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The time patterns of carbohydrate intake in UK adults – the National Dietary and Nutrition Survey (NDNS) 2008/09-2015/16 programme

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Declaration of Authorship

I, Chaochen WANG, declare that this thesis titled, "The time patterns of carbohydrate intake in UK adults – the National Dietary and Nutrition Survey (NDNS) 2008/09-2015/16 programme" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a MSc degree on Medical Statistics at this University.
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- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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Signed:

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"All models are wrong, but some are useful."

George E. P. Box

Abstract

The National Dietary and Nutrition Survey (NDNS) database of detailed four-day food diaries was used to ...

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List of Abbreviations

AIC	**A**kaike **I**information **C**riterion
BMI	**B**ody **M**ass **I**ndex
BIC	**B**ayesian **I**information **C**riterion
CI	**C**onfidence **I**nterval
DM	**D**iabetes **M**ellitus
EM	**E**xpectation **M**aximazation
FSA	**F**ood **S**tandards **A**gency
A1c	Haemoglobin **A1c**: Glycated hemoglobin
LCA	**L**atent **C**lass **A**nalysis
MAFF	**M**inistry of **A**griculture, **F**isheries and **F**ood
MLCA	**M**ultilevel **L**atent **C**lass **A**nalysis
ML	**M**aximum **L**ikelihood
NDNS	the **N**ational **D**ietary and **N**utrition **S**urvey
OR	**O**dds **R**atio
PHE	**P**ublic **H**ealth **E**ngland
PSUs	**P**rimary **S**ampling **U**nits
WC	**W**aist **C**ircumference

Chapter 1

Introduction

Background

The widely accepted standard these days seems to be that we eat three times a day. However, whether this is really an ideal temporal eating pattern for everyone has never been answered with evidence. More importantly, the actual temporal patterns of eating in the population, proportions of people who actually manage/fail to follow this so-called doctrine have not been described thoroughly.

The importance of the circadian rhythm in regulating physiological responses has been recognised for long, while the impact of which on nutrition and metabolism is still largely unknown (Johnston, 2014; Asher and Sassone-Corsi, 2015).

Although nutritional studies have extensively examined the influence of the quantity and quality of dietary and nutrients intake and their alteration on morbidity and mortality, investigations on temporal eating patterns and their effects are still scarce. Some recent evidence have found that meal timing is associated with a wide variety of health outcomes. Skipping breakfast is associated with higher risk of type 2 diabetes (Uemura et al., 2015). Shift workers have a higher risk of developing metabolic syndrome (De Bacquer et al., 2009) and type 2 diabetes (Pan et al., 2011). Evening intake of energy is positively associated with overweight/obesity (Almoosawi et al., 2016).

More recently, discernible temporal eating patterns that differed by sociodemographic and eating profiles were revealed by latent class analysis using nutrition survey data (Leech et al., 2017; Mansukhani and Palla, 2018). Based on total energy consumption, the presence of 3 groups of eaters: grazers, early eaters, and late eaters were identified. So far, the temporal eating patterns were only based on averaging the total energy intake calculated from one or two days dietary recall, and therefore could not capture the day-to-day variation in temporal eating patterns.

(some review of articles about carbohydrate eating)

The National Dietary and Nutrition Survey (NDNS)

The National Diet and Nutrition Survey (NDNS) programme (NatCen Social Research, 2018) was initially established in 1992 and started off as a joint initiative between the Ministry of Agriculture, Fisheries and Food (MAFF) and the Department of Health. In 2008, a new continuous cross-sectional survey was started, the NDNS Rolling Programme (RP). The NDNS RP is funded by Public Health England (PHE), an executive agency of the Department of Health, and the UK Food Standards Agency (FSA). The survey covers a representative sample of around 1000 people per year. Fieldwork began in 2008 and is now beginning its (**y**)ear. NDNS provides essential evidence on the diet and nutrition of the UK population to enable PHE to identify and address nutritional issues in the population and monitor progress towards public health nutrition objectives.

The NDNS RP has now completed and analysed its eighth year. The sample was randomly drawn from a list of all the addresses, clustered into postcode sectors from across the UK. Overall, for years 1-8 combined, a sample of 39,300 addresses was selected from 799 (year 1-4), 323 (year 5-6), and 316 (year 7-8) postcode sectors. At each address, one household was selected at random (in cases where there were two or more households). For each household, either an adult and a child, or a child only, was selected to participate.

These individuals were asked to keep a four-day diary on their food and drink consumption on consecutive days. An interview and a nurse visit were also conducted to collect information regarding height and weight, smoking and drinking habits, physical activity, blood pressure, prescribed medicines, dietary supplements, fasting blood sample, and 24-hour urine sample.

Aims and objectives

Our goal is to explore and make use of the NDNS RP (2008/09-2015/16) database to describe and identify the potential relationship between the timing of eating within the day and specific nutrient–carbohydrate intake. We aimed at finding time patterns of consumption of carbohydrate and defining latent groups in the UK adults. Subsequently, an additional potential aim, is to investigate the association between eating time patterns with diabetes and obesity.

Chapter 2

Methods

Dietary diary collected in the NDNS RP

Participants were asked to keep a record of everything eaten or drunk over four consecutive days. Interviewers undertook three visits with each participant. At the first visit, the interviewer explained the method followed a protocol, taking participants through the sections in the diary including how to describe details of food and drink and portion size and an example day. The second was a brief visit to check for compliance, answer questions or deal with problems and review the diary to identify and edit possible omissions and missing detail. The third visit was to collect the diary and again review and edit possible omissions.

In the diary, participants were asked to record portion sizes in household measures (e.g. one tablespoon of beans, one Kit Kat finger-size), or for packaged foods to note the weight indicated on the packet. For homemade dishes, participants were asked to record on a separate page in the diary the individual ingredients and quantities for the whole dish along with a brief description of the cooking method and how much of dish they had consumed. In addition to details of what and how much was eaten, participants recorded for each eating occasion; when was it, where they were, who they were eating with. An example, used as guidance for participants, of a food diary for one day is shown in **Appendix C**.

Definition of carbohydrate intake

Detailed dairy checking was performed to code and convert the food consumption into energy and nutrients intake. Intakes of nutrients were calculated from the food consumption records using a specially adapted Nutrient Databank (Smithers, 1993), which was originally developed by the Ministry of Agriculture, Fisheries and Food (MAFF) for the Dietary and Nutritional Survey of British Adults. Further details of data coding and editing are outlined in Appendix A of the NDNS official reports

(Department of Health, 2018). Specifically, the main variables that we adopted in the current analysis were defined as:

- Total Energy intake = (protein(gramme) $\times$ 17) + (fat(gramme) $\times$ 37) + (carbohydrate(gramme) $\times$ 16) + (alcohol(gramme) $\times$ 29) kJ;
- Carbohydrate intake = total sugars (gramme) + starch (gramme);

Time across a typical survey day was divided into 7 time slots in the dietary diary of NDNS RP: 6 am to 9 am, 9 am to 12 noon, 12 noon to 2 pm, 2 pm to 5 pm, 5 pm to 8 pm, 8 pm to 10 pm, and 10 pm to 6 am. To produce a sequence of discrete responses regarding the carbohydrate intake we are interested, the energy consumption within each time slot over the four days of survey for each participant were calculated. The percentages of energy that contributed by carbohydrate within each time slot were then estimated. Since we planed to apply latent class analysis (LCA) in the current study, in which the observed indicators for latent classes must be categorical, we then dichotomised the responses according to the carbohydrate contribution to the energy intake at cut-off value of 50%, i.e. if within a time slot there is any energy intake occured, carbohydrate consumption was categorised into whether it's energy contribution was lower or higher/equal to 50% of total energy intake within that time slot. Consequently, for each day of the recording, there were 7 data points generated by the diary, each data point included one of the following responses:

- Not eating any food (Energy intake = 0 kJ);
- Eating, and carbohydrate contributed less than 50% of the total energy intake;
- Eating, and carbohydrate contributed higher or equal to 50% of the total energy intake.

Survey Data

Survey selection method

The NDNS RP participants were drawn from the UK Postcode Address File, a list of all the addresses in the UK. The addresses were clustered into Primary Sampling Units (PSUs), small geographical areas, based on postcode sectors, randomly selected from across the UK. A list of 27 or 28 addresses was then randomly selected from each PSU.

Overall, for years 1 to 8 combined, a sample of 39,300 addresses was selected from 1,438 PSUs. The sampling selection process was:

- Randomly select PSUs from the Postcode Address File;
- Randomly select 27 or 28 addresses in that postcode area;
- Randomly select one household at that address;
- Selected addresses were randomly allocated to one of two groups to determine whether an adult (aged 19 years or older) and a child (aged 1.5 to 18 years), or a child only, were selected for interview.

Response rates

The response rates for completion of the dietary diary (three or four days) were 56%, 53%, 53%, for years 1 to 4, 5 to 6, and 7 to 8, respectively. A total of 6,155 adults aged 19 years and over were kept in our analyses.

Strata and weightings

It is necessary to apply weighting factors to the data collected in the NDNS RP for two reasons: to remove any bias in the observed results which may be due to differences in the probability of households and individuals being selected to take part; and to attempt to reduce differential non-response bias by age, sex and geographical region.

The strata that used to calibrate proportions in the sample include: age-group (1.5-3, 4-6, 7-10, 11-15, 16-18, 19-24, 25-29, 30-39, 40-49, 50-59, 60-64, 65-69, and over 70 years); sex (men or women); and regions (Northern Ireland, Scotland, Wales, and the nine regions of England).

Two steps of weighting system are designed in the NDNS RP to assure that the combined sample will be representative of the UK population:

1. An overall selection weight, which is the product of the address, dwelling unit, catering(household) unit, and individual selection weights, was generated to correct for the unequal selection probabilities. These weights are the inverse of the selection probabilities at each level of the random sampling process and they can be used to compensate for differences in the chance of selection of an individual.
2. An iterative procedure was used to adjust the selection weights until the distribution of the weighted sample matched that of the population for age-group, sex and geographical region. Population distributions were taken from the mid-year population estimates (Office for National Statistics, 2018).

Another two sets of weights were generated to correct for differential non-response (either due to refusal or inability) to 1) nurse visit, and 2) giving a blood sample. Response rates to the nurse visit among those completed a dietary diary was approximately 75%, to blood sample in adults were 51%, 57%, and 50% for years 1 to 4, 5 to 6, and 7 to 8, respectively. In creating the nurse/blood sample weight, a logistic regression model was used by the NDNS RP study team to model the relationship between response to nurse visit/giving blood sample and a set of predictor variables (socio-demographic, participant and catering/household unit characteristics). The model generated a predicted probability for each participant, which is the probability would agree to a nurse visit/provide blood sample, given the characteristics of the individual and the household unit. Participants with characteristics associated with non-response were under-represented in the sample and therefore receive a low predicted probability. The inverse of these predicted probabilities were used as a set of non-response weights so that participants with a low predicted probability got a larger weight, increasing their representation in the sample. Then the nurse/blood sample weights were re-scaled so that the sum of the weights equalled the number of participants who had a nurse visit/who provided a blood sample. The final nurse/blood weights should therefore make the sample participants representative of all eligible persons in the population.

Further details of the weighting system developed by the NDNS RP are described in the Appendix B of the reports published by Public Health England (PHE) (Bates et al., 2014; Roberts et al., 2018; Department of Health, 2018).

Socio-demographic status, lifestyle, physical activity, anthropometric measurements and biochemical analyses

Computer assisted personal interviews were conducted for the selected individuals by trained interviewers to collect background information on smoking habits (current, past, never smokers), ethnicity (white, non-white), education level, living with a partner or not and other socio-demographic related variables. Participants also had their height, weight, blood pressure, waist circumferences (WC) measured by the nurses.

Specifically, blood pressure was measured in a sitting position using an automated, validated machine, the Omron HEM907, after a five minute rest. The means of second and third readings, taken at one minute intervals, were used in the current report. Hypertension was defined as with systolic blood pressure of 140 mmHg or above, and/or diastolic blood pressure of 90 mmHg or above, and/or taking any medication specifically to reduce blood pressure.

