study in general better delineates the impact of these factors on body weight change compared with previous studies on the topic. To date, our study is the first to test the impact of the dynamics of behavior factors (i.e., smoking, drinking, and physical activity) on BMI trajectories for adults.

Our findings on the impact of SES and race on BMI changes are generally in line with the evidence that the individuals with lower SES or in minority racial/ethnic groups have the highest rates of obesity [34, 35, 43, 57, 130-132]. Specifically, Aboriginal females were more likely to be in the higher BMI groups (N-OV, OV-OB and OB-UP) as opposing to the N-S group in our data; this is in line with the previous findings in [35, 43]. For instance, Ng C. *et al.* established that Aboriginal Canadians had a higher BMI trajectory with higher increasing rate of BMI and BMI peak values compared with their non-Aboriginal counterparts [35]. Thus, Aboriginal populations, specifically females, need intense interventions in order to reduce excess weight during adulthood. However, we found that educational attainment measured by whether graduating from high school was not a significant predictor of trajectory group membership in either women or men.

This finding is in agreement with the results in the studies [133, 134], but not with others [14, 57, 135]. For instance, Ostbye *et al.* reported that increased year of education lowered of the BMI trajectory within each group. This inconsistence may be because we considered education indicator (if graduated from high school) as a risk factor; by contrast, Ostbye *et al.* considered educational attainment as a TVC. Additionally, previous results indicated that different racial groups may not benefit from educational attainment on weight management in the same way [136]. One limitation of our study is that only Aboriginal and Non-Aboriginal Populations were distinguished.

Our finding on the impact of the accumulation of smoking on obesity show that increased years of smoking was associated with lowering the trajectory in each group in both women and men. Nonnemaker *et al.* considered smoking as a risk factor (for youth aged 12-23), and found that current smokers were more likely to be in the middle two trajectory groups (low-to-moderate risk and moderate-to-high risk for becoming obese BMI trajectories) when compared with the reference group (low risk for becoming obese BMI trajectory). This difference probably can be explained by different age groups considered as well as the difference in the way of measuring smoking. Smoking was measured in years and considered as a TVC in our study, whereas smoking status was measured once and considered as a time-constant variable in the study by Nonnemaker *et al.*[16]. In addition, one BMI trajectory study used CGM and found that smoking was associated with a lower BMI at the baseline, as well as a slower rate of change over time [33]. Likewise, a pooled cross-sectional study suggested that smoking was associated with a lower BMI [65]; others studies showed that smokers weighed less than non-smokers on average [45, 137]. One strongpoint of our study is that the data (through age

20-55 years) used in this research includes the ages with the most prevalent years of smoking as suggested by other studies [71]. On the other hand, one limitation of our study is that we did not consider the amount of smoking to distinguish heavy smokers and light smokers due to the unavailable data on smoking in the NPHS. The amount of smoking in terms of heavy or light ones may play an important role on weight change according to the previous research in [45].

Our study shows that increased years of being physically active was associated with lowering the trajectory in women and men, except for the N-S group in men. This finding implies that individuals who maintain moderate or active physical levels can reduce the likelihood of weight gain over adulthood. It conforms to the documented inverse relationship between body weight and physical activity [138]. In the Canadian context, one previous study declared that BMI was inversely associated with the level of physical activity, particularly for women [44].

Moreover, we found that increased years of regular drinking was associated with the lowering the trajectory in each group in women whereas this association was only observed in the risky BMI trajectories (N-OV, OV-OB, and OB-UP) in men. This finding can be explained from a biological perspective. There is evidence that long-term and daily alcohol consumption can affect macronutrient absorption, decreasing overall energy intake [139]. Besides, our study population is young to middle-aged adults, whose metabolic functions are generally better than the general population. The results in our study are in agreement with the findings in a recent prospective cohort study with a 12.9 year follow-up, which reported that women with a light to moderate alcohol consumption habit were less likely to gain weight or become obese; this association was consistent even after adjusting for other behavioral and clinical factors [140]. Our findings confirm the paradox of alcohol intake and body weight [141]. Although many researchers agree that alcohol consumption tends to add energy intake rather than compensate, there is no clear evidence on the association between drinking and gaining weight. Previous research on the association between obesity and alcohol consumption is quite mixed: positive, negative, or no associations [46]. The inconsistent findings may be because other studies did not consider the potential heterogeneity in BMI development in the studied population. Nonetheless, there are some limitations with our findings on the impact of alcohol intake on obesity due to the unavailable data in the NPHS. First, we did not distinguish different types of alcoholic beverages, while previous research suggested that various types of alcoholic beverages affect body weight differently. For example, light-to-moderate wine intake may protect against weight gain, whereas the intake of spirits may lead to weight gain [46]. Secondly, we defined "regular drinking" as drinking more than once a month, failing to consider the dose-dependent relationship between drinking and weight changes. Finally, our study cannot distinguish drinking patterns such as binge drinkers, which may play a determinant role in the association between obesity and alcohol intake [142].

Our findings indicate gender differences in terms of the impacts of increased years of living in low-income, rural living, and younger cohorts on obesity. Increased years in low-income was associated with raising the trajectory in each trajectory group in women but the association was only observed in the OV-OB and OB-UP groups for men. This finding is consistent with the one in [143], which reported that low-income was associated with an increased obesity risk among women rather than men. However, this finding is inconsistent with the one in the study by Ostbye *et al.*, which reported that increased years in poverty was not associated with trajectory change in any BMI trajectory group after considering other covariates. The difference may come from the fact that Ostbye *et al.* did not model BMI trajectory for men and women separately.

On the impact of rural living on obesity, we found that longer rural living was associated with raising the trajectory in women but not in men. This is partly in agreement with the evidence that obesity is more prevalent in rural areas compared with urban areas in developed countries [144]. This may be because rural residents are more likely to be influenced by limited resources and experience unpleasant environmental conditions in terms of health care systems, accessibility to healthy food, and a lack of resources for physical activity facilities [144, 145]. Therefore, rural populations need special attention in the development of strategies to deal with the obesity epidemic.

Moreover, a younger age cohort at baseline (20-29 years vs. 30-39 years) was associated with raising the BMI trajectory in all men's groups but not in women in our study. Previous studies found that younger cohorts tended to have higher BMI increasing rates over adulthood [14, 35, 146]. In our findings, increased years in employment was associated with raising the trajectory in all groups in both women and men, except for OB-UP in men. The argument that employees may be more likely to consume high-dense foods because of a stressful work schedule proposed in [61, 147] may help explaining our findings. Thus, work-related stress deserves special attention, since it may play an important role in weight gain.

In addition, food insecurity was associated with raising the trajectory in each group for both women and men. This finding is consistent with previous studies that individuals plagued with food insecurity were more likely to be overweight, obese or morbid obese [85, 148, 149]. One limitation of our study is that the NPHS do not have information on people who lived on reserves, who might be the most vulnerable population to suffering from food insecurity problems. The findings in our study contribute to new evidence by using a latent variable to capture subgroups that are more likely to experience food insecurity. Therefore, coordinated policy or program responses are needed to address food insecurity in Canada and to make sure all adults have access to healthy food.

One important strongpoint of our study is the use of LCGM and a population-representative sample from the NPHS to investigate the heterogeneity of BMI changes and the impacts of cumulative behavior factors and SES on the development of obesity. However, this study cannot avoid the weakness of the use of self-reported data as well as the lacking information in the amount of smoking, on various types of alcoholic beverages, or on binge drinkers. There is no such measured longitudinal data that allows the investigation of the cumulative impact of factors on obesity.

Chapter 4

BMI Trajectories among Middle-aged to Older Adults (40-55 years) and Health Outcomes

4.1 Introduction

In 2011, Canadians aged 45 to 64 had the highest self-reported rates of being overweight or obese, as high as 60% [150]. The prevalence of obesity increases markedly among middle-aged and older adults globally [151]. Previous research found that excess body weight was associated with numerous chronic conditions and cognitive problems [152-154].

There is evidence that body weight changes better predict obesity-related health conditions rather than static BMI status [155]. BMI trajectory analyses using LCGM can better capture body weight change over time and offer new insights on adverse health outcomes due to excess weight [5]. However, there is limited knowledge on the BMI trajectories from middle-age onward. Also, one of the most important purposes of identifying distinct BMI trajectories is to test if such trajectories carry differential morbidity potentials [5]. Only two studies have studied the heterogeneity in BMI development using LCGM and its association with adverse health outcomes in midlife [14, 15]. The two studies both reported that adverse health conditions were more prevalent in trajectories which represent a higher rate increase of BMI, but both were based on the US population. Ostbye *et al.* investigated four BMI trajectories in adults (18-

49 years) and used the health status indicators when respondents turned 40 years old, whereas chronic conditions may not be developed at the age of 40 [14]. Likewise, Finkelstein *et al.* identified four BMI trajectory groups for adults (25-33 years) with class I obesity [15]; however, the study by Finkelstein *et al.* was not representative of general population.

The purpose of this chapter is to apply LCGM to capture distinct BMI trajectories for middle-aged to older adults (40-55 in 1994/95), examine the associations between individual characteristics and BMI trajectories, and evaluate the association between trajectory class and midlife health for the Canadian population.

4.2 Methods

In order to identify BMI trajectories for middle-aged to older adults, 3070 respondents who aged 40-55 years at baseline and had at least four BMI records in the NPHS were included in this study. Similar to chapter 3, the ALD allowed us to analyze the pattern of BMI change over a period of 31 years (40-70 years). Respondents aged 40-55 years in 1994/95 were selected in order to: 1) represent the middle-aged and older adults; 2) ensure an adequate number of individuals in each BMI category; and 3) enable observation of health conditions at the age of 55 for each respondent.

Similar to section 3.2.3, age was used to define the time variable and BMI was used as the trajectory variable. In this chapter, sex, race (white vs. non-white) and education attainment (the highest level of education) were included as risk factors with the assumption that they had a potential impact on group membership probabilities. All respondents who self-identified as white were categorized as white group and all others were categorized as non-white. We changed race/ethnicity indicator in this chapter to ensure sufficient sample size. The NPHS derived a variable denoting the highest level of education. We further defined those who completed high school only or less as 'non-post-secondary education' and those who had some post-secondary education or a post-secondary degree as 'post-secondary education'. We changed education indicator because our preliminary analyses showed that the highest educational level was a more important risk factor than whether graduated from high school. In addition, it is reasonable to hypothesize that the highest educational levels were constant for respondents aged 40-55 at baseline, considering that risk factors need to be established before the initial period of the trajectory [12].

Variables such as years of being physically active, years of smoking, years as a regular drinker, years of living in low-income, years of retirement, years of rural living, years in married, food insecurity, and cohort effects during the observational years (1994-2011) were TVCs at the trajectory level. Those TVCs were defined in the same way as those in section 3.2.3, except for years of retirement (since 1994) and years married (since 1994). There are common life events which occur in middle to late adulthood, such as retirement and marital status changes, which are two of the most important social transitions of late adulthood [84, 156]. Therefore, 'years of retirement' was used instead of 'years in employment' and 'years in married' was added to the analyses. Years of retirement (since 1994) was defined based on the respondents' working status, specifically, we first dichotomized a variable on working status derived by the NPHS as employment and unemployment, then defined the variable as that introduced previously. Years married (since 1994) was defined based on the respondents' marital status in the

NPHS. The NPHS asked respondents “What is your current marital status?” The marital status was categorized into married, common-law, living with a partner, single, widowed, separated, and divorced. Changes were made on categories after the fourth cycle (in that common in-law and living with a partner were combined as living common law). We defined a binary variable: married (married, common-law, or living with a partner) versus not married (single, widowed, separated, or divorced), to accommodate the changes to define years married (since 1994). Age cohort variable was defined based on the respondents’ age at baseline: those aged 40–47 years in 1994/95 were coded as 1 and those aged 48–55 years in 1994/95 were coded as 0.

In order to test whether the prevalence and risks of health outcomes varied with different BMI trajectory groups, health outcomes were screened and selected based on our literature review (section 2.3). We used self-reported health outcomes of individuals at the age of 55 in the NPHS. The associations with BMI trajectories of health outcomes including asthma, arthritis or rheumatism (excluding fibromyalgia), back problems (excluding fibromyalgia and arthritis), high blood pressure, chronic bronchitis or emphysema, diabetes, heart disease, cognitive problems, emotional problems, and health description index - Self-rated health were analyzed in this chapter (detailed information on these health indicators can be found in Appendix A4-2).

Basic model selection and the extended model including all covariates were all based on LCGM, and followed the same procedure as that in section 3.2.4. To examine if the prevalence and relative risks of the adverse health conditions differ by BMI trajectory groups, chi-square tests and logistic regression analyses were conducted. All analyses were conducted for the cohort of ages 40-55 at baseline including both female and male subjects, given that our preliminary analysis showed that BMI trajectory patterns did not change substantially by sex for this cohort. Accordingly, we modeled the BMI trajectory in the same model for both men and women and considered gender as a risk factor of group membership. Descriptive statistics and logistic regression analyses were appropriately weighted based on the survey sampling weights and bootstrap weights, which were provided and suggested by Statistics Canada. Within LCGM, no weights were used (detailed explanation seen section 3.2.4).

4.3 Results

Four BMI trajectory groups, a Normal weight-Stable (N-S), an Overweight Stable (OV-S), an Obese class I-Stable (OB I-S), and an Obese class II-Stable (OB II-S), were identified for middle-aged and older adults. Individuals who were male, white, or had no post-secondary education were at greater risk of being in the OV-S, OB I-S and OB II-S groups, relative to N-S. Increased years of being physically active was associated with lowering the trajectory in each group. Increased years of smoking was associated with lowering the trajectory in the OV-S, OB I-S and OB II-S groups. Increased years of drinking raised the trajectory in N-S and OV-S, but lowered the trajectory in OB I-S and OB II-S. Additionally, increased years of retirement was associated with raising the trajectory only in the OB I-S and OB II-S groups. Food insecurity and younger age cohorts were associated with raising the trajectory in the OV-S, OB I-S, and OB II-S groups. On the other hand, increased years of living in low-income was associated with raising the trajectory only in OB II-S group, whereas lowering the trajectory in N-S. Increased years of rural living was associated with raising the trajectory in N-S, and OV-

S, but lowering the trajectory in the OB II-S group. Increasing years married was associated with raising the trajectory in N-S, but lowering the trajectory in OB I-S. Moreover, members of the higher trajectories (OV-S, OB I-S, and OB II-S) were more likely to have asthma, arthritis, hypertension, diabetes, heart disease, cognitive problems, and reduced self-rated health. In comparison, only subjects in the highest group (OB II-S) were more likely to develop back problems, chronic bronchitis or emphysema, and emotional problems.