A self-completion questionnaire - the Recent Physical Activity Questionnaire (Besson et al., 2009) (RPAQ, developed by the MRC Epidemiology Unit Cambridge) was used to estimate physical activity from year 2 of the survey. The RPAQ was designed to assess usual physical activity in the last month in four domains: home, work, commuting to work, and leisure activities. Detailed descriptions of the assessment of adult physical activity in the NDNS RP and the processing of data are available in Appendices G and V of the published reports (Bates et al., 2014; Roberts et al., 2018; Department of Health, 2018).

Blood samples were stored at 4 °C, and sent directly by post to the Department of Haematology and Department of Clinical Biochemistry and Immunology, Addenbrooke's Hospital, Cambridge within tow hours of their collection. Serum samples were obtained by centrifugation of the coagulated blood sample. Serum total, High Density Lipoprotein (HDL) and Low Density Lipoprotein (LDL) cholesterol, triglycerides, blood glucose, haemoglobin A1C were measured. A1C value of 6.5% was used as the cut off point for diagnosing diabetes.

Body mass index (BMI) was calculated as weight in kilograms and weight in kilograms divided by height in square meters. BMI was then categorised into less than 25 kg/m^2 (normal weight), 25 to 30 kg/m^2 (overweight), and higher or equal to 30 kg/m^2 (obese).

Ethics approval

Ethics approval for the survey was obtained form the Oxfordshire A Research Ethics Committee. The letters of approval for the original submission and subsequent substantial amendments, together with approved documents, were sent to all Local Research Ethics Committees covering areas where fieldwork was being conducted. Research governance approval was sought for all participating NHS laboratories and obtained where required by the Research and Development Committee for each laboratory. Ethics approval for the current project was obtained from the MSc Research Ethics Committee of London School of Hygiene & Tropical Medicine (LSHTM MSc Ethics Ref: 15624).

Statistical methods

Latent Class Analysis (LCA)

Latent class analysis is a statistical technique that identifies categorical latent (unobserved) class variables on the basis of observed categorical variables (Collins and Lanza, 2010). It belongs to the family of latent variable models, and is directly analogous to the factor analysis model. The major difference is that the latent variable in LCA is categorical, not continuous as in factor analysis. The basic assumptions in LCA are independent observations, and local independence, as shown in the fundamental expression of a typical LCA model:

$$P(U_{i1} = s_1, U_{i2} = s_2, \cdots, U_{ik} = s_K) = \sum_{t=t}^{T} P(C_i = t) \prod_{k=1}^{K} P(U_{ik} = s_k | C_i = t) \quad (2.1)$$

Where,

- $P(U_{i1} = s_1, U_{i2} = s_2, \cdots, U_{ik} = s_k)$ is the probability of observing a particular vector of responses;
- $P(C_i = t)$ is the probability that a randomly selected ith observation will be in class t;
- $P(U_{ik} = s_k | C_i = t)$ is the probability of a particular observed response pattern $U_{ik} = s_k$ conditional on membership in latent class t.

Equation 2.1 indicates that responses for an observation to the measuring variables are independent of one another given its membership in latent class t. However, in the NDNS RP data set, the assumption of independent observations is violated. Each individual completed their dietary diary for four consecutive days, their diary recordings were later converted into four sequences of categorical responses reflecting the type of carbohydrate consumption at each time slot of the day. The four observed sequences (observed days) are nested in the participants and therefore are not independent. This nested data structure requires multilevel techniques.

Multilevel Latent Class Analysis (MLCA)

Multilevel latent class analysis accounts for the nested structure of the data by allowing latent class intercepts to vary across level 2 units and thereby examining if and how level 2 units influence the level 1 latent classes. These random intercepts allow the probability of membership in a particular level 1 (observation days) latent class to vary across level 2 units (e.g., here in the current context are the individuals). Essentially this allows the probability that an observation day will belong to a particular day level latent class to vary across individual levels.

Parametric approach

Proposed by Vermunt (Vermunt, 2003; Vermunt, 2008) and Asparouhov and Muthén (Muthén and Asparouhov, 2009), a traditional, parametric approach can be applied using a logistic regression model. For example, let's assume that there are two types of observation days in the dietary survey–high and low carbohydrate eating days. In an unconditional logistic regression model, the probability of the outcome (i.e. an observed high carbohydrate eating day vs. a low carbohydrate eating day) is constant within individual level which means for each person throughout his/her survey there is some probability of following a high carbohydrate eating day. A random effect model considers the individuals (level 2) to be drawn from the adult population in the UK, and the probability of the outcome (i.e. high carbohydrate eating days) across individuals is considered to be a random variable (Snijders and Bosker, 2011).

Thus, for a binary outcome $C_{ij} = 0, 1$ (low $= 0$ or high $= 1$ carbohydrate eating days), where i denotes the observation days ($i = 1, 2, 3, 4$), and j denotes the individual ($j = 1, 2, \cdots, 6155$). The 2-level random intercept logistic regression model can be expressed as:

$$
\begin{aligned}
\text{logit}[P(C_{ij} = 1)] &= \beta_{0j} + \beta_1 x_{ij} \qquad \textbf{(day level)} \\
\beta_{0j} &= \gamma_0 + \gamma_1 w_j + u_{0j} \ \textbf{(individual level)} \\
\Rightarrow P(C_{ij} = 1) &= \frac{\exp\left(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j}\right)}{1 + \exp\left(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j}\right)}
\end{aligned}
\tag{2.2}
$$

Where we define:

- $P(C_{ij} = 1)$ as the probability that the randomly selected ith observation day of jth individual is a high carbohydrate eating day;
- β_{0j} as the random intercept, for outcome $C_{ij} = 1$;
- the random deviation of the individuals u_{0j} are assumed be normally distributed (i.e. $u_{0j} \sim N(0, \sigma^2_{u_0})$), the magnitude of the u_{0j} variance ($\sigma^2_{u_0}$) indicates the influence of the individuals (level 2);
- x_{ij}, w_j is the predictors for day level (weekdays or weekends) and individual level, such as age, and sex.

Same framework can be used to consider random effects in an LCA model, but instead of saying that C_{ij} is either low or high carbohydrate eating days as if we already know, it is now replaced by a latent variable G_{ij} which indicates the typologies of carbohydrate eating patterns. Then we can use the day level data to assess the log-odds of belonging to kth type of carbohydrate eating pattern on a specific day of survey, and we allow the log-odds to vary across individuals. Therefore, for some persons the log-odds of having a kth type of carbohydrate eating pattern during the survey can be high, but for the other persons, the log-odds of following the kth type of carbohydrate eating pattern can be low.

If the day level LCA model (carbohydrate eating pattern typologies) is best defined by $T(T \geqslant 2)$ latent classes, then $T-1$ random intercept will be specified by a two-level multinomial logistic regression model. Similar to the typical LCA models, the latent class variable in a MLCA is defined by multiple observed indicators (here is defined by the responses of eating carbohydrate within each time slots, throughout 4 consecutive days of survey period). Considering the latent class indicators are indicator variables (U_{ijk}), the MLCA model can be written as follows:

$$P(U_{ij1} = s_1, U_{ij2} = s_2, \cdots, U_{ijk} = s_K) = \sum_{t=1}^{T} P(G_{ij} = t) \prod_{k=1}^{K} P(U_{ijk} = s_k | G_{ij} = t) \tag{2.3}$$

Where,

- U_{ijk} represents the response of eating carbohydrate (one of the following: not eating any food, $< 50\%$ of the energy, or $\geqslant 50\%$ of the energy) on ith day of the survey ($i \in (1, 2, 3, 4)$) in jth individual at the kth time slot of the day ($k \in (1, 2, 3, \cdots, 7)$);
- G_{ij} denotes the latent class membership for jth individuals on ith day of the survey, the total number of day level latent class is T;
- $P(U_{ijk} = s_k | C_{ij} = t)$ is the probability of a specific response pattern, conditional on membership in latent class t.

The $P(G_{ij} = t)$ in equation 2.3 is what we have already defined in equation 2.2:

$$P(G_{ij} = t) = \frac{\exp(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j})}{1 + \exp(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j})} \tag{2.4}$$

Non-Parametric approach

Since the parametric approach discussed above can be extremely computationally demanding (Van Horn et al., 2008; Vermunt, 2008), an alternative approach is using a non-parametric MLCA (Davidian et al., 2008). In this approach, separate latent class models are specified for level 1 (observation days) and level 2 (individuals). Similar with the parametric MLCA approach, there are $T-1$ random intercepts, where T is the number of level 1 latent classes. However, rather than assuming the random intercepts following a normal distribution, the non-parametric MLCA assumes a multinomial (discrete) distribution of the level 2 latent classes. This approach is less computationally demanding compared with the parametric approach. These level 2 (individual) latent classes reflect differences in the probability of belonging to a specific day level latent class, so that individuals that contain observation days with similar probabilities for the level 1 latent classes will be grouped together. The non-parametric MLCA model can be defined as follows:

$$P(C_{ij} = t|CB_j = m) = \frac{\exp(\gamma_{tm})}{\sum_{r=1}^{T} \exp(\gamma_{tm})} \tag{2.5}$$

Where,

- CB_j is individual level latent class membership for jth individual;
- γ_{tm} is day level and individual level indicators.

According to Finch and French's simulation study (Finch and French, 2014), non-parametric approach generally resulted in more accurate recovery of the underlying latent structure of the data at both levels and provided better latent class model. Specifically, we are interested in exploring both meaningful individual (level 2) latent classes and the daily carbohydrate consumption classification. Therefore, non-parametric MLCA was employed 1) to identify latent classes of observation days (level 1) based on the subjects' responses to the 4-day food and drink diary and 2) to form distinct latent classes of individuals (level 2) based on the distribution of observation-level latent classes within individuals.

Strategy of conducting MLCA in the current analysis

To identify the best-fitting model, we used the following sequential modelling strategy (Henry and Muthén, 2010):

- Firstly, we ignored the multilevel structure of the data and estimated a series of traditional LC models to determine the number of classes at the observational-level;
- Next, a series of MLCA models were fitted to account for the multi-level structrure of the data. In these models, the number of observational-level classes was based on the best fitting LCA model from the first step, and the

LCA model at the individual level was estimated to identify the number of individual level latent classes;

- Thirdly, when number of individual level latent classes is defined based on the previous stage, observational-level classes was modified (one class lower and one class higher than in the second step), to see the effect of changing level 1 classes and confirm the best fitting model.

The number of classes in either level 1 were determined by 1) the evaluation of model fit indices, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), adjusted Bayesian information criterion (aBIC) where smaller values indicate better, and entropy which is a statistic that summarizes latent class probabilities where values near 1 indicate better latent class separation; 2) the Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT) (Lo, Mendell, and Rubin, 2001; Nylund, Asparouhov, and Muthén, 2007) which compare q vs. $q-1$ class models, where q is the number of latent classes and 3) pattern interpretability. In the step of performing multilevel LCA, where LMR-LRT is available, same rules of model fit indices and pattern interpretability were used to determine the optimal combination of latent classes in observation day level and individual level. MLCA models were fitted in Mplus 7.4 (Muthén and Muthén, 2017), the Mplus codes and outputs are shown in **Appendix B**.

Characteristics of day level latent classes and individual level latent classes

Day level latent classes identified by the first step of MLCA were tabulated according to day of week and also whether the diary was recorded during weekdays or not. A contingency table giving the frequency of responses across the 7 time slots of the survey days was produced. Descriptive statistics for the dietary day level recordings according to the latent class memberships were presented. Pearson χ^2 test was used ot compare the distribution of categorical variables. One-way Analysis of Variance (ANOVA) was used to compare the means across the multiple groups for continuous variables.

Person level point estimates and 95% confidence intervals (CIs) were determined by applying individual, nurse visiting, and blood sample weights accordingly which accounted for the probability of participant selection and the clustered survey design. Descriptive statistics for sample characteristics are presented as weighted means (95% CI) or weighted percentages (95%CI). After examining the distribution of the data, the following variables were log-transformed to improve normality:

blood glucose, A1C, TC, LDL, HDL, TG, and average physical activity duration per day. Weighted geometric means (95% CI) were used for all log-transformed variables. For continuous variables, the *F* test was used to determine differences between latent classes with Bonferroni correction to account for multiple testing across > 2 classes. For categorical variables, differences between latent classes were assessed using the adjusted Pearson χ^2 test for survey data.