4.3.1 Baseline characteristics

Approximately half of the 3070 individuals included in this research were female (48.5%) and half males (51.5%). They were predominantly white (90.9%), with 0.44% being from an Aboriginal population. 62.5% of the individuals had some post-secondary education (Table 4.1). From 1994 to 2011, the weighted prevalence of overweight (25≤BMI<30 kg/m2), obese-class I (30≤BMI<35 kg/m2), obese-class II (35≤BMI<40 kg/m2), and obese-class III (BMI≥40 kg/m2) increased from 41.8% to 42.2%, 12.2% to 18.9%, 2.8% to 5.8%, 1.2% to 2.4%, respectively. By contrast, the weighted percent of underweight (BMI<18.5 kg/m2) and normal weight (18.5≤BMI<25 kg/m2) declined from 1.6 to 1.1% and 40.5 to 29.5%, respectively.

Table 4.1 Characteristics of subjects aged 40-55 at baseline from the NPHS (1994/95)

Characteristics	Sample size (n=3070) No. (%)
Sex	
Males	1489 (48.5)
Females	1581 (51.5)
Race	
White	2791 (90.9)
Aboriginal	12 (0.44)
Other races	267 (8.7)
Education	
High school graduate or less	1151 (37.5)
post-secondary education	1919 (62.5)
BMI	
Underweight	49 (1.6)
Normal	1243 (40.5)
Overweight	1283 (41.8)
Obese class-I	371 (12.1)
Obese class-II	87 (2.8)
Obese class-III	37 (1.2)

4.3.2 BMI Trajectories

Four trajectory groups with quadratic polynomial (N-S, OV-S, OB I-S, and OB II-S) best characterized the long-term patterns of BMI change for those aged 40-55 at baseline (Figure 4.1). Trajectory results, including estimated parameters, GMP, and AvePP are shown in Tables 4.2. The AvePP value of each group in the four-group model exceeded 0.95.

The GMP of the N-S group is 23.7% (marked by number "1" in Figure 4.1) and this group often remains in the normal weight range through the ages of 40 to 70. Most members assigned to this group remained under/normal weight through age 40 to 70 years.

The OV-S group is the largest group among this sample, with a group membership probability of 45.4% (marked by number "2" in Figure 4.1). This trajectory group starts at a nearly overweight status (average BMI = 24.8 at 40 years) then remains in the overweight range thereafter. In this group, the prevalence of overweight was greater than 50% at each age from 40-70 years. Additionally, around 30% or more of individuals in this group had a BMI of <25 until around the age of 50, the proportion of obese subjects in this group did not exceed 10% at any age.

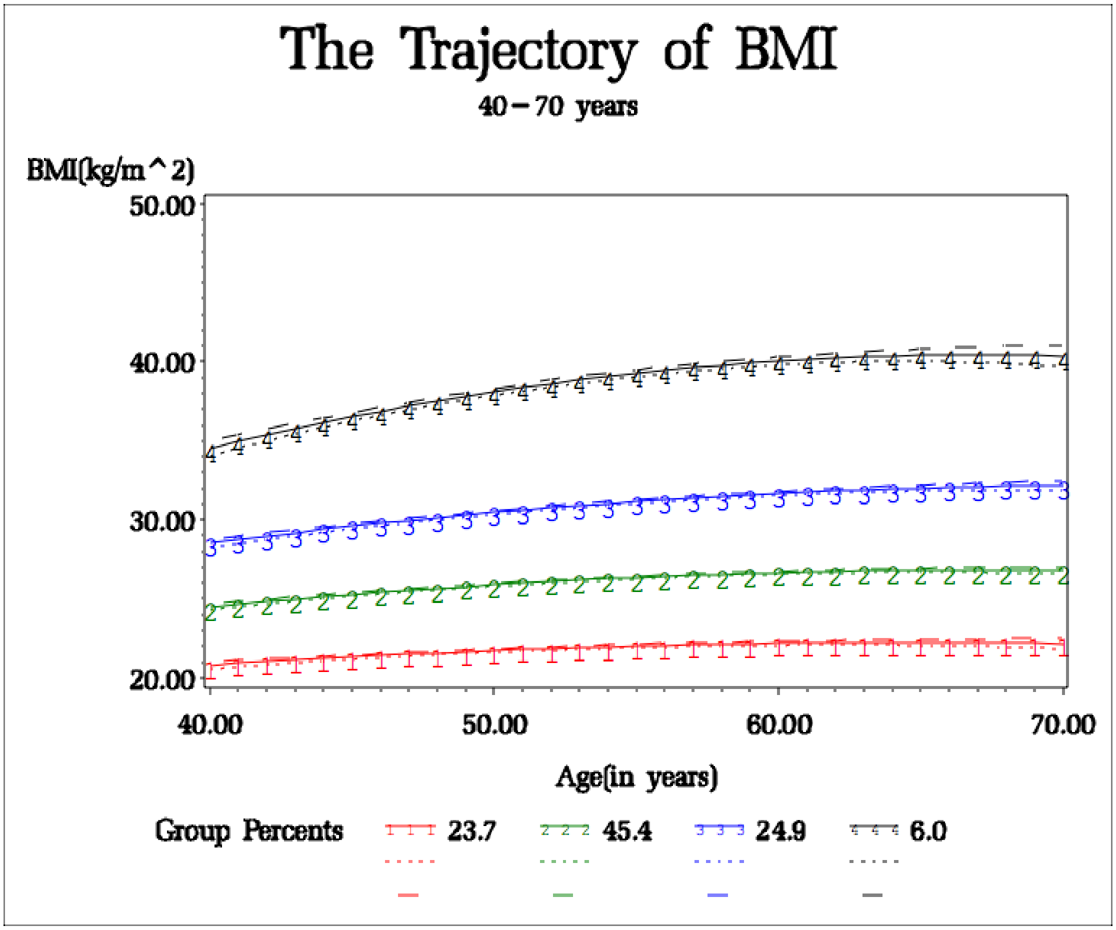

Figure 4.1 BMI trajectories for mid-late adults (40-70 years), with 95% confidence intervals (four group model, no covariates included), NPHS, 1994-2011.

Table 4.2 The parameters estimated for BMI trajectories (40-70 years), NPHS(1994-2011).

The Trajectory of BMI	Intercept-BMI at age 40 (s.e)	Linear term (s.e)	Quadratic term (s.e)	GMP	AveP P
N-S	21.51(1.83)	0.31(0.07)	-0.002(0.0006)	23.7%	0.97
OV-S	24.76(1.32)	0.42(0.05)	-0.003(0.0004)	45.4%	0.96
OB I-S	27.85(1.83)	0.52(0.07)	-0.004(0.0006)	24.9%	0.96
OB II-S	34.73(3.73)	1.09(0.14)	-0.008(0.001)	6.0%	0.98

The OB I-S group (GMP: 24.9%, marked by number “3” in Figure 4.1), starts with an overweight status at age 40 years (average BMI = 27.9), and slowly increases to obese class I around 50 years (average BMI=30.5) and never reaches obese class II from 40-70 years. In this group, the proportion of under/normal weight individuals in OB I-S was less than 20% for all ages. Additionally, about half of its members (45%) were overweight around the age of 40; this proportion reduced to 30% by 60 years of age. Further, the proportion of obese subjects in this group was about 50% by age 27 years, and exceeded 70% by age 60 years.

The GMP of the OB II-S group is 6.0% (marked by number “4” in Figure 4.1). The OB II-S group starts with an obese class II status at the age of 40 (average BMI =34.7), then slowly increases but remains in obese class II status through age 40-70 years. The weighted prevalence of under/normal weight and overweight were negligible for all ages in this group. Most members classified as in the OB II-S group were obese at the age of 40 and the proportion of obese subjects in this group kept increasing through age 40-70 years.

4.3.3 Associated Factors

The impacts of risk factors and TVCs on BMI trajectories were examined with the covariate model including all risk factors and TVCs. As shown in Table 4.3, individuals who were white, or had no post-secondary education had higher odds of being in the OV-S, OB I-S and OB II-S groups, relative to N-S. Specifically, males were at greater risk of following higher BMI trajectories compared with females (OR=3.0 and 2.9 for OV-S and OB I-S, respectively), though the association lost significance in OB II-S. An individual without any post-secondary education was more likely to be in the OV-S, OB I-S, and OB

Table 4.3 Risk factors for BMI trajectory group membership, and time-varying covariates influencing trajectory level within each group: multivariable analysis, NPHS, 1994-2011

Predictors	Fully adjusted Odds[1]	P-value
Male		
N-S	1.0	-
OV-S	3.0	<.001
OB I-S	2.9	<.001
OB II-S	1.4	0.07
No post-secondary education		
N-S	1.0	-
OV-S	1.6	<.001
OB I-S	1.5	0.001
OB II-S	1.6	0.007
White (Non-white)		
N-S	1.0	-
OV-S	1.6	0.013
OB I-S	2.0	0.002
OB II-S	5.5	0.004

TVCs	Alter in BMI traj per unit change in TVCs	P-value
Years of PA		
N-S	-0.04	0.001
OV-S	-0.05	<.001
OB I-S	-0.13	<.001
OB II-S	-0.47	<.001
Years of smoking		
N-S	-0.07	<.001
OV-S	-0.07	<.001
OB I-S	-0.06	<.001
OB II-S	0.14	<.001
Years of regular drink		
N-S	0.05	<.001
OV-S	0.03	<.001
OB I-S	-0.03	<.001
OB II-S	-0.09	<.001
Years of living in low-income		

N-S	-0.04	0.004
OV-S	-0.01	0.307
OB I-S	0.01	0.346
OB II-S	0.11	<.001
Years of retirement		
N-S	-0.08	0.01
OV-S	0.04	0.17
OB I-S	0.18	<.001
OB II-S	0.25	<.001
Years of rural living		
N-S	0.06	<.001
OV-S	0.03	<.001
OB I-S	0.01	0.434
OB II-S	-0.10	<.001
Years in married		
N-S	0.02	0.01
OV-S	-0.001	0.90
OB I-S	-0.02	0.02
OB II-S	0.02	0.37
Food insecurity [2]		
N-S	0.11	0.31
OV-S	0.95	<.001
OB I-S	1.85	<.001
OB II-S	2.68	<.001
Age Cohort effects [3]		
N-S	-0.01	0.935
OV-S	0.62	<.001
OB I-S	1.84	<.001
OB II-S	3.45	<.001

[1]: relative adjusted odds ratios for membership in each trajectory using the N-S group as the reference class.
[2]: latent variable which record the most probability food insecurity group of individuals (Appendix A4-1)
[3]: Age cohorts: 40-47 years at baseline vs. 48-55 years at baseline (ref.)

II-S groups compared with N-S (OR=1.6, OR=1.5, and OR=1.6 for OV-S, OB I-S, and OB II-S, respectively). Compared with non-white subjects, white individuals had a greater probability of belonging to higher BMI trajectories as opposed to non-white people (OR=1.6, 2.0, and 5.5 for OV-S, OB I-S, and OB II-S, respectively) (Table 4.3).

It was found that increased years of being physically active was associated with lowering the trajectory in each group, being the greatest influence observed in the OB II-S group. The impacts of persistent employment, low-income, and rural living on BMI trajectories were found to differ by different BMI level. Increased years of smoking was associated with lowering the trajectory in the N-S, OV-S, and OB I-S groups, but raising the trajectory in OB II-S. Increased years of drinking was associated with lowering the trajectory in OB I-S and OB II-S, but raising the trajectory in N-S and OV-S. Increased years of living in low-income was associated with raising the trajectory only in the OB II-S group, but lowering the trajectory in N-S; on the other hand, this association was insignificant in OV-S and OB I-S. Increased years of retirement was associated with raising the trajectory in OB I-S and OB II-S, whereas lowering the trajectory in N-S; in addition, the association was insignificant in OV-S. Increased years of rural living was associated with raising the trajectory in N-S and OV-S, but lowering the trajectory in OB II-S; in addition, this association lost significance in OB I-S. Younger cohort (40-47 years) (compared with 48-55 years at baseline) and food insecurity were associated with raising the trajectory in the OV-S, OB I-S, and OB II-S groups, though the results lost significance in N-S (Table 4.3).

4.3.4 Health Outcomes

The prevalence of obesity-related health conditions was generally the highest among the OB II-S group, followed by the OB I-S and OV-S groups, and the lowest among the N-S group. For each health problem, the odds of having the condition were higher for those in the highest trajectory group (OB II-S) compared with those in the N-S group, and in most cases, the odds ratios for those in OV-S or OB I-S groups were somewhere in between (Table 4.4). Members of the OV-S, OB I-S, and OB II-S groups were more likely than N-S group members to have asthma, arthritis, hypertension, diabetes, heart disease, cognitive problems, and reduced self-rated health. In comparison, only members of the OB II-S group were more likely to have back problems, chronic bronchitis or emphysema, and emotional problems as opposed to N-S (Table 4.4).

Compared with adults in the N-S group, those in the OB II-S group were more likely to develop the following health outcomes: asthma (OR=2.6; 95% CI, 2.56-2.63), back problems (OR = 1.28; 95% CI, 1.26-1.29), chronic bronchitis or emphysema (OR = 2.52; 95% CI, 2.48-2.57), cognitive problems (OR=1.58; 95% CI, 1.56-1.59), self-rate as somewhat happy (happy as the comparison group, OR=1.88; 95% CI, 1.87-1.90), and self-rate as in very good health (excellent health as the comparison group, OR = 2.27; 95% CI, 2.24-2.31). Individuals in the topmost trajectory (OB II-S) were four times more likely to experience arthritis or rheumatism (OR=3.79; 95% CI, 3.76-3.83), heart disease (OR = 3.75; 95% CI, 3.69-3.82), and self-report as unhappy (happy as the comparison group, OR=3.90; 95% CI, 3.83-3.98). Additionally, members in the OB II-S group were 5 (95% CI, 4.91-5.08), 11.48 (95% CI, 11.27-11.69), 9.53 (95% CI, 9.30-9.76) times more likely to self-rate as in good health, fair health, or poor health status respectively (excellent health as the comparison group). Moreover, those in the OB II-S group were eight times more likely to develop hypertension (OR=8.03; 95% CI, 7.95-8.11), and 26 times more likely to experience diabetes (OR=25.56; 95% CI, 25.10-26.03).