Association between individual level latent classes and the prevalence of hypertension, and measurements of obesity

Associations between individual level carbohydrate eating classes and hypertension (yes/no), body mass index (BMI, kg/m^2), and waist circumference (WC, cm) were explored in men and women separately. Point estimates of weighted means and proportions and 95%CI of the characteristics were determined by applying either nurse visiting weights (for outcomes of hypertension, BMI, and WC) or blood sample weights (for diagnosis of DM) accordingly. Similarly, *F* tests (for continuous variables) and adjusted Pearson χ^2 tests (for categorical variables) were used to determine sex-specific differences by hypertension status, and BMI categories.

Survey-designed logistic regression models (for hypertension), and linear regression models (for WC, BMI), were used to test for associations between latent classes of carbohydrate eating patterns and hypertension, BMI, and WC, in the NDNS RP sample, separately. Since diabetic participants might or might not modify their carbohydrate eating habits, we also conducted all the above mentioned regression models restricted to those without diabetes.

For the multiple regression models, model fitting strategies are as follows:

1. The crude association between the carbohydrate eating groups and the outcomes was first examined.

2. Potential confounders of the association between carbohydrate eating groups (exposure) and the outcomes were selected depending on the descriptive statisitics conducted above, i.e. those are associated with both the exposure and the outcome and also not on the causal pathway were selected as potential confounders. Those are strongly related with the outcomes but may not associated with carbohydrate eating groups may reduce the standard errors and so improve the precisions are also considered.

3. Confounding and/or interaction effect from each of the potential factors were checked one by one. Interaction effect were tested using the adjusted Wald test comparing models with and without the interaction terms.

4. A preliminary model that includes all of the variables suggested to be confounders in the previous step was established.

5. The remaining variables were added to the preliminary model one by one to see if any of them may be a confounder in condition of the presence of the other covariates.

6. For logistic regression models (hypertension) under the survey data, goodness-of-fit was assessed using the adapted `svylogitgof` command in Stata (Archer and Lemeshow, 2006). Other diagnostics for regular logistic regression models, such as estimating the pseudo-R^2, AIC or BIC, checking the standardized Pearson residuals, or covariate pattern residuals are currently not available for weighted survey data.

7. For linear regression models (WC, BMI), assumption of independent observations is violated as soon as we weighted the sample. General checking such as QQ plots of the residuals (normality), plotting the residuals against fitted values (constant variance) are not available as well. Outliers, leverage, and Cook's distance cannot be check either, however, samples with extreme weightings (if exist) were checked by removing them and refit the models as a sensitivity analysis.

8. Since under survey design data, the sampling-weighted least squares are not maximum likelihood, it would not be possible to compare models using likelihood ratio test. Instead, adjusted Wald tests with $p < 0.05$ were used as criteria for variable inclusion in the final model. Another Stata command `linktest` was also used to decide whether quadratic and cubic terms of continuous variables were necessary in improving the fitting of model (Pregibon, 1980).

Data manipulation and preparation **(Appendix A)** were done in R version 3.5.1 (R core Team, 2018). All statistical analyses, except for MLCA models, were performed with `svyset` command as implemented in Stata software version 15.1 (StataCorp LLC, 2017). All p values were two-sided.

Chapter 3

Results

Model selection, and interpretation

A series of traditional LCA of the responses to carbohydrate intake within 7 time slots of day was first examined. These initial analyses ignored the clustering of observation days within participants of the survey. **Table 3.1** shows the latent class solutions for one to five classes (see rows under the Fixed effects model section). The BIC declines with the number of day level classes increases. However, the improvement of BIC dropped to less than 1000 from 3 classes to 4 classes solutions (658.9) and from 4 classes to 5 classses solutions (361.7). Entropy index indicates that the 4 classes model could explain about 51% percent of the data, while p values of Lo-Mendell-Rubun LRT suggest that the more classes we fit, the better model we will have until up to 6 classes (p = 0.06 and is not shown in the table). From the parsimony point of view, we extended the model with random effects building on 2 classes, 3 classes and 4 classes solutions.

The results of the random effect included models are presented in **Table 3.1** under the Random effects model section. It is obvious that the BIC improves with the addition of the random effects which account for the nested structure of the data. Entropy indicates that 4 classes in individual level and 2 classes in the day level may be the best solution mathematically. However, after these solutions were checked in more details, the potentially most substantively interpretable model was found to be the 3×3 random effect model, which is the model with 3 latent classes in the day level, and 3 latent classes in the individual level. We must emphasize that different researchers may have made decision slightly different from ours, we provided the descriptions and figures for other solutions in the **Appendix xxx** for reference.

In the 3×3 random effect model solution we have chosen, there were 39.5%, 20.4%, and 40.1% observations classified into 3 latent groups in the day level. The overall counts and percentages for each responses within every time slot and the distributions of the solution are presented in **Table 3.2**. The trajectories illustrating the change of the probabilities of each response to carbohydrate eating during the hours of the day are shown separately by the three types of days in **Figure 3.1**.

TABLE 3.1: Fit criteria for each model specification.

	Number of day level classes				
Model	**1 class**	**2 classes**	**3 classes**	**4 classes**	**5 classes**
Fixed effects model					
No. of free parameters	14	29	44	59	74
Log-likelihood	-173793.306	-172669.771	-172039.204	-171633.941	-171377.292
BIC	347728.092	345632.608	344523.060	343864.121	343502.409
Lo-Mendell-Rubun LRT	–	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Entropy	1	0.310	0.392	0.510	0.481
Random effects model					
2 individual level classes					
No. of free parameters		59	89	119	
Log-likelihood		-169331.132	-168700.96	-168366.193	
BIC		339258.502	338301.338	337934.968	
Entropy		0.581	0.569	0.555	
3 individual level classes					
No. of free parameters		89	134	179	
Log-likelihood		-166936.279	-166348.815	-166062.761	
BIC		334771.968	334051.799	333934.448	
Entropy		0.677	0.630	0.644	
4 individual level classes					
No. of free parameters		119	179		
Log-likelihood		-165441.731	-164845.696		
BIC		332086.045	331500.318		
Entropy		0.729	0.659		

Note:
Abbreviation: No, number; BIC, Bayesian information criterion; Entropy, a pseudo-r-squared index;
Lo-Mendel-Rubin LRT, likelihood ratio test comparing q classes models with $q-1$ classes models.

Class 1 days **(Figure 3.1-A)** were given the name of "high carbohydrate day" since in these days of survey, the probabilities of carbohydrate contributed higher or equal to 50% of the energy consumed were always higher than that in the other two types of days. Specifically, high carbohydrate days were characterised with probabilities of over 0.6 in time slots between 6 am to 9 am, 9 am to 12 am, and also 2 pm to 5 pm, during which the time slots may be interpreted as breakfast, morning snack, and afternoon snack time periods for many participants. Moreover, even during late night time period, such as 8 pm to 10 pm, and 10 pm to 6 am time slots, the probabilities of having higher carbohydrate contained food were still as high as 0.412, and 0.246, respectively.

TABLE 3.2: Day level latent class solution for three classes LCA model. (No individual level model)

Time slots of the day	**Responses to carbohydrate intake**	n	(%)	**Class 1 (39.5%) High carbohydrate day**	**Class 2 (20.4%) Low carbohydrate day**	**Class 3 (40.1%) Regular meals day**
6 am – 9 am						
	Not eating any food	7655	31.2	0.129	0.450	0.320
	Carbohydrate < 50%*	4500	18.4	0.130	0.267	0.128
	Carbohydrate ⩾ 50%†	12328	50.4	0.741	0.283	0.552
9 am – 12 am						
	Not eating any food	5447	22.2	0.237	0.079	0.401
	Carbohydrate < 50%	7227	29.5	0.158	0.492	0.173
	Carbohydrate ⩾ 50%	11809	48.2	0.605	0.429	0.426
12 noon – 2 pm						
	Not eating any food	4783	19.5	0.156	0.356	0.019
	Carbohydrate < 50%	11112	45.4	0.405	0.413	0.560
	Carbohydrate ⩾ 50%	8588	35.1	0.439	0.231	0.421
2 pm – 5 pm						
	Not eating any food	6926	28.3	0.130	0.123	0.659
	Carbohydrate < 50%	8277	33.8	0.249	0.602	0.076
	Carbohydrate ⩾ 50%	9280	37.9	0.621	0.276	0.266
5 pm – 8 pm						
	Not eating any food	3043	12.4	0.114	0.199	0.034
	Carbohydrate < 50%	14240	58.2	0.516	0.590	0.639
	Carbohydrate ⩾ 50%	7200	29.4	0.370	0.211	0.328
8 pm – 10 pm						
	Not eating any food	8722	35.6	0.322	0.291	0.480
	Carbohydrate < 50%	8898	36.3	0.266	0.551	0.212
	Carbohydrate ⩾ 50%	6863	28.0	0.412	0.158	0.308
10 pm – 6 am						
	Not eating any food	16295	66.6	0.680	0.590	0.751
	Carbohydrate < 50%	4144	16.9	0.074	0.294	0.101
	Carbohydrate ⩾ 50%	4044	16.5	0.246	0.115	0.148

Note:

Abbreviation: LCA, latent class analysis

* Carbohydrate < 50% indicates that within the time slot, carbohydrate contributed < 50% total energy intake.

† Carbohydrate ⩾ 50% indicates that within the time slot, carbohydrate contributed ⩾ 50% total energy intake.

Class 2 days **(Figure 3.1-B)** were named as "low carbohydrate day" because first of all, in these days the possibility of participants skipping breakfast was 0.45. And after 9 am, within low carbohydrate days, the probability of having food contained lower carbohydrate (contributed less than 50% of total energy intake), was always higher than having higher carbohydrate contained food. In these days, participants also turned to have morning snacks (with only 0.079 possibility of not eating any food and similar probabilities of having either high or low carbohydrate contained food). This phenomenon may also be interpreted as having a long and late breakfast (brunch) in these mornings. The probability of not eating any food was the lowest for low carbohydrate days during the midnight time slot (10 pm to 6 am), with probability of 0.590 compared with 0.680 and 0.751 in the class 1 and class 3 days, respectively.

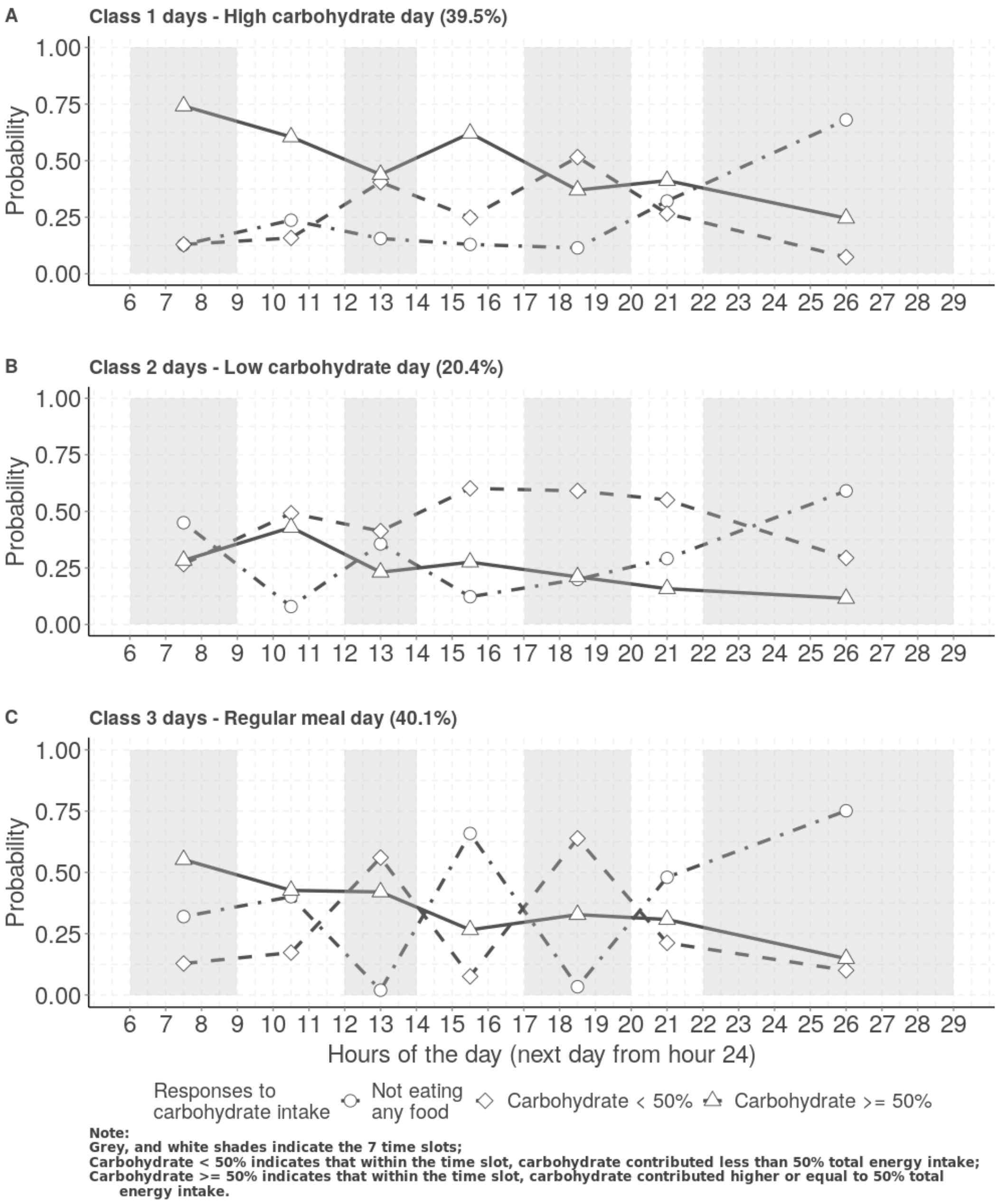

FIGURE 3.1: Day Level Latent Classes Solution.

Class 3 days **(Figure 3.1-C)** were called "regular meals day" due to the following reasons: 1) participants' dietary recordings showed that in these days there was almost 0 possibility of not eating any food at lunch (0.019 between 12 noon and 2

TABLE 3.3: Means (standard deviations), and counts (%) of the characteristics of different types of days according to carbohydrate intake.

	High carbohydrate day	Low carbohydrate day	Regular meals day	*P* value*
Counts (%)	9667 (39.5)	5002 (20.4%)	9814 (40.1%)	
Country (%)				< 0.001
England	5627 (58.2)	2972 (59.4)	5291 (53.9)	
Northern Ireland	1194 (12.4)	527 (10.5)	1400 (14.3)	
Scotland	1527 (15.8)	813 (16.3)	1774 (18.1)	
Wales	1318 (13.6)	690 (13.8)	1349 (13.7)	
Day of Week (%)				< 0.001
Monday	1303 (13.5)	715 (14.3)	1370 (14.0)	
Tuesday	1266 (13.1)	674 (13.5)	1290 (13.1)	
Wednesday	1225 (12.7)	740 (14.8)	1233 (12.6)	
Thursday	1272 (13.2)	752 (15.0)	1425 (14.5)	
Friday	1458 (15.1)	797 (15.9)	1479 (15.1)	
Saturday	1537 (15.9)	703 (14.1)	1495 (15.2)	
Sunday	1605 (16.6)	621 (12.4)	1522 (15.5)	
Weekend, Yes (%)	3142 (32.5)	1324 (26.5)	3017 (30.7)	< 0.001
Total energy (kJ)	7539.98 (2875.87)	7160.22 (2922.15)	7439.68 (2978.91)	< 0.001
Carbohydrate (g)	222.79 (89.84)	209.70 (86.17)	206.59 (84.42)	< 0.001
Protein (g)	71.36 (29.79)	69.55 (30.20)	73.29 (32.94)	< 0.001
Fat (g)	65.44 (33.27)	63.94 (33.76)	67.24 (34.73)	< 0.001
Alcohol (g)	11.76 (27.31)	8.85 (24.25)	13.80 (33.00)	< 0.001
Total sugars (g)	98.63 (56.03)	88.03 (50.50)	86.39 (50.96)	< 0.001
Starch (g)	124.07 (55.84)	121.59 (56.13)	120.11 (54.62)	< 0.001
Non-milk extrinsic sugar†	59.45 (49.31)	50.07 (43.41)	50.41 (44.84)	< 0.001
Fruit (g)	107.40 (137.97)	103.15 (129.08)	92.76 (126.02)	< 0.001
Yellow Red Green Vegetables (g)	26.52 (46.44)	26.84 (47.99)	26.16 (45.99)	0.681

Note:
* *P* values were obtained from Pearson χ^2 test for categorical variables, and one-way ANOVA comparing the means in multiple groups for continuous variables;
† Non-milk extrinsic sugar is defined as: additionally added free sugar, such as table sugar, honey, glucose, fructose and glucose syrups, sugars added to food and sugars in fruit juices.

pm) and dinner (0.034 between 5 pm and 8 pm); 2) the probabilities of not eating during morning snack time (9 am to 12 am) and afternoon snack time (2 pm to 5 pm) were also the highest among the three types of days (0.401 and 0.659). 3) during these days, participants may have some high carbohydrate contained food between 8 pm and 10 pm (0.308), but the probability of not eating any food during 10 pm to 6 am next morning was 0.751, the highest among the three types of days.

Features of the three carbohydrate eating time patterns

The details of the characteristics of the three types of carbohydrate eating time pattern were listed in **Table 3.3**. Specifically, regular meals day turned to be recorded slightly more often in Northern Ireland, and Scotland. In terms of day of week distribution in the three types of days, there is strong evidence ($p < 0.001$) that high carbohydrate days appeared more frequently in weekends (32.5%) compared with low carbohydrate day (26.5%) and regular meals day (30.7%).

As expected, consumption of total energy (7539.98 kJ), total carbohydrate (222.79 g), total sugar (98.63 g), starch (124.07 g), and non-milk extrinsic sugar (59.45 g) were highest among high carbohydrate days (all $p < 0.001$). On the other hand, the consumption of protein (73.29 g), total fat (67.24 g), and alcohol (13.80 g) were the highest in the so-called regular meals days. Moreover, in high carbohydrate days, participants turned to consume the highest amount of fruit (107.40 g). There was no evidence of any difference for the consumption of yellow, red, or green vegetables across the three types of days ($p = 0.681$).

Individual level LCA solution

In the random effect models we utilized the non-parametric approach, in which we added a level 2 (individual level) latent classes based on the random means from the level 1 (day level) latent class solution. The results of the individual level LCA solution for 2 and 3 classes are presented in **Figure 3.2**, and **3.3**.

With two individual level latent classes **(Figure 3.2)**, one individual class is comprised of individuals with a relatively slightly higher proportion of having "low carbohydrate day" (22.1%) compared to the other (17.4%). This class represents nearly 65% of the individuals. However, we believe these individual classes are not very distinguishable to each other.

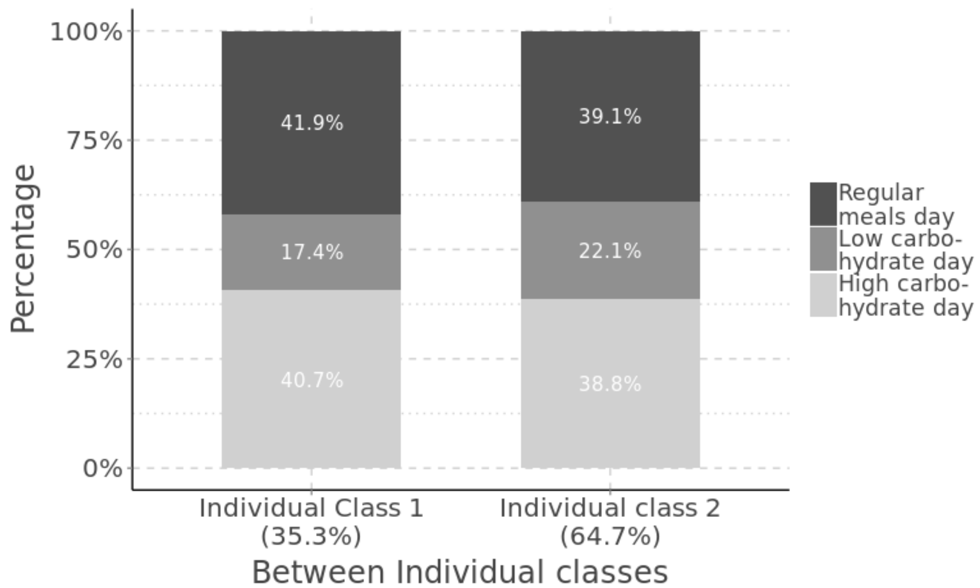

FIGURE 3.2: Multilevel Latent Class Solution, 3 classes in day level, 2 classes in individual level.

With three individual level latent classes **(Figure 3.3)**, a low-carbohydrate eaters class, a moderate-carbohydrate eaters class, and a high-carbohydrate eaters class emerges. 43.1% participants were identified as high-carbohydrate eaters, in these individuals, about 50% of the days (2 out of 4 days) of their dietary diary could be classified as having high carbohydrate days. Nearly 1 out of 4 days of their dietary diary were either "regular meals day" or "low carbohydrate day". 28.1% participants fell into the low carbohydrate eaters class in the left hand side of **Figure 3.3**, their recordings of food intake showed that in more than 60% of their days, they were having "regular meals" which was characterised as with highest amount of fat and alcohol consumptions as already described in **Table 3.3**. Moderate carbohydrate eaters have comparable proportions (42.0% vs. 40.0%) of having high carbohydrate days and regular meals day, 18.0% of their dietary diary were identified as low carbohydrate days.

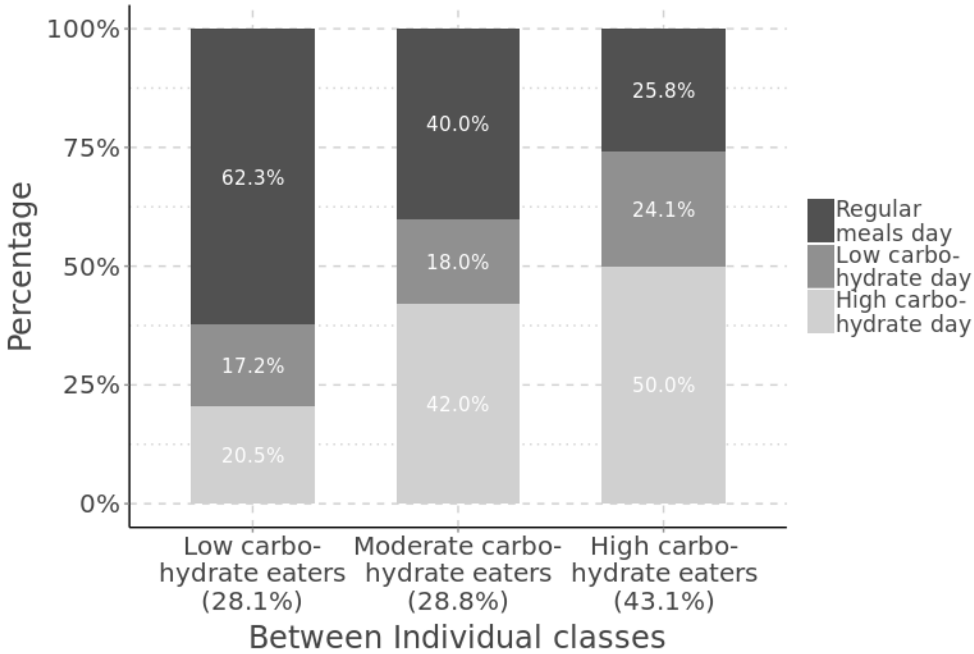

FIGURE 3.3: Multilevel Latent Class Solution, 3 classes in day level, 3 classes in individual level.

The social-demographic characteristics of the UK adults according to their individual level latent class membership are shown in **Table 3.4**. Moderate carbohydrate eaters were relatively younger ($p < 0.001$), and slightly less from England ($p = 0.007$). Gender distribution across the three types of carbohydrate eaters was fairly even ($p = 0.119$). Distribution of the carbohydrate eater types turned out to be changing with the year of survey. Low carbohydrate eaters represented 32.5% of the population in the first year of survey, but later dropped to lower than 30% (lowest in the third year, 22.6%) until the most recent year. Proportion of high carbohydrate eaters increased from 41.2% to the highest (50.6%) in the second year of the survey, but then started to decline to 38.4% in the 8th year of survey ($p = 0.015$). There was no evidence of difference in employment status across three types of carbohydrate eaters. However, strong evidence suggested that high carbohydrate eaters had the highest proportion (61.3%) of living with a partner ($p < 0.001$); moderate carbohydrate eaters had the lowest average income (27180.8 £/year), highest proportion of non-white population (20.5%), and lower education level (23.3% with degree of higher education) compared with either low or high carbohydrate eaters.