In general, individuals in the OV-S and OB I-S groups had higher odds of developing adverse health outcomes as opposed to the N-S group. The exceptions include that individuals in the OV-S group were 0.91(95% CI, 0.90-0.91) times less likely to have back problems, and people in the OB I-S groups were 0.38 (95% CI, 0.37-0.39) times and 0.90 (95% CI, 0.89-0.90) times less likely to experience chronic bronchitis/emphysema and to be somewhat happy (as happy as the comparison group), respectively, as opposed to the N-S group.

Table 4.4 weighted prevalence and odds of health outcomes as self-reported when respondents turned 55 years by BMI trajectory group, NPHS, 1994-2011.

Health outcome	The trajectory of BMI								P-trend
	N-S		OV-S		OB I-S		OB II-S		
	%[a]	OR[b]	%	OR (95%CI)	%	OR(95%CI)	%	OR (95%CI)	
Asthma**	4.4	ref.	7.1	1.65 (1.63-1.67)	9.2	2.18(2.16 2.21)	10.8	2.60 (2.56-2.63)	<.0001
Arthritis or rheumatism**	20.9	ref.	26.9	1.39 (1.39-1.40)	30.3	1.65 (1.64-1.66)	50.0	3.79 (3.76-3.83)	<.0001
Back problems*	19.6	ref.	18.1	0.91 (0.90-0.91)	23.9	1.29 (1.28-1.30)	23.7	1.28 (1.26-1.29)	<.0001
Hypertension**	12.3	ref.	22.1	2.03 (2.02-2.04)	28.5	2.86 (2.84-2.88)	52.9	8.03 (7.95-8.11)	<.0001
Chronic bronchitis or emphysema**	2.8	ref.	3.1	1.12 (1.10-1.14)	1.1	0.38 (0.37-0.39)	6.7	2.52 (2.48-2.57)	<.0001
Diabetes**	1.4	ref.	5.7	4.30 (4.22-4.37)	9.6	7.49 (7.36-7.62)	26.6	25.56 (25.10-26.03)	<.0001
Heart disease**	2.5	ref.	5.5	2.29 (2.26-2.32)	6.0	2.49 (2.45-2.52)	8.7	3.75 (3.69-3.82)	<.0001
Cognitive problems**	20.5	ref.	21.5	1.06 (1.05-1.07)	24.7	1.27 (1.26-1.28)	28.9	1.58 (1.56-1.59)	<.0001
Emotional problems**									<.0001
Happy	79.7	ref.	77.5	ref.	80.4	ref.	64.9	ref.	
Somewhat happy	17.8	ref.	19.2	1.12 (1.11-1.12)	16.0	0.90 (0.89-0.90)	27.2	1.88 (1.87-1.90)	
Unhappy	2.5	ref.	3.2	1.33 (1.31-1.35)	3.6	1.43 (1.40-1.45)	7.9	3.90 (3.83-3.98)	
Self-rated health**									<.0001
Excellent	23.0	ref.	18.8	ref.	16.2	ref.	6.4	ref.	
Very good	38.8	ref.	37.3	1.18 (1.17-1.18)	38.6	1.41 (1.40-1.42)	24.7	2.27 (2.24-2.31)	
Good	28.7	ref.	30.7	1.31 (1.30-1.32)	32.5	1.61 (1.59-1.62)	40.1	5.00 (4.91-5.08)	
Fair	6.9	ref.	8.5	1.49 (1.48-1.51)	10.3	2.11 (2.08-2.13)	22.3	11.48 (11.27-11.69)	
Poor	2.4	ref.	4.6	2.33 (2.30-2.36)	2.3	1.35 (1.32-1.37)	6.5	9.53 (9.30-9.76)	

*P-value <0.1 ; ** P-value <0.05

4.4 Discussion

Four BMI trajectory groups, N-S, OV-S, OB I-S, and OB II-S, were identified among middle-aged and older adults. There was no pronounced weight gain or loss in body mass trajectory groups for aged 40-70 in our findings, which is in agreement with other BMI trajectory research based on LCGM [5, 7]. For instance, Zheng *et al*. identified six trajectory groups with slight BMI increases over time for adults aged 51 to 77 years [7] and Botoseneanu *et al.* showed that the change of BMI over time was moderate for people aged 51-61 years [5].

We found that men had a higher propensity to follow the high-BMI trajectories compared to women; this finding conforms to previous trajectory analyses [5, 14]. On the other hand, some other BMI trajectory studies reported no gender differences [33, 34], but these studies used one average BMI change pattern to represent the whole population, which may conceal the gender differences. In our analyses, white people were more likely to belong to higher BMI trajectories. This is partly in agreement with the documented evidence that white population normally have higher BMI than other race groups (with the exception of Aboriginals) in Canada [44]. By contrast, previous studies reported that African Americans and Hispanics were more likely to follow higher BMI trajectories compared to the white population [5, 14, 15, 17]. This inconsistency may be due to the fact that these studies were based on the US population, whereas there are ethnicity composite differences between US and Canada [44]. Additionally, respondents with lower educational levels (no post-secondary education) were at greater risk of being in the higher BMI trajectory groups (i.e., OV-S, OB I-S, and OB II-S) in our findings. This evidence is in keeping with the study by Ostbye *et al.*, which found that increasing educational level lowered the trajectory within each group [14].

Moreover, increased years of being physically active was associated with lowering the trajectory in each group in our analyses, similar to our findings presented in chapter 3. Increased years of smoking was associated with lowering the trajectory in the N-S, OV-S, and OB I-S groups, and raising the trajectory in OB II-S over midlife (40-70 years) in our results. By contrast, in chapter 3, increased years of smoking was associated with lowering the BMI trajectory in each BMI trajectory group in young to middle-aged adults (20-55 years). These different findings between different age groups indicate that the protect impact of smoking on gaining weight may not apply to the very obese group (OB II-S) in people's midlife. Moreover, this finding supports the evidence from our literature review that the association between smoking and obesity depended on age (section 2.2). Increased years of regular drinking was associated with lowering the trajectory in the obese groups (OB I-S and OB II-S), but raising the trajectory in N-S and OV-S. These findings imply that the impact of drinking on body weight may differ in distinct BMI trajectory groups. We also found that the increased years of retirement was associated with raising the trajectory in OB I-S and OB II-S. This is in line with previous evidence that people tended to gain weight after their retirement and the positive relationship between weight gain and retirement was stronger among overweight and obese people than that among their normal weight counterparts [64]. Further, increased years married was associated with lowering the trajectory only in OB I-S, but raising the trajectory in N-S. Østbye *et al* found that the longer people were married, the lower the BMI trajectory in each group through their adulthood (aged 18-49) was. This inconsistence may be due to the different age groups considered given that age may play a vital role in the relationship between obesity and marital status [84]. Thus, in the development of strategies to deal with the obesity epidemic, it is important to be aware that factors determining obesity may depend on age and different BMI trajectories.

Our results suggest that there is an increased risk of developing obesity-related conditions among those with consistently high BMI status in middle-aged and older adults. We found that people in the higher trajectory groups (i.e., OV-S, OB I-S, and OB II-S) were more likely to have asthma, arthritis, hypertension, diabetes, heart disease, cognitive problems, and reduced self-rated health compared to their normal weight counterparts. However, only subjects in the highest group (OB II-S) were more likely to have back problems, chronic bronchitis or emphysema, and emotional problems. These findings are in agreement with previous evidence that for many, people being on a higher/steeper BMI trajectory were at a greater risk of developing adverse health outcomes [14, 15, 17]. For example, Ostbye *et al* found that higher BMI trajectory groups had higher prevalence of health problems, including hypertension, diabetes, heart problems, arthritis, joint pains, asthma, back problems, and reduced self-rated health [14]. Finkelstein *et al*. also reported that obesity-related health conditions were more prevalent in trajectories representing high body mass [15]. Along the same line, the prevalence of cognitive impairment, hypertension, and diabetes varied with the different obesity trajectories in [17]. Clarke *et al*. additionally demonstrated that respondents who remained overweight over time were at greater risk of being diagnosed with any chronic health conditions (hypertension, diabetes, asthma, chronic lung disease, heart disease, and cancer) [36]. Moreover, our results generally conform to long-standing findings from other studies regarding the health risks of excess weight. For instance, a systematic review showed that obesity was associated with developing asthma or worsening the symptoms of asthma [157]. Crowson CS *et al.* likewise concluded that obesity increased the odds of developing arthritis [88], whereas both of Rodriguez LA *et al.* and Cerhan JR *et al.* did not find this association based on case control and cohort studies, respectively [158, 159]. These findings may be results of the different methods used and that the majority of previous studies did not consider the heterogeneity in BMI trajectories.

In addition, we found that people in the two obese trajectories (OB I-S and OB II-S) were more likely to have back problems, but this was not the case for people in the OV-S group. Accordingly, the interventions for losing weight to prevent back pain may need to target obese rather than overweight individuals. Moreover, people in the higher BMI trajectory groups (OV-S, OB I-S, and OB II-S) had substantially higher odds of developing diabetes in our analyses. This evidence is in keeping with the previous findings that being overweight, even moderately, was an independent risk factor for developing numerous chronic diseases, specifically for diabetes [21]. Therefore, we suggest that weight management for diabetes prevention should target obese subjects as well as overweight individuals. An awareness of different BMI trajectories is important to identify people who are at the highest risks of diseases due to obesity in order to intervene appropriately to reduce morbidity.

The thesis has several limitations. Findings in the current study may underestimate the association of excess weight with selected disease for not including the BMI changes before the age of 40. For example, there is evidence that adolescent BMI may be a more important predictor of heart disease rather than adulthood BMI [21]. In addition, we did not adjust other confounders in assessing the associations between selected health conditions and BMI trajectory groups, thus further research is needed.

Chapter 5

BMI trajectories of elderly (65-79 years) and mortality

5.1 Introduction

The Canadian population is aging and the prevalence of obesity is progressively rising among the elderly [160]. Obesity-related medical care costs among the growing elderly population are substantial [161]. Although there is clear evidence that excess weight is associated with an increased risk of all-cause mortality in young to middle-aged adults [21, 107], it may not be the case for seniors.

Previous studies presented conflicting evidence on the association between BMI and mortality in the elderly population. Some studies reported J- or U-shaped association between mortality and BMI [22, 23], while others reported a positive linear relationship between BMI and mortality [107, 108].These findings are likely a result of limited BMI measurements that were used in the majority of these studies [110-112, 114]. Consequently, these studies failed to detect the development of BMI over time and the impact of BMI changes on survival time. Moreover, it is documented that BMI changes, rather than static BMI status, is more predictive on mortality risk [7, 162, 163].

Trajectory analyses using LCGM can better capture BMI changes over time. One of the most important purposes of identifying distinct BMI trajectories is to test if such trajectories carry differential mortality potentials [5]. Only one study has examined both the heterogeneity in BMI trajectories and the mortality risk of BMI trajectories based on LCGM [7]. Zheng *et al.* reported that people in the overweight stable group had a higher survival rate than normal weight and obese trajectory groups [7]; however, the study by Zheng *et al.* was for the US population and the covariates they adjusted in survival analysis were all obtained from the baseline interview. Further, former research has reported that there was a gender difference in mortality and the development of BMI trajectory [5]. For example, compared to women, men had a higher mortality risk in late years; in addition, men had higher odds of being in obese trajectories [5, 14]. Therefore, we aim to identify BMI trajectories in subjects of 65-79 years at baseline and examine the mortality consequences of BMI trajectories for men and women separately for the Canadian population.

5.2 Methods

The final sample was limited to 1,480 individuals, aged 65-79 years at baseline (1994/95) and having at least four BMI records in the NPHS. Based on this sample, ALD allowed us to analyze the pattern of BMI changes over a period of 32 years (65-96 years). We selected respondents aged 65-79 years in 1994/95 in order to represent Canadian seniors, to ensure an adequate number of individuals in each BMI category, and to ensure a sufficient number of events in survival analysis.

Similar to section 3.2.3, age was used to define the time variable and BMI was used as the trajectory variable. The NPHS defined two variables recording year and month of death (YOD and MOD) for respondents who were deceased. For respondents who died during the follow-up period (1994-2011), the duration of survival was defined as the number of months from the month of the first interview until the month of death. For people who completed the cycle 9 interview (or who were known to be alive), the survival time was censored. Survival time was defined as the number of months elapsed between the first (cycle 1) and last (cycle 9) interviews.

The selection of covariates for the proportional hazards models were based on the literature review, as well as on the available information from the NPHS. Previous studies found that the association between BMI (BMI change) and mortality risk may differ by age [164], gender [165, 166], race [165], SES (e.g., education and income) [165, 166], marital status [7], lifestyle factors (physical activity, smoking, and drinking) [167], the number of chronic conditions [5, 168], and disability [165]. The following covariates obtained from the baseline were analyzed in the survival analysis: age, race (white/non-white), education level (if graduated from high school), place of residence (rural/urban), and disability (yes/no).

We used the nominal BMI trajectory groups (no covariates model) as a latent variable in order to investigate the long term impact of BMI change on survival time. Each individual was specified to the most probable BMI trajectory that he/she belonged to.

Additionally, we defined six other latent variables using LCGM in order to investigate the long term impact of PA, smoking, drinking, low-income, marital status, and the number of chronic conditions on survival time. As shown in Table 5.1, we defined the probability of being a smoker, a regular drinker, low-income, physically active, and married. Detailed model results on these latent variables based on LCGM can be found in Appendix A5-1-A5-5. For illustration, we defined a latent variable using

LCGM to capture the change and level of physical active between ages 65-96. As mentioned in section 3.2.3, we assigned a value of 1 if the respondents were physically active or moderately active, and 0 otherwise. The data was then rearranged based on ALD, in order to model the probability of being physically active between ages 65-96. LCGM was used to identify if there were different trajectories for the probability of being physically active over time in the population [12]. After capturing different PA trajectories, each individual was assigned to their most likely PA trajectory (either low-decrease PA trajectory or high-decrease PA trajectory in our data; table 5.1, Appendix A5-1). This approach was used to define the four other latent variables, including the probability of being a smoker, a regular drinker, low-income status, and married.