Weighted means, percentages of anthropometric measurements, average of main nutrients intake, as well as biochemical characteristic profiles according to the latent carbohydrate eater groups are given in **Table 3.5**. Low carbohydrate eaters had higher mean BMI (27.8 kg/m^2) and larger mean WC (98.9/89.9 cm in men/women) compared with 27.2, 27.3 kg/m^2, and 95.9/88.7 (men/women), 98.1/87.2 (men/women) cm in moderate and high carbohydrate eaters. Moderate carbohydrate eaters had the highest prevalence of being a current smoker (27.8%), shortest time of daily physical activity (geometric mean: 0.87 hours/day), and the lowest prevalence of hypertension (20.2%).

Average total energy intake over the 4 days of dietary survey was the highest (7985.8 kJ) in the low carbohydrate eaters group. As expected, the mean of total carbohydrate intake was 203.8 g, 218.3 g, and 233.4 g for low, moderate, and high carbohydrate eaters, respectively. Energy contribution from carbohydrate was close to 50% in the high carbohydrate eaters, but was only 40.6% in the low carbohydrate eaters. It is noteworthy that low carbohydrate eaters consumed the highest average amount of protein (79.9 g, 17.2% of total energy), fat (74.7g, 35.4% of total energy), and alcohol (20.8 g, 6.8% of total energy).

From the results of blood tests, 6.9% of low carbohydrate eaters were found to be diabetic (diagnosed by A1C > 6.5%), while the percentages of diabetes in the moderate and high carbohydrate eaters were 3.5%, and 4.1% ($p < 0.011$), respectively. Although there was some evidence ($p = 0.027$) that fasting blood glucose level may be slightly higher in non-diabetic low carbohydrate eaters, the geometric mean for A1C was probably lower in moderate carbohydrate eaters (4.72, 95%CI: 5.39, 5.47). Cholesterol, HDL, and LDL were all lower in the moderate carbohydrate eaters, while no evidence of any difference of TG was found across three types of carbohydrate eaters.

TABLE 3.4: Weighted means, percentages, and 95% CIs of the social-demographic characteristics by carbohydrate eating latent class memberships in the UK adults.
(NDNS RP 2008/09-15/16, sample size = 6155)

Variables	**Low carbo-hydrate eaters (n = 1730)**	**Moderate carbo-hydrate eaters (n = 1772)**	**High carbo-hydrate eaters (n = 2653)**	***P* value** *
Total (%)	28.4 (26.9, 29.9)	28.7 (27.1, 30.3)	43.0 (41.3, 44.7)	
Country (%)				0.007
England	84.5 (81.7, 86.9)	82.0 (79.3, 84.5)	84.7 (82.3, 86.8)	
Northern Ireland	2.1 (1.6, 2.8)	4.2 (3.2, 5.6)	2.2 (1.7, 3.0)	
Scotland	9.1 (7.0, 11.8)	8.6 (6.7, 11.1)	8.0 (6.3, 10.2)	
Wales	4.3 (3.3, 5.6)	5.1 (4.0, 6.4)	5.1 (4.0, 6.4)	
Age (years)	51.0 (49.9, 52.1)	40.3 (39.1, 41.6)	51.7 (50.7, 52.7)	< 0.001
Sex (%)				0.119
Men	50.0 (46.9, 53.1)	50.2 (47.0, 53.5)	46.6 (44.0, 49.1)	
Women	50.0 (46.9, 53.1)	49.8 (46.5, 53.0)	53.4 (50.9, 56.0)	
Survey years (% in rows)				0.015
1	32.5 (28.4, 36.9)	26.3 (21.9, 31.2)	41.2 (36.6, 46.0)	
2	26.8 (22.6, 31.3)	22.6 (18.6, 27.3)	50.6 (45.8, 55.4)	
3	22.6 (18.8, 26.9)	33.7 (28.6, 39.2)	43.6 (38.7, 48.7)	
4	27.9 (24.1, 32.2)	27.6 (23.8, 31.8)	44.4 (40.2, 48.7)	
5	27.9 (24.2, 32.0)	28.7 (24.4, 33.5)	43.3 (38.2, 48.6)	
6	28.0 (24.0, 32.4)	31.5 (26.9, 36.6)	40.5 (35.8, 45.3)	
7	29.1 (25.2, 33.4)	29.0 (24.5, 34.0)	41.8 (37.1, 46.7)	
8	31.1 (27.3, 35.3)	30.5 (25.9, 35.5)	38.4 (34.1, 42.8)	
Paid employment† (%)				0.907
Yes	40.3 (37.0, 43.6)	40.8 (37.1, 44.5)	39.8 (37.1, 42.6)	
No	59.7 (56.4, 63.0)	59.2 (55.5, 62.9)	60.2 (57.4, 62.9)	
Live with partner‡ (%)				< 0.001
Yes	56.9 (53.6, 60.1)	38.4 (35.2, 41.8)	61.3 (58.7, 63.7)	
No	43.1 (39.9, 46.4)	61.6 (58.2, 64.8))	38.7 (36.3, 41,3)	
Household income, £/year	36558.5 (34800.2, 38316.8)	27180.8 (25597.9, 28763.7)	32171.6 (31024.9, 33318.2)	< 0.001
Ethnicity (%)				
White	94.2 (92.4, 95.6)	79.5 (76.4, 82.3)	91.9 (90.1, 93.4)	< 0.001
Non-White	5.8 (4.4, 7.6)	20.5 (17.7, 23.6)	8.1 (6.6, 9.9)	
Education (%)				
Degree or higher	29.0 (26.1, 32.1)	23.3 (20.5, 26.3)	26.2 (24.1, 28.5)	0.019
Lower than degree	71.0 (67.9, 73.9)	76.7 (73.7, 79.5)	73.8 (71.5, 75.9)	

Note:

Abbreviations: CI, confidence intervals; NDNS RP, national dietary and nutrition survey rolling programme.

Variables were weighted by individual weights.

* For continuous variables, the *F* test was used to determine differences between latent classes with Bonferroni correction to account for multiple testing across > 2 classes. For categorical variables, differences between latent classes were assessed using the adjusted Pearson χ^2 test for survey data.

† Paid employment was defined as being in paid employment during the last 4 weeks prior to the survey.

‡ Live with partner was defined as either living with a married husband/wife or a legally recognised civil partnership.

TABLE 3.5: Weighted means, percentages, and 95% CIs of the anthropometric measurements, average main nutrients intake and biochemical characteristics by carbohydrate eating latent class memberships in the UK adults. (NDNS RP 2008/09-15/16, sample size = 6155)

Variables	**Low carbohydrate eaters (n = 1730)**	**Moderate carbohydrate eaters (n = 1772)**	**High carbohydrate eaters (n = 2653)**	***P* value** *
BMI (kg/m^2)	27.8 (27.4, 28.2)	27.2 (26.7, 27.7)	27.3 (26.9, 27.6)	0.006
WC (cm)				
Men	98.9 (97.4, 100.5)	95.9 (94.1, 97.8)	98.1 (96.9, 99.2)	0.056
Women	89.9 (88.7, 91.3)	88.7 (87.1, 90.3)	87.2 (86.1, 88.2)	0.005
Smoking status (%)				
Current	20.4 (18.0, 23.0)	27.8 (25.0, 30.9)	17.1 (15.4, 19.0)	< 0.001
Ex-smoker	29.3 (26.5, 32.2)	16.8 (14.6, 19.2)	26.1 (24.9, 28.3)	
Never	50.3 (47.2, 32.2)	55.4 (52.2, 58.6)	56.8 (54.3, 59.3)	
Physical activity (hours/day) ¶	1.08 (0.97, 1.19)	0.87 (0.77, 0.97)	1.07 (0.98, 1.16)	0.005
Hypertension†, Yes (%)	33.8 (30.2, 37.5)	20.2 (17.0, 24.0)	30.9 (26.9, 31.0)	< 0.001
Total energy intake (kJ)	7985.8 (7823.3, 8146.3)	7341.8 (7825.3, 8146.3)	7677.0 (7555.8, 7799.8)	< 0.001
Carbohydrate intake (g)	203.8 (199.8, 207.8)	218.3 (212.9, 223.7)	233.4 (229.6, 237.2)	< 0.001
Carbohydrate percent‡ (%)	40.6 (40.2, 41.0)	47.3 (46.8, 47.8)	48.3 (47.9, 48.6)	< 0.001
Protein intake (g)	79.9 (77.9, 81.8)	69.3 (67.6, 71.0)	73.7 (72.5, 74.8)	< 0.001
Protein percent (%)	17.2 (16.9, 17.5)	16.3 (16.0, 16.6)	16.5 (16.3, 16.6)	< 0.001
Fat intake (g)	74.7 (73.1, 76.4)	63.8 (62.1, 65.5)	65.7 (64.4, 67.0)	< 0.001
Fat percent (%)	35.4 (34.9, 35.8)	32.5 (32.1, 32.9)	32.0 (31.7, 32.3)	< 0.001
Alcohol intake (g)	20.8 (18.3, 23.2)	10.7 (9.4, 11.9)	8.9 (8.1, 9.8)	< 0.001
Alcohol percent (%)	6.8 (6.3, 7.4)	3.8 (3.4, 4.3)	3.2 (2.9, 3.4)	< 0.001
Glucose (mmol/l)	5.17 (5.12, 5.23)	5.05 (4.99, 5.13)	5.10 (5.05, 5.15)	0.027
A1C (%)	5.47 (5.44, 5.51)	5.43 (5.39, 5.47)	5.50 (5.48, 5.53)	0.010
DM §	6.9 (5.0, 9.3)	3.5 (2.3, 5.3)	4.1 (2.9, 5.6)	0.011
TC (mmol/l)	4.95 (4.84, 5.05)	4.72 (4.62, 4.83)	4.95 (4.87, 5.03)	0.001
HDL (mmol/l)	1.39 (1.35, 1.43)	1.32 (1.28, 1.35)	1.39 (1.36, 1.42)	0.003
LDL (mmol/l)	2.88 (2.79, 2.97)	2.77 (2.68, 2.86)	2.93 (2.86, 3.00)	0.024
TG (mmol/l)	1.14 (1.08, 1.19)	1.11 (1.05, 1.17)	1.10 (1.06, 1.15)	0.629

Abbreviations: CI, confidence intervals; NDNS RP, national dietary and nutrition survey rolling programme; BMI body mass index; WC, waist circumference; A1C, haemoglobin A1c; DM, diabetes mellitus; TC, total cholesterol, HDL, high density lipoproteins; LDL, low density lipoproteins; TG, triglycerides.

Glucose, A1C, TC, HDL, LDL, TG, and physical activity were expressed in geometric means (95% CI) because the data were positively skewed.

Variables from the blood tests (glucose and A1C) were weighted by blood sample weights, the other variables were weighted by nurse visiting weights. Glucose and A1C levels are estimated in subgroups of people without diabetes.

* For continuous variables, the *F* test was used to determine differences between latent classes with Bonferroni correction to account for multiple testing across > 2 classes. For categorical variables, differences between latent classes were assessed using the adjusted Pearson χ^2 test for survey data.

¶ Physical activity was calculated as mean time spent at moderate or vigorous physical activity including both work-related and recreational activities during the most recent month before the survey.

† Hypertension was defined as either systolic blood pressure $\geqslant$ 140 mmHg or diastolic blood pressure $\geqslant$ 90 mmHg, or under treatment for hypertension.

‡ Carbohydrate percent indicates the percentage of energy from carbohydrate in total energy intake.

§ DM was defined by A1C > 6.5%.

Association between individual level latent classes and hypertension, and obesity.