We identified a two-trajectory model for the probability of being physically active (the low-decrease and high-decrease groups), smoking (low-stable and high-decrease), drinking (low-decrease and high-decrease), married (low-decrease and high-decrease), and low-income status (high-stable and low-stable). The average probability of being physically active at the age 80 was 0.1 and 0.7 for people in the low-decrease PA group and the high-decrease PA group, respectively. The average probability of smoking at the age of 80 was less than 0.01 and around 0.7 for people in the low-stable smoking group and in the high-decrease smoking group, respectively. The average probability of drinking regularly at the age of 80 was 0.05 and 0.8 for people in the low-decrease drinking group and in the high-decrease drinking group, respectively. The average probability of being married at the age of 80 was 0.01and around 0.9 for people in the low-decrease of being married group and in the high-decrease of being married group, respectively. The average probability of living in low-income at the age of 80 was 0.2 and

0.9 for people in the high-stable income group and in the low-stable income group, respectively. Further, the NPHS derived a variable on the number of chronic conditions based on the counts of chronic conditions self-reported by the respondents. Similarly, LCGM was used to identify different patterns for the development of the number of chronic conditions [12]. Two trajectories for the development of the number of chronic conditions were identified: less than 3 chronic conditions group and more than 3 chronic conditions group. The average number of chronic conditions at the age of 80 was 2 and 5 for people in the trajectory with less than 3 chronic conditions and with more than 3 chronic conditions, respectively. Therefore, this study incorporates all available information reported in the 1994-2011 interviews, making most use of the longitudinal data.

Table 5.1 **Latent variable description based on LCGM from the NPHS (1994-2011) for seniors through age 65-96 years.**

Variable name	Label	Identified[1] Trajectories	Average Pro[2] at 80 years old	Name in NPHS[3]
Physical activity				
Inactivity Activity	The probability of being physical active	Low-decease High-decease	0.1 0.7	PACnDPAI
Smoking				
Non-smoker smoker	The probability of being a smoker	Low-stable High-decease	<0.01 0.7	SMCnDTYP
Alcohol usage				
Non-drinker Regular drinker	The probability of being drinking regularly	Low-decease High-decease	0.05 0.8	ALCnDTYP
Marital status				
Non-Married Married	The probability of being married	Low-decease high-decease	<0.01 0.9	DHCn_MAR
Low-income				
High-stable Low-decrease	The probability of being poor	High-stable Low-stable	0.2 0.9	INCnDIA4
The number of chronic conditions				
Less than 3 More than 3	Different patterns of the changes of the number of chronic conditions	Less than 3 More than 3	2 5	CCCnDNUM

[1] The trajectories of these patterns were all fitted by two-group model based on LCGM.
[2] The average probability of being physically active, a smoker, a regular drinker, in low-income, and married at 80 years old or the mean of the number of chronic conditions at 80 years old
[3] Cycle 1,2,3,4,5,6,7,8,9 was denoted by n =4,6,8,0,2,A,B,C,D in the NPHS.

Within BMI trajectory analyses, the basic model selection followed the same procedure as that for section 3.2.4. After identifying the development of BMI trajectories, cox proportional hazards models were used to estimate hazard ratios (HRs) for mortality in different BMI trajectory groups while adjusting for potential confounders.

In our study, the impact of BMI trajectory groups on survival time was considered as the main effect. Three models were fitted in our analyses: unadjusted model (only included main effect), partly adjusted model (adjusted for socio-demographic characteristics including age at baseline, race, and educational level), and fully adjusted model (further adjusted for disability, place of residence, as well as the six latent variables of PA, smoking, drinking, low-income, marital status, and the number of chronic conditions). Stepwise selection within cox proportional hazards models were used to select covariates in the fully adjusted model, and the main effect and socio-demographic characteristics remained in the model regardless of their significance. Moreover, we tested any potentially meaningful interactions for each pair of variables among the covariates (i.e., age and the other covariates; BMI trajectory groups and the rest of covariates), and retained significant terms in the model ($p < 0.05$). Previous research has demonstrated that there was a gender difference in mortality and BMI trajectories [5, 14]; therefore, all analyses in this study were stratified by sex. The sampling weights suggested by Statistics Canada were used in cox proportional hazards models. In addition, we also checked the functional form for continuous covariates (age at baseline) and examined proportional hazards assumption for each variable in the final model.

5.3 Results

Four distinct BMI trajectories were identified in the elderly population by sex: a Normal weight-Down (N-D), an Overweight-Down (OV-D), an Obese I-Down (OB I-D), and an Obese II-Down (OB II-D) for women; and a Normal weight-Downward (N-D), an Overweight-Downward (OV-D), an Overweight-Stable (OV-S), and an Obesity-Stable (OB-S) for men. We found that men in the OV-D group had the lowest mortality risk followed by men in the N-D, and OB-S groups and the results persisted after controlling for confounding factors; however, no corresponding association was revealed among women.

5.3.1 Baseline Characteristics

Of the 1480 individuals (aged 65-79) included in this study, 62.2% were women and 37.8% were men. They were predominantly white (95.7%), and 49.3% of the individuals had graduated from high school by 1994/95 (Table 5.2). From 1994 to 2011, the prevalence of overweight ($25 \leq BMI < 30$ kg/m^2), obese ($BMI \geq 30$ kg/m^2) slightly decreased from 43.6% to 37.2%, and 14.6% to 9.3%, respectively. On the other hand, the weighted percent of underweight ($BMI < 18.5$ kg/m^2) and normal weight ($18.5 \leq BMI < 25$ kg/m^2) increased from 1.7 to 4.5% and 40.1 to 50.0%, respectively. Additionally, 79.3% of respondents reported having more than one chronic condition; 22.7% of respondents having long-term disabilities; and 46.5% of participants reporting a very good or excellent health status. Further, during 18 years of follow-up, 54.1% of the 560 men and 36.9% of the 920 women died.

Table 5.2 Characteristics of subjects aged 65-79 at baseline from the NPHS (1994/95)

Characteristics	Sample size (n=1480) No. (%)
Sex	
Males	560 (37.8)
Females	920 (62.2)
Race	
White	1416 (95.7)
Other races	64 (4.3)
High school graduate	
Yes	730 (49.3)
No	750 (50.7)
BMI	
Underweight	25 (1.7)
Normal	593 (40.1)
Overweight	645 (43.6)
Obese class-I	176 (11.9)
Obese class-II	33 (2.2)
Obese class-III	8 (0.5)
Has at least one chronic condition	
Yes	1174 (79.3)
No	306 (20.7)
Disability	
Yes	336 (22.7)
No	1144 (77.3)
Health description index	
Poor	44 (3.0)
Fair	223 (15.1)
Good	524 (35.4)
Very good	460 (31.1)
Excellent	228 (15.4)

5.3.2 BMI Trajectories

We identified four trajectory groups for both sexes in a nationally representative sample of those aged 65-79 at baseline. The trajectory groups were a N-D, an OV-D, an OB I-D, and an OB II-D for women (Figure 5.1); and a N-D, an OV-D, an OV-S, and an OB-S for men (Figure 5.2). Our analyses revealed that BMI trajectories differ by sex in terms of the shapes and percentages of each trajectory group. The average posterior probability value of each group in the four-group models exceeded 0.90 in both women and men.

The GMP of the N-D group (marked by number “1” in Figure 5.1 and 5.2) is 31.6% in women and 14.0% in men. For women, the N-D group starts with a normal weight status at the age of 65 (average BMI = 22.2) and slowly declines to a BMI of 19.7 at age 96 (Figure 5.1). For men, the N-D group starts with a normal weight status at age 65 (average BMI = 21.7) and slowly declines to a BMI of 16.2 at the age of 96 (Figure 5.2). It is likely that for the N-D group in men, few people were still alive or reported BMI after 90 years of age. In addition, most members classified in this group remained under/normal weight between ages 65-96 for both women and men.

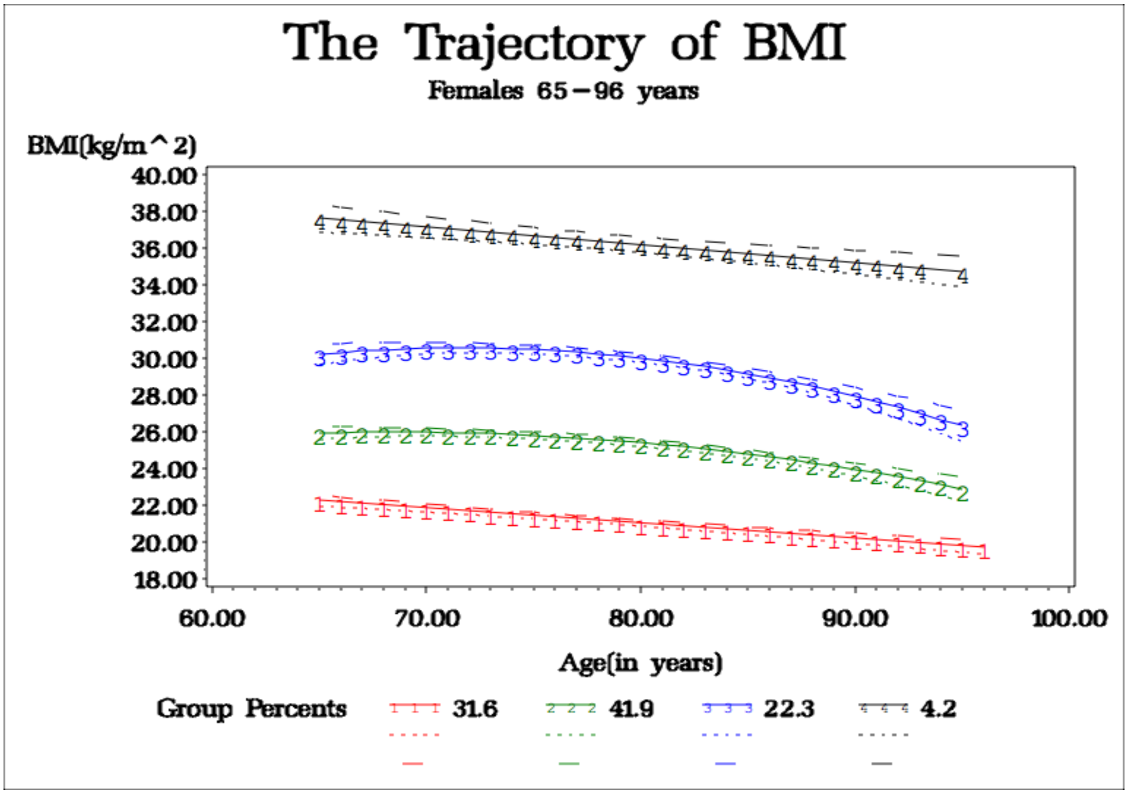

Figure 5.1 BMI trajectories for females (65-79 years), with 95% confidence intervals (four group model, no covariates included), NPHS, 1994-2011.

Table 5.3 The parameters estimated for BMI trajectories for females (65-79 years), NPHS (1994-2011).

The Trajectory of BMI	Intercept-BMI at age 65 (s.e)	Linear term (s.e)	Quadratic term (s.e)	GMP (%)	AvePP
N-D	22.24(0.76)	-0.08(0.01)	-	31.6	0.96
OV-D	25.91(6.69)	0.61(0.17)	-0.004(0.001)	41.9	0.95
OB I-D	30.21(9.29)	1.11(0.24)	-0.008(0.002)	22.3	0.96
OB II-D	37.61(1.85)	-0.10(0.02)	-	4.2	0.97

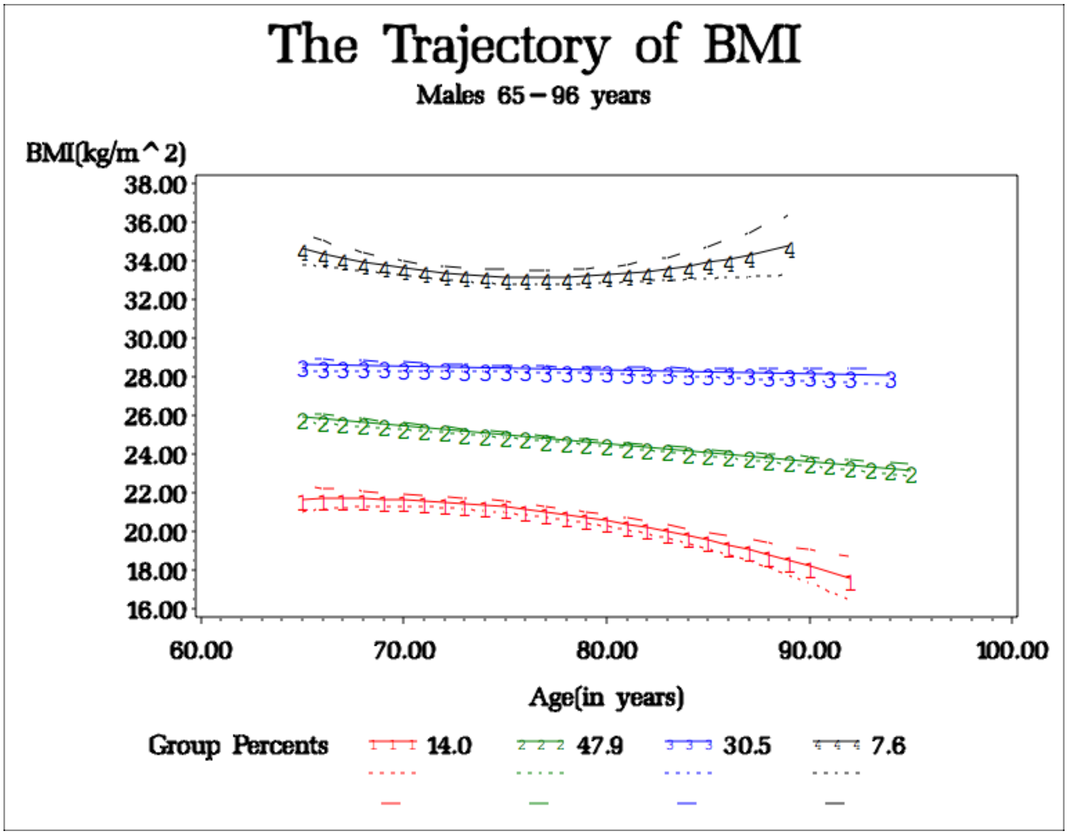

Figure 5.2 BMI trajectories for males (65-79 years), with 95% confidence intervals (four group model, no covariates included), NPHS, 1994-2011.

Table 5.4 The parameters estimated for BMI trajectories for males (65-79 years), NPHS (1994-2011).