Hypertension

Table 3.6 presents the characteristics of men and women participants in the NDNS RP 2008/09-15/16 by hypertension status. The weighted prevalences of hypertension were 30.4% in men and 27.5% in women. Among both sexes, there were strong evidence of differences by hypertension status for age, education level, living with a partner or not, smoking status, BMI, WC, and prevalence of diabetes ($p < 0.01$). Differences were also found for carbohydrate eating patterns defined previously, total energy intake, as well as total carbohydrate intake ($p < 0.001$). No difference was found among either men or women for geographic location, and ethnicity. Strong evidence of difference was found in women for average household income (32741.5 £/year in non-hypertensive vs. 27862.0 £/year in hypertensive, $p < 0.001$), and physical activity level (geometric mean: 0.81 hours/day in non-hypertensive compared with 0.53 hours/day in hypertensive, $p < 0.001$) but not in men.

The sex-specific associations of carbohydrate eating patterns with hypertension with or without diabetes are shown in **Table 3.7**. In the crude models, moderate carbohydrate eaters had statistically significant lower odds of having hypertension than low carbohydrate eaters in both men and women irrespective to diabetes status. Among men, after adjustment for selected confounders, which includes: age, live with partner or not, education level, BMI, smoking status, and total energy intake, the odds ratio (OR) comparing moderate carbohydrate eaters was 0.68 (95% CI: 0.43, 1.07) and remained borderline significant ($p = 0.093$). 95% CI of the OR became narrower (OR: 0.64, 95% CI: 0.41, 1.01, $p = 0.054$) when BMI was replaced with WC in model 2. When diabetic men were excluded in the models, the ORs (95%CI) for moderate and high carbohydrate eaters compared with low carbohydrate eaters were 0.65 (0.41, 1.03) and 0.73 (0.51, 1.06), respectively. The negative associations between carbohydrate eaters patterns were still observed in women, however, without any statistical evidence in the full adjusted models.

Obesity (BMI and WC)

Table 3.9 shows the characteristics for participants according to their obesity status stratified by sex. The survey design-weighted prevalence for being overweight and obese in the UK adults were estimated to be 43.4% and 25.7% in men, and 30.9% and 27.4% in women. As expected, WC increased significantly with the elevated BMI level in both men and women. Strong evidence of differences by obesity level

TABLE 3.6: Weighted means, percentages, and 95 % CIs of the characteristics by hypertension status in the UK adults. (NDNS RP 2008/09-15/16, sample size = 6155)

	Men (n = 2537)			Women (n = 3618)		
	Non-hypertensive	**Hypertensive**	***P* value***	**Non-hypertensive**	**Hypertensive**	***P* value***
Weighted prevalence (%)	69.6 (66.6, 72.5)	30.4 (27.5, 33.4)		72.5 (69.8, 75.0)	27.5 (25.0, 30.2)	
Age (years)	43.2 (41.7, 44.7)	59.9 (58.0, 61.7)	< 0.001	43.9 (42.7, 45.1)	64.9 (63.4, 66.5)	< 0.001
Country (%)			0.109			0.631
England	84.7 (80.9, 87.2)	85.4 (81.2, 88.8)		84.0 (81.0, 86.6)	83.5 (79.1, 87.0)	
Northern Ireland	3.3 (2.2, 4.8)	1.6 (0.8, 3.1)		2.5 (1.9, 3.5)	2.6 (1.5, 4.3)	
Scotland	8.6 (6.3, 11.7)	7.1 (4.6, 10.9)		8.7 (6.5, 11.7)	7.9 (5.1, 11.8)	
Wales	3.9 (2.7, 5.6)	5.9 (4.0, 8.5)		4.7 (3.7, 6.0)	6.1 (4.3, 8.6)	
Ethnicity (%)			0.534			0.126
White	89.6 (86.5, 92.0)	91.1 (86.2, 94.4)		85.7 (82.7, 88.3)	90.2 (85.0, 93.7)	
Non-white	10.4 (8.0, 13.5)	8.9 (5.6, 13.8)		14.3 (11.7, 17.3)	9.8 (6.3, 15.0)	
Education (%)			0.006			< 0.001
Degree or higher	30.3 (26.6, 34.2)	21.5 (17.3, 26.5)		33.0 (29.9, 36.3)	19.7 (15.8, 24.3)	
Lower than Degree	69.7 (65.8, 73.4)	78.5 (73.5, 82.7)		67.0 (63.7, 70.1)	80.3 (75.7, 84.2)	
Household income,£/year	34006.5 (31972.9, 36040.1)	32280.5 (29875.6, 34685.4)	0.284	32741.5 (31009.9, 34473.1)	27862.0 (25557.0, 30167.0)	< 0.001
Live with partner‡, Yes, (%)	56.1 (51.8, 61.4)	66.6 (61.3, 71.5)	0.002	48.7 (45.1, 52.3)	58.9 (53.6, 63.9)	0.002
Smoking status			< 0.001			< 0.001
Current	19.7 (16.6, 23.1)	12.9 (9.5, 17.2)		15.2 (13.1, 17.6)	8.5 (6.2, 11.6)	
Ex-smoker	24.2 (21.1, 27.6)	38.8 (33.4, 44.5)		21.6 (19.1, 24.4)	32.2 (27.3, 37.4)	
Never	56.2 (52.1, 60.1)	48.3 (42.7, 54.0)		63.2 (60.1, 66.2)	59.3 (54.0, 64.4)	
Physical activity (hours/day) †	1.52 (1.33, 1.72)	1.29 (1.08, 1.53)	0.134	0.81 (0.73, 0.89)	0.53 (0.42, 0.64)	< 0.001
BMI (kg/m^2)	26.8 (26.4, 27.2)	29.5 (28.9, 29.9)	< 0.001	26.4 (26.1, 26.8)	29.8 (29.2, 30.5)	< 0.001
WC (cm)	95.0 (93.9, 96.2)	104.6 (103.2, 106.1)	< 0.001	85.7 (84.8, 86.6)	95.7 (94.2, 97.2)	< 0.001
DM§ (%)	3.7 (2.4, 5.7)	12.6 (8.9, 17.5)	< 0.001	1.8 (1.0, 3.3)	7.9 (5.1, 11.9)	< 0.001
Carbohydrate eating patterns (%)			< 0.001			< 0.001
Low	28.3 (24.8, 32.2)	37.1 (32.0, 42.5)		26.9 (24.1, 29.9)	32.0 (27.2, 37.2)	
Moderate	30.8 (26.9, 35.0)	19.3 (15.3, 24.1)		29.6 (26.4, 33.0)	18.4 (14.5, 22.9)	
High	40.8 (36.9, 44.9)	43.6 (38.2, 49.2)		43.5 (40.3, 46.8)	49.7 (44.1, 55.2)	
Total energy intake (kJ)	9021.4 (8791.9, 9251.0)	8366.2 (8094.9, 8637.4)	< 0.001	6802.6 (6681.1, 6924.0)	6396.7 (6217.1, 6576.2)	< 0.001
Carbohydrate intake (g)	259.2 (252.9, 265.3)	235.3 (227.8, 242.8)	< 0.001	198.0 (194.2, 201.8)	184.5 (178.8, 190.1)	< 0.001

Note:

Abbreviations: CI, confidence intervals; NDNS RP, national dietary and nutrition survey rolling programme; BMI body mass index; WC, waist circumference.

Variables are weighted by nurse visiting weights.

* Significant sex-specific differences by hypertension status assessed using an F test for continuous variables or design-adjusted Pearson χ^2 test.

‡ Live with partner was defined as either living with a married husband/wife or a legally recognised civil partnership.

† Physical activity was calculated as mean time spent at moderate or vigorous physical activity including both work-related and recreational activities.

§ DM was defined by A1C $>$ 6.5%.

were found for age, total energy intake, and carbohydrate intake in both sexes. Specifically, education level (p = 0.022 for men, < 0.001 for women), average household income (p = 0.011 for men, < 0.001 for women) were lower with increasing BMI. Living with partner or not was strongly positively associated with obesity in men but not in women. Men with obesity were found to have the lowest proportion of never being a smoker (47.9 %), and the highest proportion of being ex-smoker (32.9%). Association between smoking status and obesity in women was only with very weak evidence (p = 0.042) but similar pattern as in men was also observed. No difference was found for length of physical activity across obesity levels in men,

TABLE 3.7: ORs (95%CI) of carbohydrate eating patterns with hypertension in the UK adults, with or without diabetes .
(NDNS RP 2008/09-15/16, sample size = 6155)

	Carbohydrate eating patterns				
Model	**Low**	**Moderate**	***P* value***	**High**	***P* value***
Men (n = 2537)					
Hypertension					
Crude model	1	0.48 (0.33, 0.70)	< 0.001	0.82 (0.59, 1.13)	0.217
Model 1†	1	0.68 (0.43, 1.07)	0.093	0.80 (0.56, 1.15)	0.227
Model 2	1	0.64 (0.41, 1.01)	0.054	0.75 (0.53, 1.08)	0.124
Hypertension in non-diabetics					
Crude model	1	0.49 (0.33, 0.73)	< 0.001	0.82 (0.59, 1.14)	0.241
Model 1†	1	0.69 (0.43, 1.09)	0.110	0.78 (0.54, 1.14)	0.197
Model 2	1	0.65 (0.41, 1.03)	0.066	0.73 (0.51, 1.06)	0.096
Women (n = 3618)					
Hypertension					
Crude model	1	0.52 (0.36, 0.75)	< 0.001	0.96 (0.72, 1.28)	0.773
Model 1‡	1	0.79 (0.45, 1.39)	0.415	0.89 (0.61, 1.30)	0.552
Model 2	1	0.78 (0.45, 1.36)	0.384	0.88 (0.62, 1.26)	0.483
Hypertension in non-diabetics					
Crude model	1	0.51 (0.35, 0.74)	< 0.001	0.98 (0.73, 1.31)	0.875
Model 1‡	1	0.79 (0.44, 1.42)	0.435	0.89 (0.61, 1.29)	0.534
Model 2	1	0.79 (0.45, 1.39)	0.415	0.87 (0.61, 1.25)	0.452

Note:
Abbreviations: OR, odds ratio; CI, confidence interval; BMI, body mass index; WC, waist circumference; NDNS RP, national dietary and nutrition survey rolling programme.
Diabetes was defined by A1C > 6.5%. BMI was replaced with WC in Model 2s, other covariates remained the same with the corresponding Model 1s.
* *P* values were obtained from wald tests from logistic regression models.
† Adjusted for age (continuous), live with partner or not (binary), education level (higher or equal to degree level or not), BMI, smoking status (current, ex-smoker, never) , total energy intake (kJ);
‡ Adjusted for age, live with partner or not, average household income (continuous), education level, BMI, smoking status, total energy intake (kJ), alcohol consumption (g/day);

TABLE 3.8: Weighted means, percentages, and 95 % CIs of the characteristics by BMI categories in the UK adults. (NDNS RP 2008/09-15/16, sample size = 6155)