The Trajectory of BMI	Intercept-BMI at age 65 (s.e)	Linear term (s.e)	Quadratic term (s.e)	Group membership probability	AvePP
N-D	21.66(14.20)	0.87(0.37)	-0.006(0.002)	14.0	0.94
OV-D	25.89(0.65)	-0.09(0.01)	-	47.9	0.96
OV-S	28.61(0.92)	-0.02(0.01)	-	30.5	0.96
OB-S	34.59(23.43)	-1.67(0.63)	0.011(0.004)	7.6	0.97

The OV-D group (GMP: 41.9% in women in Figure 5.1, 47.9% in men in Figure 5.2, and both marked by number "2 "), starts with an overweight status at age 65 (average BMI = 25.89 in men, BMI = 25.91 in women), gradually decreases to a normal weight around 70-80, and then continues to decrease with increasing age without reaching the underweight range in both sexes (average BMI = 23.07, 22.63 at age 96 for men and women respectively). In this group, more than 80% of women and more than 60% of men were overweight at 65 years of age, and most members (>50%) classified in this group became normal weight after 80 for both women and men. Additionally, the proportion of obese subjects in this group was negligible in both women and men.

The GMP of OB I-D group is 22.3% of women (Figure 5.1, marked by number "3") and the GMP of OV-S group is 30.4% of men (Figure 5.2, marked by number "3"). The OB I-D group starts with an obese class I status at age 65 (BMI = 30.2), and slowly declines to an average BMI of 25.94 at 96. Within the OB I-D group, around 65% or more of women were obese (BMI >30) at the age of 65; the proportion of obese individuals in this group was decreasing between ages 65-96. The OV-S group of men begins with an overweight status at age 65 (average BMI = 25.89) and slightly declines to an average BMI of 27.98 at 96. In OV-S, 80% or more of men were overweight through ages 65-96 and there was a gradual decrease in the proportion of obese subjects over time.

The GMP of OB II-D group is 4.2% of women (Figure 5.1, marked by number "4") and the GMP of OB-S group is 7.6% of men (Figure 5.2, marked by number "4"). For females, the OB II-D group starts with an obese class II status at age 65 (average BMI = 37.61), and slowly decreases to a BMI of 34.6 at 96 (Figure 5.1). For males, the OB-S group starts with an obese class I status at the age of 65 (BMI = 34.59), and remains in the obese class I status until the age of 90 (Figure 5.2). It seems that for the OB-S group, few men were still alive or reported BMI after the age of 90. The proportion of obese subjects was greater than 90% for each age between 65-96 in both women (OB II-D) and men (OB-S).

5.3.3 Mortality risk

Table 5.5 and 5.6 show the results about the impact of BMI trajectories on mortality from the unadjusted, partly adjusted, and fully adjusted models for men and women. Among men, there were 50.4%, 69.7%, 48.9%, and 69.2% of respondents who died in the OV-D, N-D, OV-S, and OB-S groups, respectively (Table 5.5). Among elderly women, there were 32.9%, 39.8%, 40.2%, and 36.7% of respondents who died in the OV-D, N-D, OB I-D, and OB II-D groups, respectively (Table 5.6). The largest group (OV-D) was used as the reference group for both men and women. Appendix A5-7 to A5-12 includes the estimated coefficients of all covariates in the three models for women and men.

Table 5.5 Adjusted Hazard Ratios of BMI Trajectories among men From Cox Proportional Hazard Models in the NPHS,1994-2011

	Men						
	Unadjusted model			**Adjusted for Demographics Factors [a]**		**Fully Adjusted Model[b]**	
	N(%) death	HR(95%CI)	P-value	HR(95%CI)	P-value	HR(95%CI)	P-value
BMI Traj							
OV-D	268(50.4)	1.00 (referent)		1.00 (referent)		1.00 (referent)	
N-D	78(69.7)	1.86(1.36-2.54)	<.0001	1.94(1.41-2.65)	<.0001	1.66(1.20-2.29)	0.003
OV-S	171(48.9)	1.13(0.84-1.51)	0.41	1.19(0.88-1.60)	0.25	1.25(0.92-1.67)	0.15
OB-S	43(69.2)	1.97(1.26-3.07)	0.003	2.01(1.28-3.14)	0.002	1.98(1.28-3.16)	0.003

Abbreviations: BMI, body mass index; CI, confidence interval; HR, hazard ratio.

[a] Adjusted for age at baseline, race/ethnicity, education.

[b] Adjusted for age at baseline, race/ethnicity, education, place of residence, disability, the probability of being physically active, smoking, and drinking, as well as the change patterns of the number of chronic conditions.

Table 5.6 Adjusted Hazard Ratios of BMI Trajectories among women From Cox Proportional Hazard Models in the NPHS,1994-2011

	Women							
	Unadjusted model			**Adjusted demographics factors**		**Fully Adjusted Model**	
						>3 conditions	**<3 conditions**
	N(%) death	HR(95%CI)	P-value	HR(95%CI)	P-value	HR(95%CI)	HR(95%CI)
BMI Traj							
OV-D	385(32.9)	1.00 (ref.)		1.00(ref.)		1.00(ref.)	1.00(ref.)
N-D	291(39.8)	1.32(1.03-1.69)	0.03	1.31(1.02-1.69)	0.04	1.23 (0.86-1.77)	1.21 (0.84-1.74)
OB I-D	205(40.2)	1.25(0.94-1.65)	0.12	1.09(0.82-1.45)	0.54	1.61 (1.12-2.31)	0.56 (0.35-0.90)
OB II-D	39(36.7)	1.05(0.55-1.98)	0.89	0.89(0.47-1.68)	0.71	0.71 (0.30-1.67)	1.34 (0.50-3.58)

Abbreviations: BMI, body mass index; CI, confidence interval; HR, hazard ratio.
[c]Adjusted for age at baseline, race/ethnicity, education.
[d] Fully adjusted for age at baseline, race/ethnicity, education, place of residence, disability, the probability of being physically active, smoking, and drinking, as well as the change patterns of the number of chronic conditions.
, and two interactions (the interaction between the BMI trajectory and the developmental of the number of chronic conditions trajectory and the interaction between age at baseline and the probability of being physically active trajectory)

In men, relative to the OV-D group, the N-D and OB-S groups were associated with an excess risk of death. As shown in Table 5.5, the N-D group was significantly associated with an 86% ($P < 0.001$) increase in mortality risk in the unadjusted model. The OB-S group was associated with an excess risk of 97% ($P < 0.05$). Adjustment for age, race, and education level had only a minor effect on the HRs for the association between the BMI trajectory and mortality. Specifically, the excess mortality risks associated with the N-D and OB-S groups slightly increased to 94% ($P <0.001$) and 101% ($P <0.05$), respectively. For the fully adjusted male model, no significant interactions were found, and the covariates retained in the final model included the baseline characteristics of age, race, education, place of residence, and disability, and latent variables of being physically active, smoking, and drinking, as well as the trajectories of the number of chronic conditions. After the adjustment for the above covariates, the excess mortality risks associated with the N-D and OB-S groups was 66% ($P =0.003$) and 98% ($P =0.003$), respectively. The OV-S group was not significantly associated with an excess risk in all of the three models.

In women, only the N-D group was associated with a 32% ($P = 0.03$) increase in mortality risk as opposed to the OV-D group without controlling for other covariates (Table 5.6). After adjusting for age, race and educational attainment, only the N-D group was significantly associated with an excess risk of 31% ($P =0.037$). The other two groups (OB I-D and OB II-D) were not significantly associated with a greater risk of death in the both of the unadjusted and partly adjusted models. For the fully adjusted female model, there were two significant interactions were found, including the interaction between BMI trajectory and the developmental of the number of chronic conditions trajectory ($P=0.001$), and the interaction between age at baseline and a latent variable of being physically active (P=0.001) (seen Appendix A5-8). Covariates retained in the final model in women included the baseline characteristics of age, race, education, place of residence, and disability, and the latent variables of being physically active, smoking, and drinking. The final model also included the trajectories of the number of chronic conditions, and the two interaction terms mentioned above. Following the adjustment for these covariates, only the OB I-D group was significantly associated with a 61% ($P < 0.001$) increase in mortality risk among women who were assigned to the trajectory characterized with more than three chronic conditions. By contrast, the OB I-D group was associated with a 44% ($P < 0.001$) decrease in mortality risk among women who were assigned to the trajectory with less than three chronic conditions. Additionally, the proportional hazard assumption was examined and no significant violation of the assumption was found. Appendix A5-11 and A5-12 includes results on the model adequacy test: a functional form test and proportional hazard assumption tests.

5.4 Discussion

This research identified four distinct BMI trajectory groups for both women (N-D, OV-D, OB I-D, and OB II-D) and men (N-D, OV-D, OV-S, and OB-D) in seniors. We observed that BMI trajectories gradually decreased between ages 65-96 and this is in agreement with previous findings. For instance, Kuchibhatla and colleagues identified three downward trajectories (normal weight, overweight, and obese) for seniors aged 65–105 from a community sample [17]. Zheng *et al.* on the other hand found one decreasing BMI trajectory and five increasing trajectories between ages 51-77 [7]. The different findings may be a result of discrepancies in the age groups considered in those studies. Moreover, previous cross-sectional and short-term longitudinal studies reported that body weight increased up to the age of 70, after which it stabilized or decreased [33, 169].

In this population-based study of elderly men and women, we found that men in the OV-D group had the lowest mortality risk followed by men in the N-D and OB-S groups, and the results persisted after adjusting for confounding factors. On the other hand, no such association was observed among women. The different findings between men and women support the gender-related disparities in mortality in old age noted in previous research [163].

We found that men who were overweight at age 65 years, then lost weight over time, but never reached underweight status through age 65-96 years had the lowest mortality risk. Men who were obese at age 65 years and remained obese through age 96 years had the highest mortality risk. This finding is in agreement with the study of Zheng *et al*, which found that people in the overweight stable group had a lower mortality risk followed by those in the overweight obesity, normal weight upward, class I obese upward, normal weight downward, and class II/III obese upward trajectories [7]. Our findings indicate that the differences between the

OV-S and OV-D trajectory groups were not statistically significant in men in our data. This finding suggests that being in overweight through age 65-96 years without reducing weight may be unrelated to lowering the probability of survival in older men compared with men in the OV-D group. Zheng *et al* also concluded that there were no significant differences between overweight stable and overweight obese trajectories [7]. Additionally, previous studies found that being overweight was not associated with increasing mortality risks [7, 114, 170]. Our data also supports the previous findings that although being overweight was associated with increased risk of developing adverse health conditions, it was not associated with excess mortality risk [171]. Overall, the results among men support the well-documented U-shaped association between BMI and mortality [7, 114, 167].

Among women, the mortality risk of the OB I-D group varied with different the number of chronic conditions trajectory groups. For women with more than three chronic conditions, only the OB I-D group was associated with increased mortality risk; by contrast, for women with less than three chronic conditions, the OB I-D group was associated with decreased mortality risk as opposed to OV-D group in our results. Our findings suggest that the association between BMI trajectory and mortality differ between healthier people with less than three chronic conditions and their counterparts (individuals with more than three chronic conditions).

One of the most important strengths of our study is that we incorporated latent class variables in survival analysis, which reflect the accumulation and incremental impact of lifestyles (e.g., the probability of being physically active, smoking, and drinking) and health status (the change of the number of chronic conditions) on mortality risk. For instance, we defined a latent variable using LCGM to capture the change of the probability of being physically active through age 65-96 years. On the contrary, the majority of studies only used the baseline interview measurement to determine if a respondent was physically active or not [7]. On the other hand, since our study population is elderly, data may unavoidably suffer from selection bias. People at baseline in our sample could be healthier than average since they had a life span of 65-79 years, whereas those most vulnerable to the impact of excess weight may have already died by the age of 65. Also, weight loss was observed in the current study, but information is not available to differentiate between intentional and unintentional weight losses from the NPHS. In summary, our findings give new insights to the debate on the association between BMI and mortality risk in seniors.

Chapter 6 Summary

This study shows that there are heterogeneities in BMI trajectories in young to middle-aged adults, middle-aged to older adults, and seniors. The change patterns of BMI trajectory are different for different age groups: rising (20-39 at baseline), stable (40-55 at baseline), and falling (65-79 at baseline).

For the young to middle-aged group, four increasing BMI trajectory groups, N-S, N-OV, OV-OB, and OB-UP were identified for both men and women. All the trajectories in men show significant curvature in terms of quadratic term but the curvature was only observed in the OB-UP trajectory group in women. Aboriginal women were found to have higher odds of being in the N-OV, OV-OB, and OB-UP groups, relative to N-S. Increased years of smoking, drinking, and being physically active were associated with lowering the trajectory in all groups for both women and men, with some exceptions in N-S for men. In addition, increased years in low-income, employment, and rural living were associated with raising the trajectory in each group for women and in some groups for men. On the other hand, younger cohorts were found to be associated with raising the trajectory in each group for men rather for women. Further, food insecurity was associated with raising the trajectory in each group in both women and men. In summary, gender difference in the associated factors of obesity development was observed while food insecurity and decreased years of smoking were significantly associated with raising the BMI trajectories in both women and men.

For the middle-aged to older adults, four BMI trajectory groups, N-S, OV-S, OB I-S, and OB II-S were identified. This study found that there were slight BMI increases over time for adults aged 40 to 70 years. Individuals who were male, white, or who had no post-secondary education had higher odds of being in the OV-S, OB I-S, and OB II-S groups, compared with the N-S group. Increased years of being physically active lowered the trajectory within each group. Additionally, our results imply that the impacts of smoking, drinking, retirement, and marital status on body weight may vary with different BMI trajectory groups. For instance, increased years of smoking was associated with lowering the trajectory in the N-S, N-OV, and OV-OB groups, and raising the trajectory in OB II-S over midlife. Increased years of regular drinking was associated with lowering the trajectory in the obese groups (OB I-S and OB II-S), but raising the trajectory in N-S and OV-S. Increased years of retirement was associated with raising the trajectory in OB I-S and OB II-S. Further, increased years married was associated with lowering the trajectory only in OB I-S. Thus, in the development of strategies to deal with the obesity epidemic, it is important to be aware that factors determining obesity may depend on age and different BMI trajectories.

Despite the moderate BMI change for the middle-aged to older adults, people who were continually severely obese in their midlife were at a greater risk of developing numerous chronic diseases, cognitive and emotional problems, and reduced self-reported health compared with the normal weight counterparts. Specifically, members of the higher trajectories (OV-S, OB I-S, and OB II-S) were more likely to have asthma, arthritis, hypertension, diabetes, heart disease, cognitive problems, and reduced self-rated health. In comparison, only subjects in the highest group (OB II-S) were more likely to develop back problems, chronic bronchitis or emphysema, and emotional problems as opposed to N-S. In brief, our research revealed that people who were continually severely obese in their midlife were at greater risk of developing numerous adverse health conditions compared with the normal weight counterparts.

For seniors, four latent BMI trajectories were identified by sex: N-D, OV-D, OB I-D, and OB II-D for women; and N-D, OV-D, OV-S, and OB-S for men. This study reveals that BMI trajectories gradually decreased in the elderly population. In addition, we found that men who were overweight at age 65 years, then lost weight over time, but never reached underweight status through age 65-96 years had the lowest mortality risk. Men who were obese at 65 years of age and remained obese through age 96 years had the highest mortality risk. Among women, the mortality risk of the OB I-D group varied with different the number of chronic conditions trajectory groups. Specifically, women with more than three chronic conditions, the OB I-D group was associated with increased mortality risk; by contrast, for women with less than three chronic conditions, the OB I-D group was associated with decreased mortality risk as opposed to the OV-D group. Our findings give new insights to the debate on the association between BMI and mortality risk in seniors.

One important strongpoint of the current research is that we used LCGM to detect the heterogeneity in BMI change patterns. In addition, we are using a population-representative sample, which allows the findings of our study to be generalizable to young to middle-aged, middle-aged to older adults, and seniors in Canada. Also this study incorporated all available information reported in 1994-2011 interviews, making most use of the longitudinal data. On the other hand, this study is unavoidably influenced by self-reported data, which may lead to underestimate the BMI level and the group membership in the higher BMI trajectories. However, it may not bias our results, since most of our results present relative risks. Another limitation is that BMI can be an unreliable tool as a measure of a person's health or as an indication of what is considered a healthy body weight. BMI does not take into account muscle mass or fat mass, body shape or body type, age, gender, and ethnicity/race. All of these factors affect body weight;

therefore a high BMI is not necessarily indicative of excess body fat. A more accurate measure of excess body fat, and therefore a healthy weight, would be body fat percentage measured using skin fold calipers, however, no longitudinal data of measured body fat could be found. This may be an interesting area for future research.

In summary, this study contributes to a better understanding of the risk factors, health outcomes, and mortality risks associated with BMI change patterns in young to middle-aged, middle-aged to older adults, and seniors. Understanding different BMI trajectories is important to identify people who are at the highest risk for selected diseases and all cause of death due to obesity in order to intervene appropriately to reduce morbidity and mortality. Awareness of different BMI trajectories may allow clinicians and policy professionals to tailor programs to specific groups, who are at risk for poorer health outcomes due to obesity, and to intervene at an early stage to alter the path of risky trajectories.

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Appendix

Appendix A3-1

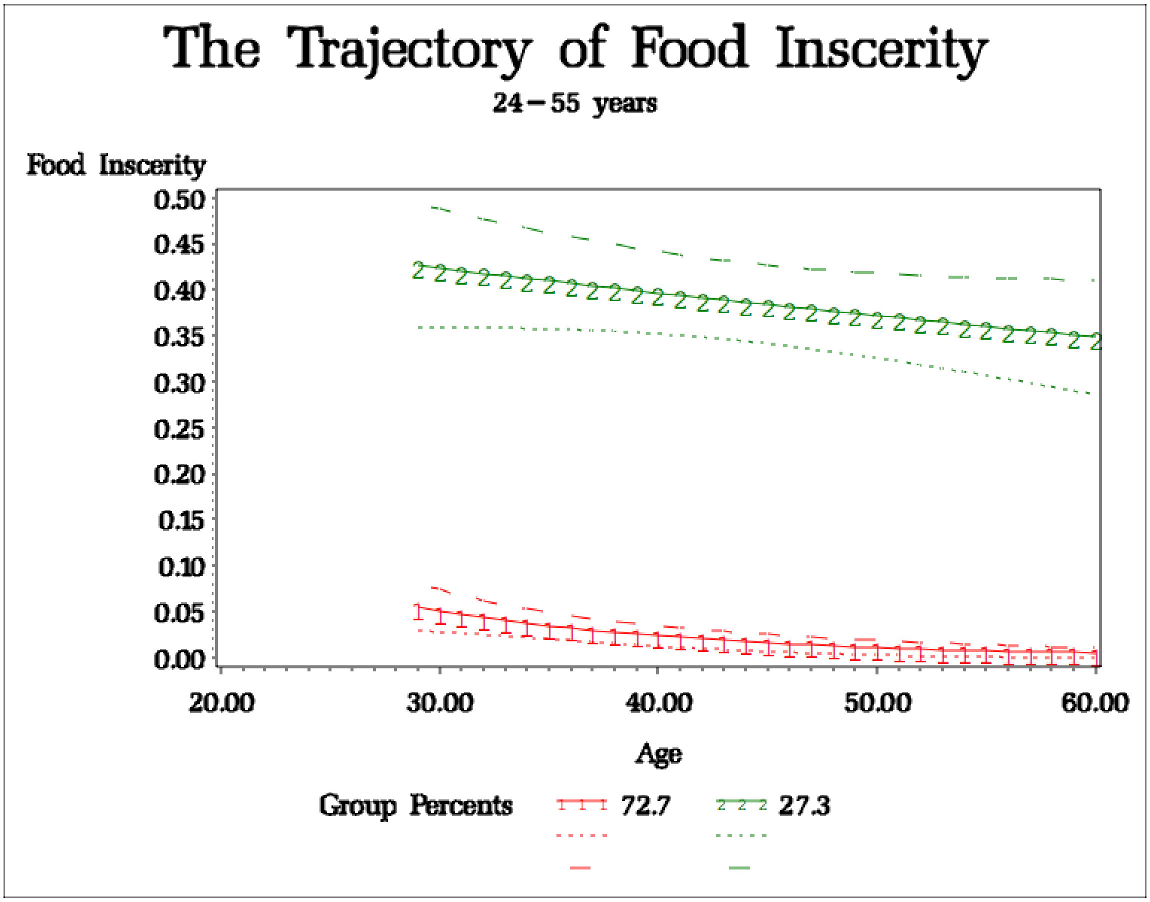


Figure A3-1 the trajectories of food insecure probability for aged 20-39 at baseline, with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of food insecure probability	Intercept (s.e)	Linear term (s.e)	Group membership probability
Food secure	-0.67 (0.72)	-0.08(0.02)	72.7%
Food insecure	--0.67(0.19)	-0.006(0.004)	27.3%

Appendix A4-1

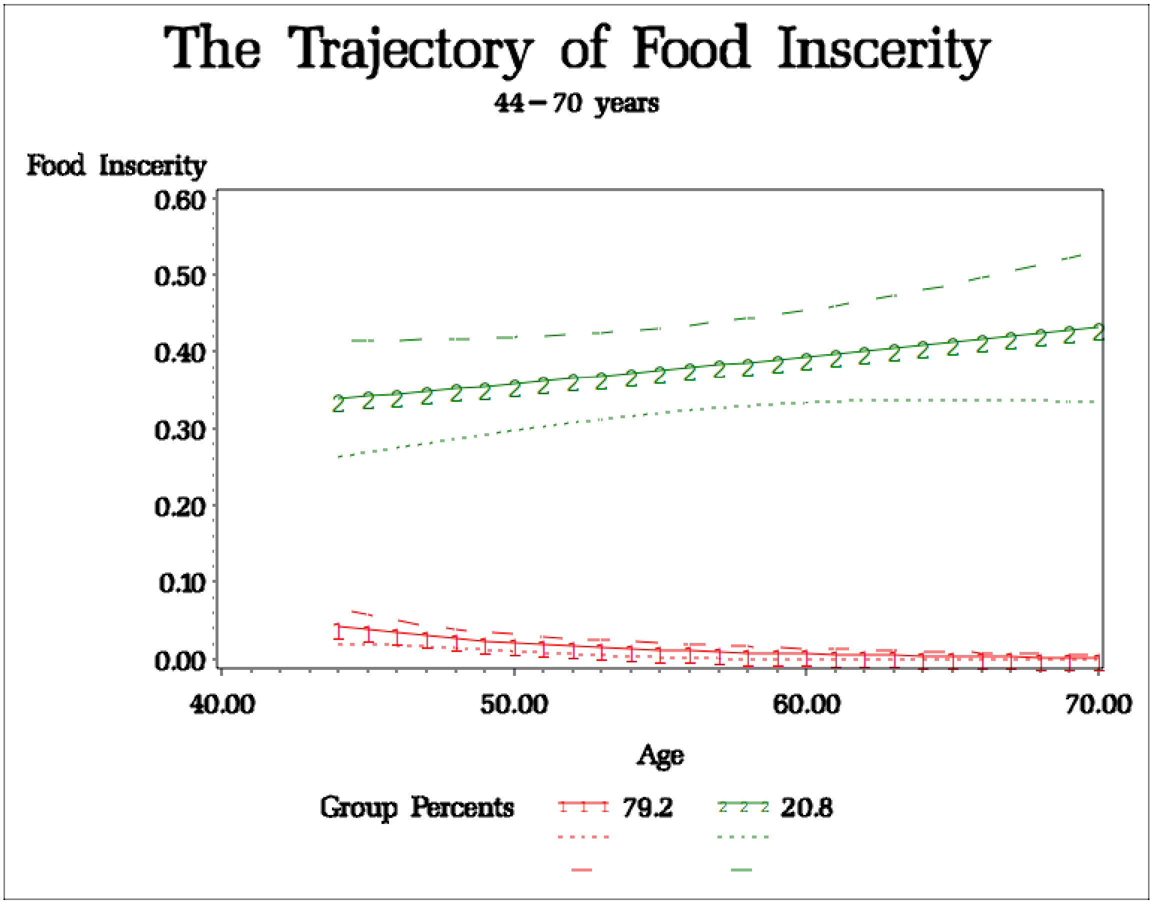


Figure A4-1 the trajectories of food insecure probability for aged 40-55 at baseline, with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of food insecure probability	Intercept (s.e)	Linear term (s.e)	Group membership probability
Food secure	2.05(2.03)	-0.12(0.04)	79.2%
Food insecure	-1.50(0.39)	0.01(0.007)	20.8%

Appendix A4-2

Health outcome	Questions asked in the NPHS	Names in the NPHS*
Food allergies	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Food allergies	CCCn_1A
Allergies (other than food allergies)	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Other allergies	CCCn_1B
Asthma	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Asthma	CCCn_1C
Has arthritis or rheumatism (excluding fibromyalgia)	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Arthritis or rheumatism	CCCn_1D
Back problems (excluding fibromyalgia and arthritis)	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Back problems, excluding arthritis	CCCn_1E
High blood pressure	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - High blood pressure	CCCn_1F
Migraine headaches	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Migraine headaches	CCCn_1G
Chronic bronchitis or emphysema	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Chronic bronchitis or emphysema	CCCn_1H
Diabetes	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Diabetes	CCCn_1J
Heart disease	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Heart disease	CCCn_1L
Cancer	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Cancer	CCCn_1M
Urinary incontinence	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Urinary incontinence	CCCn_1P

Cataracts	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Cataracts	CCCn_1S
Other long-term condition	Do you have any of the following long-term conditions that have been diagnosed by a health professional? - Any other long-term condition	CCCn_1V
Has a chronic condition	Derived variable (Based on CCC4DNUM)This derived variable indicates whether or not the respondent has one or more chronic health conditions which were diagnosed by a health professional	CCCnDANY
Cognitive problems	Derived variable (based on variables HSCn_26 HSCn_27)	HSCnDCOG
No cognitive problems	HSC4_26 : How would you describe your usual ability to remember things? (categories: able to remember most things; somewhat forgetful; very forgetful; unable to remember anything at all) HSCn_27 : How would you describe your usual ability to think and solve day-to-day problems? (categories: able to think clearly and solve problems; having a little difficulty; having some difficulty; having a great deal of difficulty; unable to think or solve problems)	
A little difficulty thinking		
Somewhat forgetful/ a little difficulty thinking		
Very forgetful/great deal of difficulty thinking /Unable to remember or to think		
Emotional problem	Derived variable (based on variables HSCn_25)	HSCnDEMO
Happy and interested in life	Questions asked: Would you describe yourself as being usually: Categories: happy and interest in life Somewhat happy Somewhat unhappy Unhappy with little interest in life So unhappy that life is not worthwhile	
Somewhat happy		
Unhappy		
Health description index - Self-rated health	Derived variable (Based on GHCn_1)	GHCnDHDI

Poor Fair Good Very good Excellent	Questions asked : In general, would you say your health is: Excellent Very good Good Fair Poor	
The number of chronic conditions (weighted mean, standard error)	Based on CCCn_1A to CCCn_1W The other chronic conditions which were excluded in our study CCC4_1I Has sinusitis CCC4_1K Has epilepsy CCC4_1N Has stomach or intestinal ulcers CCC4_1O Suffers from the effects of a stroke CCC4_1R Has Alzheimers disease or other dementia CCC4_1T Has glaucoma CCC4_1V Has other long-term condition CCC4_1W Has acne	CCCnD NUM

*n=4,6,8,0,2,A,B,C,D which denote cycle 1-cycle 9 of NPHS

Appendix A4-3

Health outcome	The trajectory of BMI				
	C-N(N=) (%)	C-O (%)	O-O (%)	O-UP (%)	P-value
Food allergies	9.6	7.0	8.1	8.4	0.35
Allergies (other than food allergies)	27.0	25.5	24.7	34.6	0.17
Asthma	4.4	7.1	9.2	10.8	0.03
Arthritis or rheumatism (excluding fibromyalgia)	20.9	26.9	30.3	50.0	<0.001
Back problems (excluding fibromyalgia and arthritis)	19.6	18.1	23.9	23.7	0.06
High blood pressure	12.3	22.1	28.5	52.9	<0.001
Migraine headaches	8.4	7.6	6.1	10.2	0.38
Chronic bronchitis or emphysema	2.8	3.1	1.1	6.7	0.001
Diabetes	1.4	5.7	9.6	26.6	<0.001
Heart disease	2.5	5.5	6.0	8.7	0.02
Cancer	1.9	1.6	2.0	5.1	0.13
Urinary incontinence	2.6	2.4	2.4	9.9	<0.001
Cataracts	3.4	1.9	1.6	2.9	0.13
Other long-term condition	13.0	11.9	11.9	20.1	0.13
Has a chronic condition	70.1	73.8	74.7	92.4	0.0002
Cognitive problem					0.05
No cognitive problem	79.5	78.5	75.3	71.1	
A little difficulty thinking	2.4	1.3	2.5	5.7	
Somewhat forgetful/ a little difficulty thinking	13.1	13.9	17.1	19.3	