	Men (n = 2537)				Women (n = 3618)			
	Normal weight	**Overweight**	**Obese**	***P* value***	**Normal weight**	**Overweight**	**Obese**	***P* value***
Weighted prevalence (%)	30.9 (28.0, 33.9)	43.4 (40.4, 46.4)	25.7 (23.2, 28.4)		41.7 (39.0, 44.4)	30.9 (28.4, 33.5)	27.4 (25.1, 29.9)	
BMI (kg/m^2)	22.6 (22.3, 22.8)	27.3 (27.2, 27.5)	33.7 (33.3, 34.2)	< 0.001	22.2 (22.0, 22.4)	27.3 (27.2, 27.5)	35.0 (34.6, 35.4)	< 0.001
WC (cm)	84.5 (83.6, 85.4)	97.1 (96.4, 97.8)	112.7 (111.6, 113.9)	< 0.001	76.9 (76.2, 77.5)	89.0 (88.3, 89.7)	103.7 (102.6, 104.7)	< 0.001
Age (years)	40.3 (38.2, 42.4)	49.6 (47.9, 51.2)	50.4 (48.5, 52.3)	< 0.001	45.0 (43.4, 46.7)	50.4 (48.6, 52.3)	50.9 (49.1, 52.7)	< 0.001
Country (%)				0.236				0.589
England	83.9 (79.2, 87.7)	86.9 (83.6, 89.7)	81.6 (76.7, 85.7)		84.3 (80.4, 87.5)	83.7 (79.7, 87.0)	82.4 (78.2, 85.9)	
Northern Ireland	3.3 (1.9, 5.8)	2.3 (1.4, 3.6)	3.2 (2.0, 4.9)		3.0 (2.1, 4.2)	2.2 (1.5, 3.2)	3.4 (2.3, 5.0)	
Scotland	9.1 (6.1, 13.5)	6.5 (4.4, 9.7)	9.0 (5.9, 13.3)		9.0 (6.1, 13.0)	9.0 (6.3, 12.8)	8.5 (5.7, 12.6)	
Wales	3.7 (2.3, 5.8)	4.3 (3.1, 5.9)	6.3 (4.0, 9.7)		3.8 (2.9, 5.1)	5.1 (3.6, 7.2)	5.7 (4.2, 7.7)	
Ethnicity (%)				0.466				0.879
White	88.7 (83.9, 92.2)	89.1 (85.6, 91.9)	91.9 (87.3, 94.9)		88.4 (84.9, 91.19	88.6 (84.5, 91.7)	87.3 (82.5, 90.9)	
Non-white	11.3 (7.8, 16.1)	10.9 (8.1, 14.4)	8.1 (5.1, 12.7)		11.6 (8.9, 15.1)	11.4 (8.3, 15.5)	12.7 (9.1, 17.5)	
Education (%)				0.022				< 0.001
Degree or higher	29.5 (24.5, 35.0)	28.3 (24.3, 32.7)	20.1 (16.0, 25.0)		35.7 (31.8, 39.8)	24.2 (20.4, 28.4)	19.4 (16.1, 23.2)	
Lower than Degree	70.5 (65.0, 75.5)	71.7 (67.3, 75.7)	79.9 (75.0, 84.0)		64.3 (60.2, 68.2)	75.8 (71.6, 79.6)	80.6 (76.8, 83.9)	
Household income, £/year	33695.9 (30462.3, 36929.7)	35059.6 (32949.7, 37169.5)	30295.5 (27948.5, 32642.6)	0.011	34594.1 (32326.8, 36861.4)	29777.7 (27808.3, 31747.2)	27230.6 (25259.1, 29202.0)	< 0.001
Live with partner‡, Yes, (%)	40.3 (34.8, 46.1)	65.3 (60.8, 69.6)	65.6 (60.1, 70.8)	< 0.001	47.6 (43.2, 52.1)	52.2 (47.5, 57.0)	51.7 (46.7, 56.6)	0.288
Smoking status				< 0.001				0.042
Current	32.0 (26.8, 37.7)	18.7 (15.5, 22.4)	19.2 (15.0, 24.3)		19.5 (16.4, 22.9)	17.8 (14.8, 21.4)	16.4 (13.1, 20.3)	
Ex-smoker	17.3 (13.5, 22.0)	28.6 (24.8, 32.7)	32.9 (27.9, 38.4)		19.0 (15.9, 22.5)	24.4 (20.8, 28.3)	26.9 (22.8, 31.6)	
Never	50.6 (44.8, 56.4)	52.7 (48.2, 57.1)	47.9 (42.1, 53.7)		61.6 (57.4, 65.5)	57.8 (53.3, 62.2)	56.7 (51.8, 61.4)	
Physical activity† (hours/day)	1.58 (1.33, 1.85)	1.42 (1.24, 1.62)	1.41 (1.15, 1.70)	0.547	0.84 (0.74, 0.94)	0.71 (0.62, 0.79)	0.65 (0.53, 0.78)	0.038
Carbohydrate eating patterns (%)				0.072				0.253
Low	25.9 (21.0, 31.5)	30.6 (26.6, 35.0)	31.4 (26.6, 36.6)		24.8 (21.5, 28.5)	26.8 (22.8, 31.2)	29.5 (25.3, 34.1)	
Moderate	34.2 (28.6, 40.4)	25.5 (21.9, 29.6)	25.5 (20.6, 31.0)		27.6 (23.8, 31.8)	26.3 (22.3, 30.8)	29.8 (25.4, 34.6)	
High	39.9 (34.2, 45.8)	43.8 (39.6, 48.2)	43.1 (37.7, 48.7)		47.6 (43.3, 51.9)	46.9 (42.4, 51.4)	40.7 (36.0, 45.6)	
Total energy intake (kJ)	9351.2 (8961.7, 9740.7)	8786.9 (8595.1, 8978.7)	8465.3 (8196.4, 8734.1)	0.001	7048.9 (6894.4, 7203.4)	6570.1 (6406.2, 6734.0)	6566.4 (6360.7, 6772.1)	< 0.001
Carbohydrate intake (g)	268.7 (258.3, 279.2)	250.1 (244.1, 256.1)	239.1 (231.3, 246.8)	< 0.001	205.8 (200.2, 211.3)	190.1 (185.3, 194.9)	189.8 (183.7, 195.9)	< 0.001

Note:
Abbreviations: CI, confidence intervals; NDNS RP, national dietary and nutrition survey rolling programme; BMI body mass index; WC, waist circumference.
Variables are weighted by nurse visiting weights.
* Significant sex-specific differences by BMI categories assessed using an F test (with Bonferroni correction to account for multiple testing across > 2 groups) for continuous variables or design-adjusted Pearson χ^2 test for categorical variables
‡ Live with partner was defined as either living with a married husband/wife or a legally recognised civil partnership.
† Physical activity was calculated as mean time spent at moderate or vigorous physical activity including both work-related and recreational activities.

while in women, somewhat weak inverse association (p=0.038) was confirmed. Interestingly, predefined carbohydrate eating patterns were seemingly not associated with BMI in men (p = 0.072) or in women (p = 0.253).

Results of the regression analyses showed inverse associations between latent classes of carbohydrate eating patterns and BMI among men **(Table 3.9)**. However, the 95%CI of the regression coefficients were all too wide and include the null value 0, indicating no statistically supported evidence of the association. But, evidence of interaction effect was found in whether live with a partner or not on the association between carbohydrate eating patterns and BMI (p for interaction = 0.014 and 0.036 for women in total and without diabetes). For women living with her partner, latent classes of carbohydrate eating patterns were negatively associated with BMI. Compared with women eating low carbohydrate meals, women having

TABLE 3.9: Associations of carbohydrate eating patterns with BMI in the UK adults, with or without diabetes.
(NDNS RP 2008/09-15/16, sample size = 6155)

	Carbohydrate eating patterns				
Model	**Low**	**Moderate**	***P* value***	**High**	***P* value***
Men (n = 2537)					
BMI					
Crude model	–	-0.78 (-1.62, 0.06)	0.068	-0.28 (-0.96, 0.41)	0.426
Model 1†	–	-0.20 (-1.06, 0.66)	0.654	-0.43 (-1.13, 0.26)	0.220
BMI in non-diabetics					
Crude model	–	-0.65 (-1.49, 0.19)	0.127	-0.21 (-0.89, 0.48)	0.557
Model 1†	–	-0.10 (-0.97, 0.77)	0.820	-0.39 (-1.10, 0.31)	0.269
Women (n = 3618)					
BMI					
Crude model	–	-0.30 (-1.18, 0.57)	0.496	-0.76 (-1.44, -0.82)	0.028
Live with partner‡	–	-0.93 (-2.33, 0.46)	0.188	-1.76 (-2.78, -0.73)	0.001
Live alone‡	–	1.17 (-0.35, 2.70)	0.132	0.57 (-0.58, 1.719	0.332
BMI in non-diabetics					
Crude model	–	-0.24 (-1.12, 0.65)	0.601	-0.71 (-1.39, -0.03)	0.040
Live with partner‡	–	-0.86 (-2.28, 0.55)	0.232	-1.62 (-2.65, -0.58)	0.002
Live alone‡	–	1.22 (-0.34, 2.78)	0.124	0.43 (-0.71, 1.56)	0.462

Note:

Abbreviations: BMI body mass index; NDNS RP, national dietary and nutrition survey rolling programme. Diabetes was defined by A1C > 6.5%.

* *P* values were obtained from wald tests from linear regression models.

† Adjusted for age, live with partner or not, education level, hypertension (yes or no), smoking status, total energy intake, alcohol consumption;

‡ Adjusted for age, average household income, education level, hypertension, smoking status, total energy intake, alcohol consumption.

the high carbohydrate eating pattern were averagely associated with 1.76 kg/m^2 lower BMI after adjusted for age, average household income, education level, smoking status, total energy intake and alcohol consumption. 95%CI for the adjusted BMI difference was 0.73 to 2.78 kg/m^2, p = 0.001. After excluding diabetic women, BMI was still 1.62 kg/m^2 (95%CI: 0.58, 2.65, p = 0.002) lower in high carbohydrate eaters versus low carbohydrate eaters on average. On the contrary, latent classes of carbohydrate eating patterns were positively associated with women who lived alone, although the regression coefficients were not statistically different from 0.

TABLE 3.10: Associations of carbohydrate eating patterns with BMI in the UK adults , with or without diabetes. (NDNS RP 2008/09-15/16, sample size = 6155)

	Carbohydrate eating patterns				
Model	**Low**	**Moderate**	***P* value***	**High**	***P* value***
Men (n = 2537)					
WC					
Crude model	–	-3.00 (-5.49, -0.52)	0.018	-0.90 (-2.84, 1.04)	0.364
Model 1†	–	1.06 (-1.50, 3.64)	0.415	-1.55 (-3.42, 0.31)	0.103
WC in non-diabetics					
Crude model	–	-2.51 (-5.00, -0.21)	0.048	-0.51 (-2.47, 1.44)	0.606
Model 1†	–	1.42 (-1.17, 4.01)	0.283	-1.29 (-3.18, 0.60)	0.181
Women (n = 3618)					
WC					
Crude model	–	-1.28 (-3.26, 0.70)	0.206	-2.81 (-4.50, -1.12)	0.001
Live with partner‡	–	0.28 (-2.85, 3.41)	0.861	-4.71 (-7.00, -2.43)	< 0.001
Live alone‡	–	3.17 (0.05, 6.30)	0.047	0.73 (-1.84, 3.30)	0.577
WC in non-diabetics					
Crude model	–	-0.91 (-2.88, 1.07)	0.368	-2.41 (-4.06, -0.76)	0.004
Live with partner‡	–	1.11 (-2.02, 4.23)	0.487	-3.74 (-5.97, -1.51)	0.001
Live alone‡	–	3.08 (-0.09, 6.25)	0.057	0.16 (-2.36, 2.69)	0.899

Note:

Abbreviations: WC, waist circumference; NDNS RP, national dietary and nutrition survey rolling programme.

Diabetes was defined by A1C > 6.5%.

* P values were obtained from wald tests from linear regression models.

† Adjusted for age, live with partner or not, average household income, education level, hypertension (yes or no), smoking status, total energy intake, alcohol consumption;

‡ Adjusted for age, education level, hypertension, smoking status, total energy intake, alcohol consumption.

Similarly, when using WC as another measurement of obesity, compared with men who had low carbohydrate eating pattern, only those had a moderate carbohydrate eating pattern were found with about 3 cm (95%CI: 0.52, 5.49 cm, p = 0.018) smaller WC in the crude model **(Table 3.10)**. After adjustment of age, living with partner or not, average household income, education level, hypertension, smoking status, total energy intake, and alcohol consumption, the association attenuated to no difference in men. Again, the interaction effect of whether living with partner or not on the association between carbohydrate eating patterns and WC was found in women in total and without diabetes. Among women who were living with her partner, high carbohydrate eaters had 4.71 cm (95%CI: 2.43, 7.00, $p < 0.001$) lower WC on average compared with low carbohydrate eaters. The association remained when restricted into non-diabetic women (-3.74 cm, 95% CI: 1.51, 5.97, p = 0.001). However, for women who lived without a partner, moderate carbohydrate eaters had 3.17 cm (95%CI: 0.05, 6.30, $p = 0.043$) larger WC compared with low carbohydrate eaters. The evidence for the positive association between moderate carbohydrate eaters and WC was weak and became borderline significant when excluding diabetic women.

Chapter 4

Discussion and Conclusion

- MLCA ignored the order of observation days.
- We used the maximum probability rule and ignored that these are just probabilities.

Main Section 1

Subsection 1

Subsection 2

Main Section 2

Bibliography

Almoosawi, S et al. (2016). "Chrono-nutrition: a review of current evidence from observational studies on global trends in time-of-day of energy intake and its association with obesity". In: *Proceedings of the Nutrition Society* 75.4, pp. 487–500.