Very forgetful/great deal of difficulty thinking /Unable to remember or to think	5.0	6.2	5.0	4.0	
Emotional problem					
Happy and interested in life	79.7	77.5	80.4	64.9	
Somewhat happy	17.8	19.2	16.0	27.2	
Unhappy	2.5	3.2	3.6	7.9	
Health description index - Self-rated health					<0.001
Poor	2.4	4.6	2.3	6.5	
Fair	6.9	8.5	10.3	22.3	
Good	28.7	30.7	32.5	40.1	
Very good	38.8	37.3	38.6	24.7	
Excellent	23.0	18.8	16.2	6.4	

Appendix A5-1

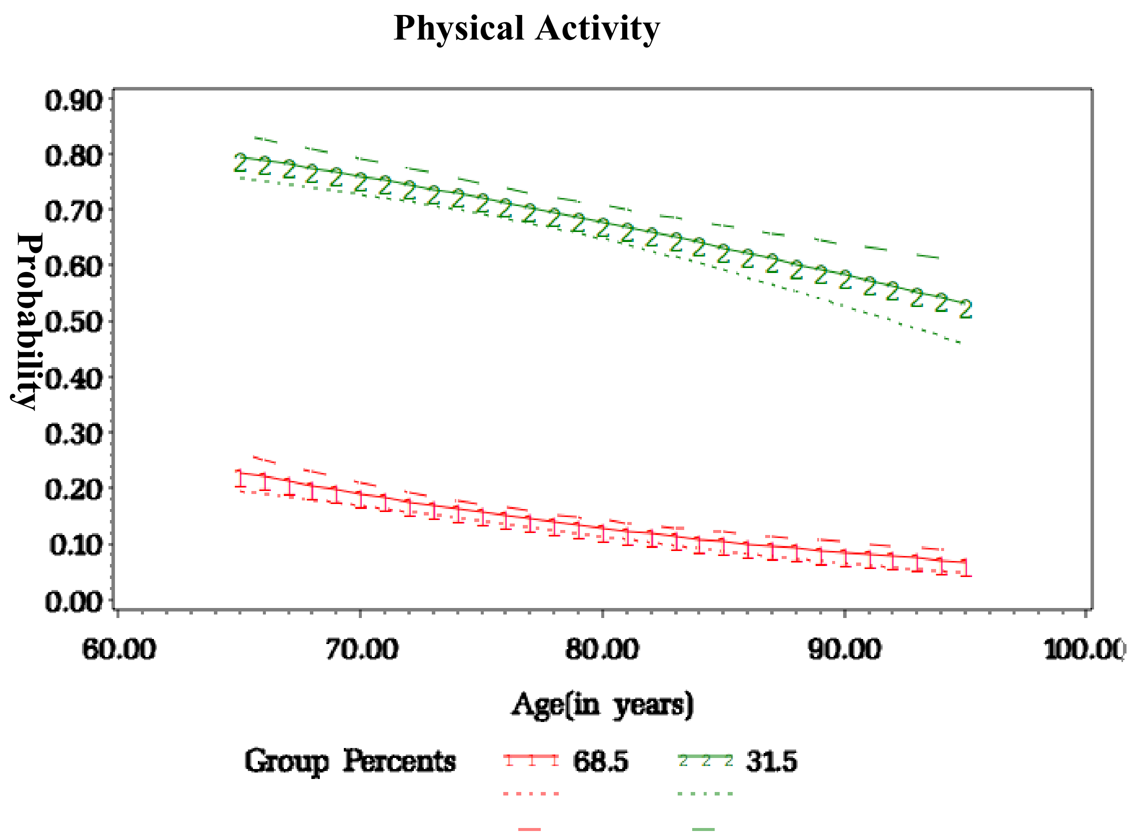
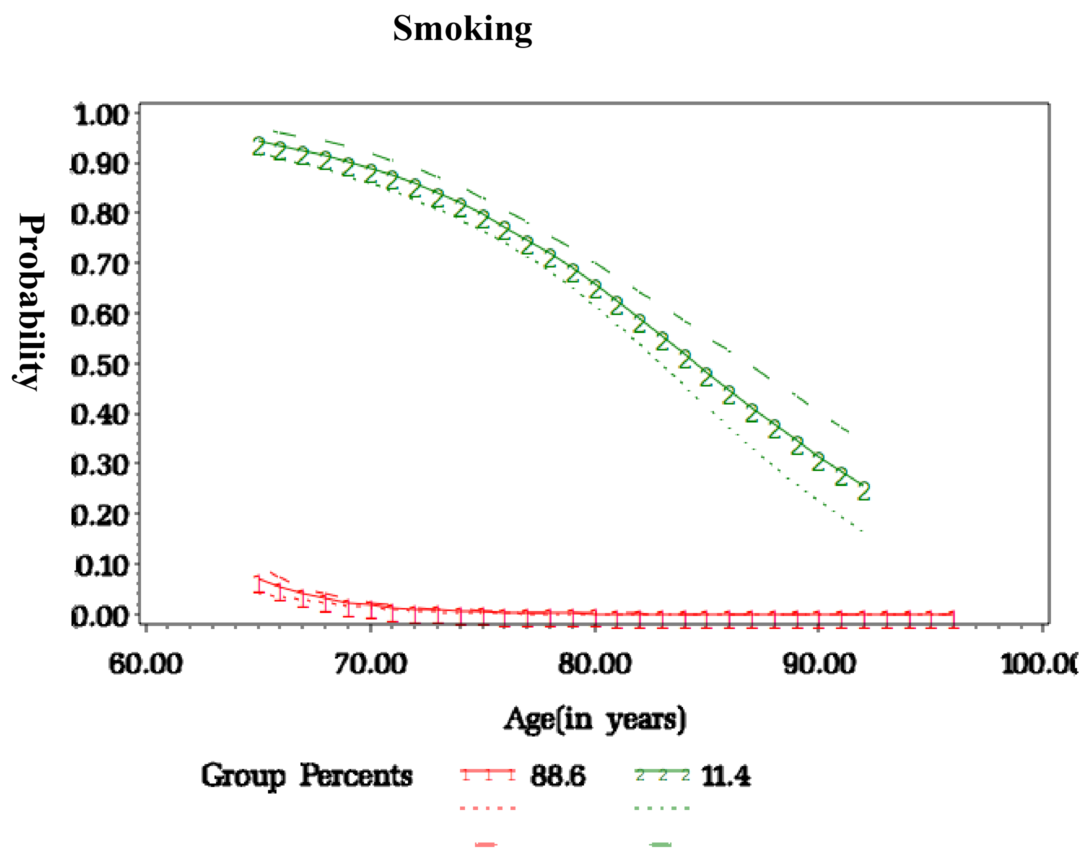


Figure A5-1. The trajectories of probability of being physically active for older adults (65-96 years), with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of physically active probability	The intercept-at (s.e)	Linear term (s.e)	Group membership probability
Low-decrease	1.82 (0.57)	-0.05(0.01)	68.5%
High-decrease	4.01 (0.61)	-0.04 (0.01)	31.5%

Appendix A5-2



FigureA5-2 the trajectories of smoking probability for older adults (65-96 years), with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of smoking probability	Intercept (s.e)	Linear term (s.e)	Group membership probability
Low-stable	16.07 (2.66)	-0.29(0.04)	88.6%
High-decrease	12.15 (1.26)	-0.14(0.02)	11.4%

Appendix A5-3

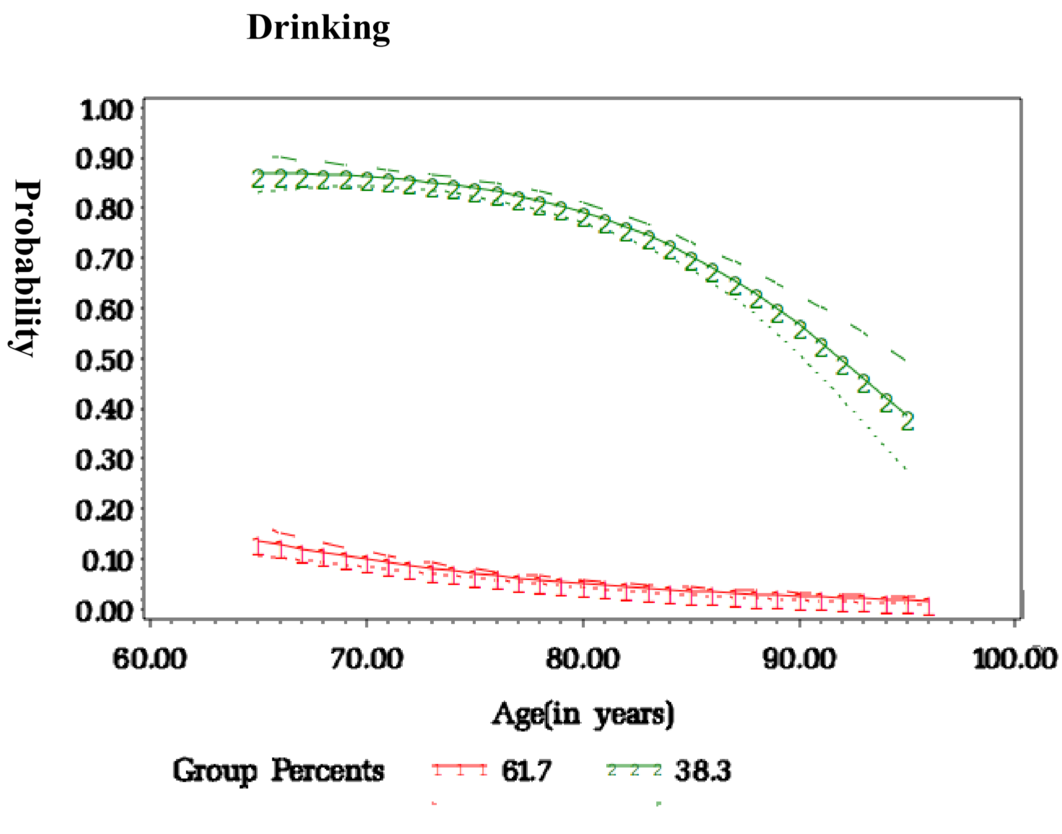


Figure A5-3 The trajectories of drinking regularly probability for older adults (65-96 years), with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of regular drinker probability	The intercept (s.e)	Linear term (s.e)	Quadratic term (s.e)	Group membership probability
Low-decrease	2.80 (0.75)	-0.07(0.01)		61.7%
High-decrease	-10.20 (5.43)	0.37(0.14)	-0.003(0.001)	38.3%

Appendix A5-4

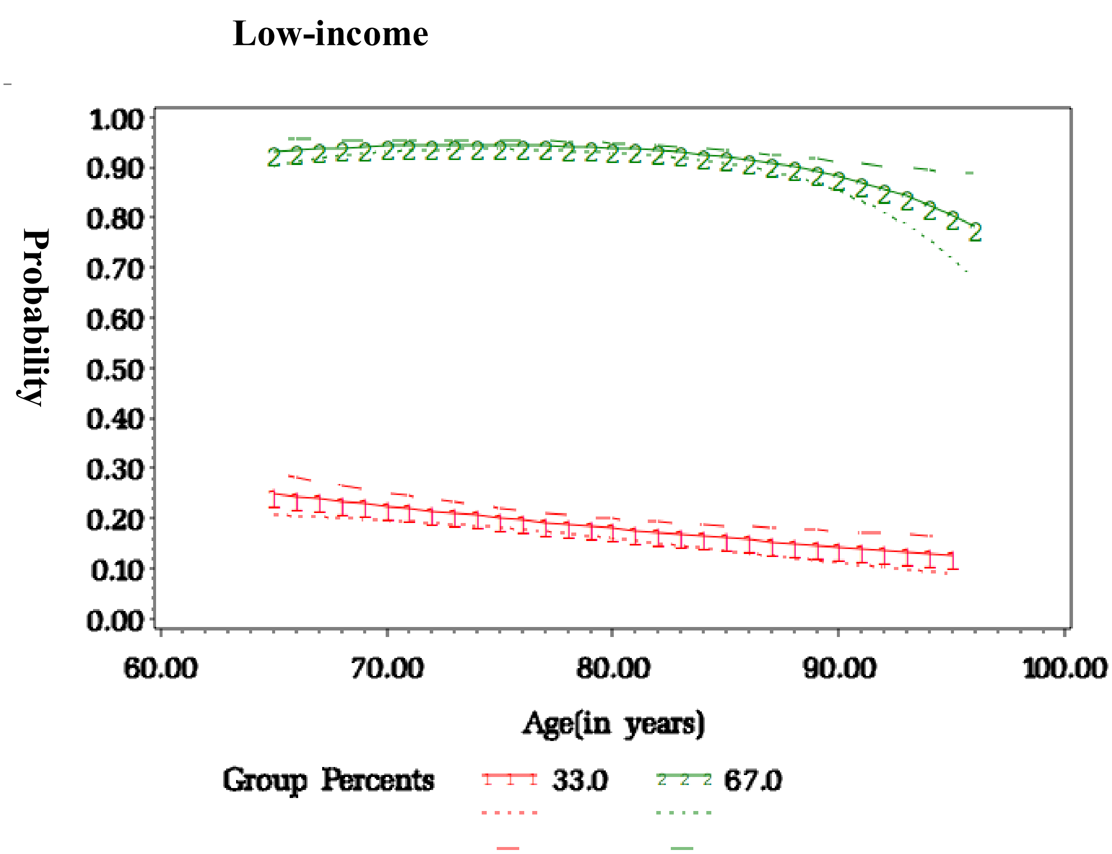


Figure A5-4 The trajectories of probability of living in low-income for older adults (65-96 years), with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011

The Trajectory of Low-income probability	The intercept (s.e)	Linear term (s.e)	Quadratic term (s.e)	Group membership probability
Low-stable	0.68 (0.66)	-0.03(0.01)		67.0%
High-stable	-14.74 (6.85)	0.48 (0.17)	-0.003(0.001)	33.0%

Appendix A5-5

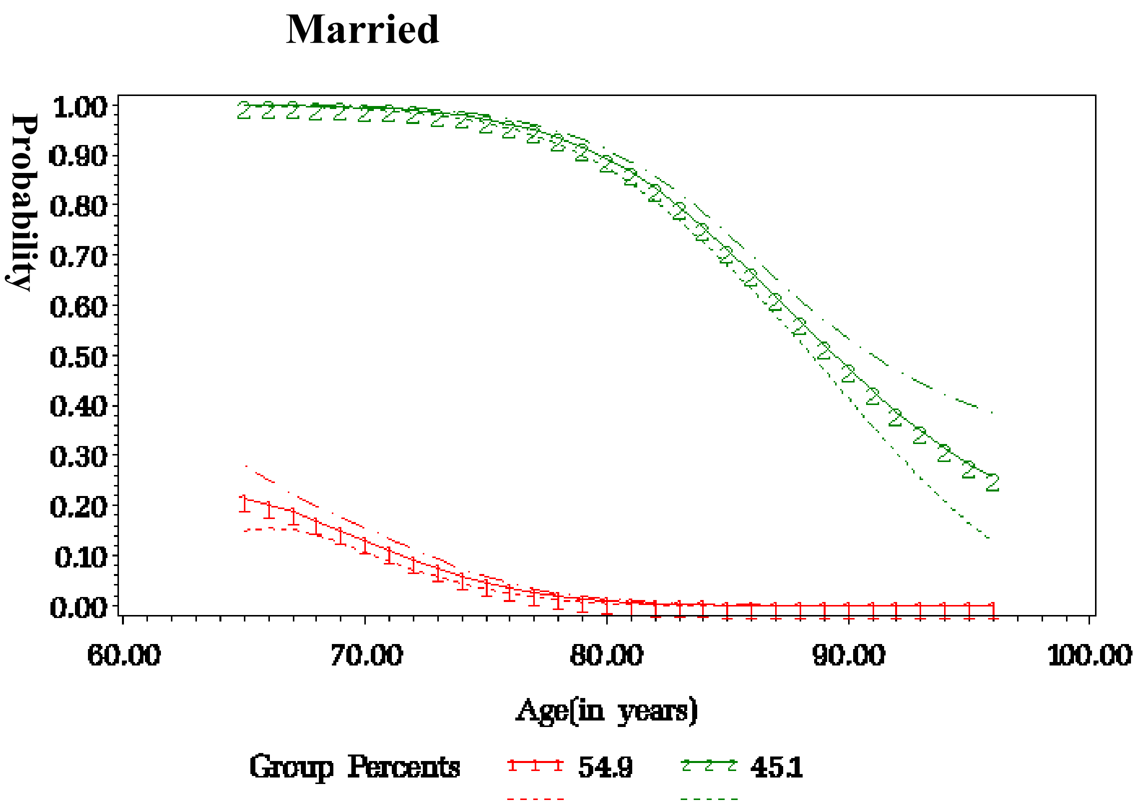


Figure A5-5 The trajectories of being married probability for older adults (65-96 years), with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of being married probability	The intercept (s.e)	Linear term (s.e)	Quadratic term (s.e)	Group membership probability
Low-decrease	-43.66 (20.91)	1.37 (0.58)	-0.01(0.004)	54.9%
High-decrease	43.79 (12.22)	-0.88 (0.30)	0.004(0.002)	45.1%

Appendix A5-6

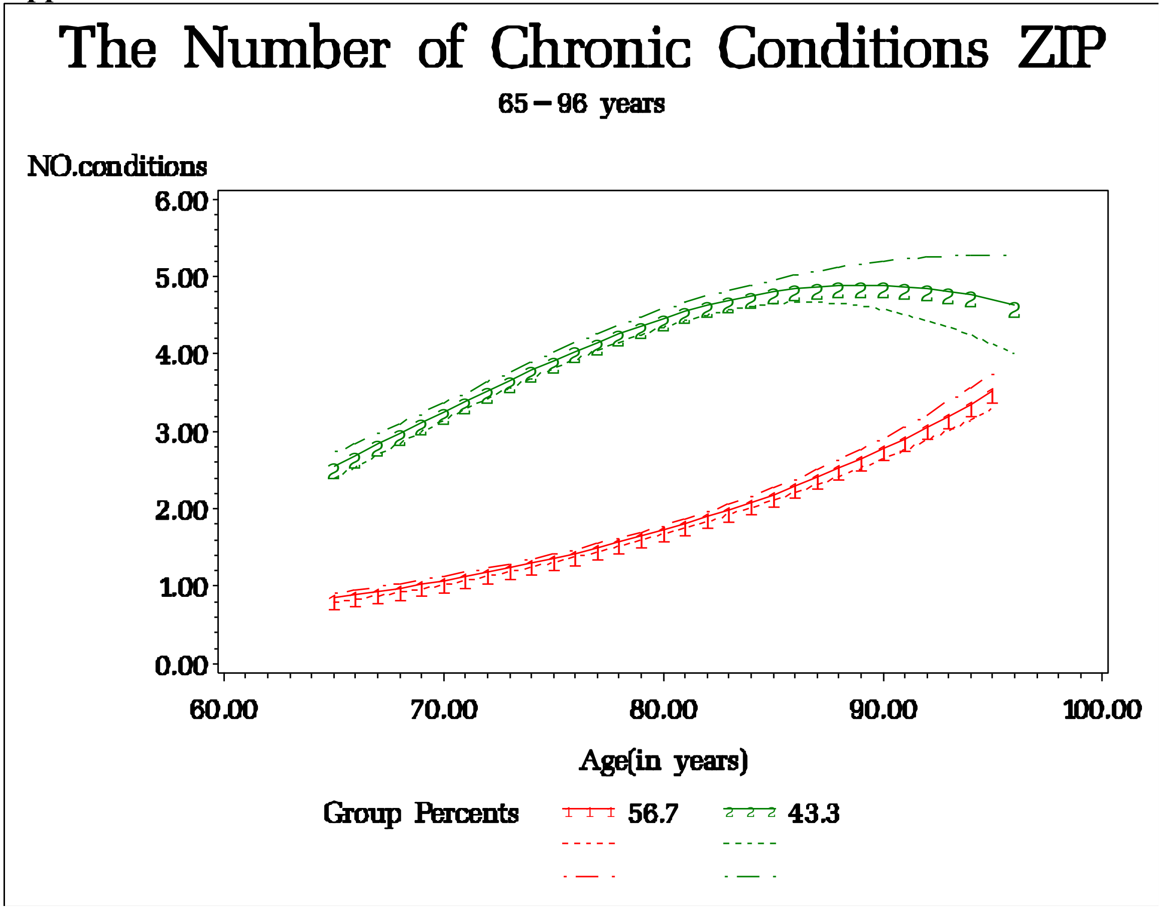


Figure A5-6 The trajectories of the number of chronic conditions for older adults (65-96 years), with 95% confidence intervals (two group model, no covariates included), NPHS, 1994-2011.

The Trajectory of the number of chronic conditions	The intercept (s.e)	Linear term (s.e)	Quadratic term (s.e)	Group membership probability
Less than 3	-3.25 (0.16)	0.05 (0.002)	-	56.7%
More than 3	-7.31 (1.23)	0.20 (0.03)	-0.001(0.0002)	43.3%

Appendix A5-7 Results of the multivariable proportional hazards Cox regression model adjusted for age at baseline, race/ethnicity, and educational level for women (partly adjusted model).

Covariates	Parameter estimate	Standard error	Pr > ChiSq	Hazard ratio	95% HR Conf. limit
BMI Traj					
OV-D(ref.)					
N-D	0.27	0.13	0.04	1.31	1.02-1.69
OB I-D	0.09	0.14	0.54	1.09	0.82-1.45
OB II-D	-0.12	0.33	0.71	0.89	0.47-1.69
Age					
	0.08	0.01	<0.0001	1.08	1.06-1.12
Race					
Non-white	-0.60	0.33	0.07	0.55	0.29-1.05
White (ref.)					
Education (if high school graduate)					
Yes	-0.32	0.11	0.006	0.73	0.58-0.91
No(ref.)					

Appendix A5-8 Results of the multivariable proportional hazards Cox regression model adjusted for age at baseline, race/ethnicity, educational level, place of residence, disability, the probability of being physically active, smoking, drinking, and the development of the number of chronic conditions for women (fully adjusted model).

Analysis of maximum likelihood estimates					
Covariates	**Parameter estimate**	**Standard error**	**Pr > ChiSq**	**Hazard ratio**	**95% HR Conf. limit**
BMI Traj					
N-D	0.19	0.19	0.32		
OB I-D	-0.59	0.24	0.02		
OB II-D	0.30	0.50	0.55		
OV-D(ref.)					
The number of chronic conditions					
More than 3	-0.07	0.19	0.70		
Less than 3					
BMI Traj* the number of chronic conditions			0.001		
N-D more than 3	0.02	0.26	0.928		
OB I-D more than 3	1.06	0.30	0.0005		
OB II-D more than 3	-0.64	0.66	0.336		
OV-D (ref.)					
Age					
	0.12	0.02	<.0001		
PA					
Active	8.01	2.54	0.002		
Inactive(ref.)					
Age * PA			0.001		
Active	-0.12	0.04	0.001		
Inactive(ref.)					
Race					
Non-white	-0.43	0.34	0.20	0.65	0.34-1.26
White (ref.)					
Disability					
Yes	0.48	0.13	0.0002	1.62	1.26-2.10
No (ref.)					
Education					
(if high school graduate)					
Yes	-0.23	0.12	0.05	0.79	0.63-0.99
No(ref.)					
Place of residence					
Rural	-0.30	0.12	0.01	0.76	0.59-0.97
Urban(ref.)					
Smoking					
smoker	0.98	0.16	<0.0001	2.57	1.86-3.56
Non-smoker (ref.)					
Drinking					
Regular drinker	-0.11	0.13	0.40	0.90	0.70-1.15
Non-drinker(ref.)					

Appendix A5-9 Results of the multivariable proportional hazards Cox regression model adjusted for age at baseline, race/ethnicity, and educational level for men (partly adjusted model).

Covariates	Parameter Estimate	Standard Error	Pr > ChiSq	Hazard Ratio	95% HR Conf. limit
BMI Traj					
N-D	0.66	0.16	<.0001	1.94	1.41-2.65
OV-S	0.17	0.15	0.25	1.19	0.88-1.60
OB-S	0.70	0.23	0.002	2.01	1.28-3.14
OV-D(ref.)					
Age					
	0.08	0.02	<.0001	1.08	1.05-1.11
Race					
Non-white	-0.11	0.32	0.72	0.89	0.48-1.66
White (ref.)					
Education (if high school graduate)					
Yes	-0.28	0.13	0.03	0.78	0.59-0.97
No(ref.)					

Appendix A5-10 Results of the multivariable proportional hazards Cox regression model adjusted for age at baseline, place of residence, disability, the probability of being physically active, smoking, drinking, and the development of the number of chronic conditions for men (fully adjusted model).

Analysis of maximum likelihood estimates					
Covariates	**Parameter estimate**	**Standard error**	**Pr > ChiSq**	**Hazard Ratio**	**95% HR Conf. limit**
BMI Traj					
N-D	0.51	0.17	0.002	1.66	1.20-2.30
OV-S	0.22	0.15	0.15	1.25	0.92-1.68
OB -S	0.68	0.23	0.003	1.98	1.26-3.13
OV-D(ref.)					
The number of chronic conditions					
More than 3	0.37	0.14	0.007	1.45	1.11-1.90
Less than 3(ref.)					
Age					
	0.11	0.02	<.0001	1.11	1.08-1.15
Race					
Non-white	0.12	0.32	0.70	1.13	0.60-2.13
White (ref.)					
Education (if high school graduate)					
Yes	-0.05	0.13	0.70	0.95	0.73-1.23
No(ref.)					
PA					
Active	-0.57	0.14	<.0001	0.60	0.43-0.74
Inactive(ref.)					
Disability					
Yes	0.34	0.14	0.01	1.41	1.08-1.84
No (ref.)					
Place of residence					
Urban	-0.24	0.13	0.06	0.79	0.61-1.01
Rural(ref.)					
Smoking					
Smoker	1.06	0.16	<.0001	2.89	2.11-3.98
Non-smoker (ref.)					
Drinking					
Regular drinker	-0.17	0.12	0.17	0.84	0.66-1.07
Non-drinker(ref.)					

Appendix A5-11 Results on the model adequacy tests including a functional form test and proportional hazard assumption tests.

Women	
Supremum Test for Functional Form	
Variable	P-value
Age	0.96
Supremum Test for Proportionals Hazards Assumption	
Variable	P-value
BMI Traj	
N-D	0.52
OB I-D	0.66
OB II-D	0.48
OV-D(ref.)	-
The number of chronic conditions	
More than 3	0.54
Less than 3(ref.)	
BMI Traj* the number of chronic conditions	
N-D more than 3	0.60
OB I-D more than 3	0.87
OB II-D more than 3	0.35
OV-D (ref.)	
Age	
	0.47
Race	
Non-white	0.36
White (ref.)	
Education (if high school graduate)	
Yes	0.92
No(ref.)	
PA	
Active	0.25
Inactive(ref.)	
Age * PA	
Active	0.23
Inactive(ref.)	-
Disability	
Yes	0.84
No (ref.)	
Smoking	
Smoker	0.53
Non-smoker (ref.)	
Drinking	
Regular drinker	0.20
Non-drinker(ref.)	
Education (if high school graduate)	
Yes	0.93
No(ref.)	
Place of residence	
Rural	0.32
Urban(ref.)	

Appendix A5-12 Results on the model adequacy tests including a functional form test and proportional hazard assumption tests.

Men	
Supremum Test for Functional Form	
Variable	
	P-value
Age	
	0.21
Supremum Test for Proportionals Hazards Assumption	
Variable	P-value
BMI Traj	
N-D	0.68
OV-S	0.12
OB –S	0.60
OV-D(ref.)	-
The number of chronic conditions	
More than 3	0.18
Less than 3(ref.)	
Age	
	0.53
Race	
Non-white	0.18
White (ref.)	
Education (if high school graduate)	
Yes	0.40
No(ref.)	
PA	
Active	0.56
Inactive(ref.)	
Disability	
Yes	0.52
No (ref.)	
Place of residence	
Urban	0.36
Rural (ref.)	
Smoking	
Smoker	0.29
Non-smoker (ref.)	
Drinking	
Regular drinker	0.60
Non-drinker(ref.)	