Archer, Kellie J, Stanley Lemeshow, et al. (2006). "Goodness-of-fit test for a logistic regression model fitted using survey sample data". In: *Stata Journal* 6.1, pp. 97–105.

Asher, Gad and Paolo Sassone-Corsi (2015). "Time for food: the intimate interplay between nutrition, metabolism, and the circadian clock". In: *Cell* 161.1, pp. 84–92.

Bates, Beverley et al. (2014). *National Diet and Nutrition Survey: Results from Years 1, 2, 3 and 4 (combined) of the Rolling Programme (2008/2009-2011/2012): A survey carried out on behalf of Public Health England and the Food Standards Agency*. Public Health England.

Besson, Herve et al. (2009). "Estimating physical activity energy expenditure, sedentary time, and physical activity intensity by self-report in adults–". In: *The American journal of clinical nutrition* 91.1, pp. 106–114.

Collins, L.M. and S.T. Lanza (2010). *Latent Class and Latent Transition Analysis: With Applications in the Social, Behavioral, and Health Sciences*. Wiley Series in Probability and Statistics. Wiley.

Davidian, Marie et al. (2008). "Growth mixture modeling: Analysis with non-Gaussian random effects". In: *Longitudinal Data Analysis*. Chapman and Hall/CRC, pp. 157–180.

De Bacquer, Dirk et al. (2009). "Rotating shift work and the metabolic syndrome: a prospective study". In: *International Journal of Epidemiology* 38.3, pp. 848–854.

Department of Health (2018). *National Diet and Nutrition Survey Rolling Programme*. https://www.gov.uk/government/collections/national-diet-and-nutrition-survey.

Finch, W Holmes and Brian F French (2014). "Multilevel latent class analysis: Parametric and nonparametric models". In: *The Journal of Experimental Education* 82.3, pp. 307–333.

Henry, Kimberly L and Bengt Muthén (2010). "Multilevel latent class analysis: An application of adolescent smoking typologies with individual and contextual predictors". In: *Structural Equation Modeling* 17.2, pp. 193–215.

Johnston, Jonathan D (2014). "Physiological responses to food intake throughout the day". In: *Nutrition Research Reviews* 27.1, pp. 107–118.

Leech, Rebecca M et al. (2017). "Temporal eating patterns: a latent class analysis approach". In: *International Journal of Behavioral Nutrition and Physical Activity* 14.1, p. 3.

Lo, Yungtai, Nancy R Mendell, and Donald B Rubin (2001). "Testing the number of components in a normal mixture". In: *Biometrika* 88.3, pp. 767–778.

Mansukhani, Raoul and Luigi Palla (Jan. 2018). "Investigating eating time patterns in UK adults from The 2008–2012 National Diet and Nutrition Survey". In: 77.

Muthén, Bengt and Tihomir Asparouhov (2009). "Multilevel regression mixture analysis". In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 172.3, pp. 639–657.

Muthén, Linda K and Bengt O Muthén (2017). *Mplus: Statistical analysis with latent variables: User's guide*. Muthén & Muthén Los Angeles.

NatCen Social Research (2018). *National Diet and Nutrition Survey Years 1-8, 2008/09-2015/16*. http://doi.org/10.5255/UKDA-SN-6533-8.

Nylund, Karen L, Tihomir Asparouhov, and Bengt O Muthén (2007). "Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study". In: *Structural Equation Modeling* 14.4, pp. 535–569.

Office for National Statistics (2018). *Mid 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, and 2016 Population Estimates*. https : / / www . ons . gov . uk / peoplepopulationandcommunity / populationandmigration / populationestimates.

Pan, An et al. (2011). "Rotating night shift work and risk of type 2 diabetes: two prospective cohort studies in women". In: *PLoS Medicine* 8.12, e1001141.

Pregibon, Daryl (1980). "Goodness of link tests for generalized linear models". In: *Applied Statistics*, pp. 15–14.

R core Team (2018). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. URL: https://www.R-project.org/.

Roberts, Caireen et al. (2018). "National Diet and Nutrition Survey: results from years 7 and 8 (combined) of the Rolling Programme (2014/2015–2015/2016)". In:

Smithers, Gillian (1993). "MAFF's nutrient databank". In: *Nutrition & Food Science* 93.2, pp. 16–19.

Snijders, T.A.B. and R.J. Bosker (2011). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. SAGE Publications.

StataCorp LLC (2017). *Stata Statistical Software: Release 15*. Version 15.1. URL: https://www.stata.com/.

Uemura, Mayu et al. (2015). "Breakfast skipping is positively associated with incidence of type 2 diabetes mellitus: evidence from the Aichi Workers' Cohort Study". In: *Journal of Epidemiology* 25.5, pp. 351–358.

Van Horn, M Lee et al. (2008). "Using multilevel mixtures to evaluate intervention effects in group randomized trials". In: *Multivariate Behavioral Research* 43.2, pp. 289–326.

Vermunt, Jeroen K. (2003). *Multilevel Latent Class Models*. Vol. 33. 1, pp. 213–239. DOI: 10.1111/j.0081-1750.2003.t01-1-00131.x.

Vermunt, Jeroen K (2008). "Latent class and finite mixture models for multilevel data sets". In: *Statistical Methods in Medical Research* 17.1, pp. 33–51.

Appendix A

R code for importing and manipulating the data

```
# NDNS analysis, data management -------------------------------------------

# Change the data path accordingly -----------------------------------------
setwd("/home/wangcc-me/Downloads/UKDA-6533-stata11_se/stata11_se/") # in Ubuntu
library(epiDisplay)
library(plyr)
library(tidyverse)

# Read the data into memory -----------------------------------------------
library(haven)
data <- read_dta("ndns_rp_yr1-4a_foodleveldietarydata_uk.dta")
data56 <- read_dta("ndns_rp_yr5-6a_foodleveldietarydata.dta")
data78 <- read_dta("ndns_rp_yr7-8a_foodleveldietarydata.dta")
names(data)
names(data56)
names(data78)
names(data)[names(data) == "seriali"] <- "id"
names(data56)[names(data56) == "seriali"] <- "id"
names(data78)[names(data78) == "seriali"] <- "id"

# Extract the data we needed ----------------------------------------------
df14d <- data[, c(113, 1, 2, 3, 5, 6, 7, 8, 9, 21, 24, 55, 57, 58,
    59, 60, 61, 62, 63, 64)]
var <- names(df14d)
df56d <- data56 %>% select(var)
```

```
df78d <- data78 %>% select(var)
dfs1 <- rbind(df14d, df56d, df78d)
dfs2 <- dfs1[dfs1$Age >= 19, ]
rm(data, data56, data78)
dfs2

# Calculate the time (minute and hour) when they eat ----------------------

dfs2$MealTime_chr <- as.character(dfs2$MealTime)
dfs2$MealTime_hm <- unlist(strsplit(dfs2$MealTime_chr, " "))[c(FALSE,
    TRUE)]
dfs2$MealHourN <- as.numeric(unlist(strsplit(dfs2$MealTime_hm, ":"))[c(TRUE,
    FALSE, FALSE)])
dfs2$MealMinN <- as.numeric(unlist(strsplit(dfs2$MealTime_hm, ":"))[c(FALSE,
    TRUE, FALSE)])
dfs2$MealMinN0 <- (60 * dfs2$MealHourN) + dfs2$MealMinN
dfs3 <- dfs2[order(dfs2$id, dfs2$DayNo, dfs2$MealMinN0), ]
length(unique(dfs3$id))  ## number of participants = 6155

# Create a subset data with only the first observation of each
# participant --------
NDNS <- dfs3[!duplicated(dfs3$id), ]
with(NDNS, tab1(SurveyYear, graph = FALSE, decimal = 2))

# #SurveyYear :
            # Frequency Percent Cum. percent
# NDNS Year 1       801   13.01        13.01
# NDNS Year 2       812   13.19        26.21
# NDNS Year 3       782   12.71        38.91
# NDNS Year 4      1055   17.14        56.05
# NDNS Year 5       625   10.15        66.21
# NDNS Year 6       663   10.77        76.98
# NDNS Year 7       703   11.42        88.40
# NDNS Year 8       714   11.60       100.00
  # Total          6155  100.00       100.00


# create a variable combine id and day No --------------------------------
```

```
dfs3 <- dfs3 %>%
mutate(id_dy = paste(id, DayNo, sep = "D"))

# For each subject, the total energy/carbohydrate intake for each eating
# time can be calculated --------
old <- Sys.time()
Energy <- ddply(dfs3, .(id_dy, id, SurveyYear, DayNo, Age, Sex,
                        DiaryDaysCompleted, MealHourN, DayofWeek),
                summarise,
                Tot_Energ = sum(EnergykJ),
                Tot_Carb = sum(Carbohydrateg),
                Tot_Sugar = sum(Totalsugarsg),
                Tot_Starch = sum(Starchg))
new <- Sys.time() - old
print(new)
# Time difference of 3.876385 mins

rm(df14d, df56d, df78d, dfs2)

# Calculate the energy from total carbohydrates ---------------------------
Energy <- Energy %>%
  mutate(KJcarbo = Tot_Carb * 16) %>%
  mutate(CarKJpercentage = KJcarbo/Tot_Energ) %>%
  mutate(Carbo = cut(CarKJpercentage, breaks = c(0, 0.26, 0.75, 2),
        right = FALSE)) %>% mutate(Carbo2 = cut(CarKJpercentage, breaks = c(0,
    0.26, 2), right = FALSE))
Energy0 <- Energy[!(Energy$Tot_Energ == 0), ]
          # some food consumption does not contain any carbohydrates
Energy0$Carbo <- factor(Energy0$Carbo, labels = c("Low_carb", "Med_carb",
    "High_carb"))
Energy0$Carbo2 <- factor(Energy0$Carbo2, labels = c("Low_carb", "Med_or_high_carb")

# Generate data sets for each day -----------------------------------------------
dta_day1 <- Energy0 %>%
  filter(DayNo == 1) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
```

```
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))

dta_day2 <- Energy0 %>%
  filter(DayNo == 2) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))

dta_day3 <- Energy0 %>%
  filter(DayNo == 3) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))

dta_day4 <- Energy0 %>%
  filter(DayNo == 4) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))
vecid1 <- unique(dta_day1$id) # n = 6153
vecid2 <- unique(dta_day2$id) # n = 6153
vecid3 <- unique(dta_day3$id) # n = 6151
vecid4 <- unique(dta_day4$id) # n = 6026

Noday1 <- setdiff(vecid, vecid1)  # two subjects did not have day 1 data
Noday2 <- setdiff(vecid, vecid2)  # two subjects did not have day 2 data
Noday3 <- setdiff(vecid, vecid3)  # four subjects did not have day 3 data
Noday4 <- setdiff(vecid, vecid4)  # 129 subjects did not have day 4 data

# Transform the data shape from long to wide ---------------------------------
dta_d1_wide <- dta_day1[, -7] %>%
```

```
  spread(key = MealHourN, value = Carbo)
names(dta_d1_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")

dta_d2_wide <- dta_day2[, -7] %>%
  spread(key = MealHourN, value = Carbo)
names(dta_d2_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")

dta_d3_wide <- dta_day3[, -7] %>%
  spread(key = MealHourN, value = Carbo)
names(dta_d3_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")

dta_d4_wide <- dta_day4[, -7] %>%
  spread(key = MealHourN, value = Carbo)
names(dta_d4_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")
# recode NA to not eating -------------------------------------------------
for (i in 5:ncol(dta_d1_wide))
  if (is.factor(dta_d1_wide[, i])) levels(dta_d1_wide[,
    i]) <- c(levels(dta_d1_wide[, i]), "Not_eating")

dta_d1_wide[is.na(dta_d1_wide)] <- "Not_eating"

for (i in 5:ncol(dta_d2_wide))
  if (is.factor(dta_d2_wide[, i])) levels(dta_d2_wide[,
    i]) <- c(levels(dta_d2_wide[, i]), "Not_eating")

dta_d2_wide[is.na(dta_d2_wide)] <- "Not_eating"

for (i in 5:ncol(dta_d3_wide))
  if (is.factor(dta_d3_wide[, i])) levels(dta_d3_wide[,
    i]) <- c(levels(dta_d3_wide[, i]), "Not_eating")

dta_d3_wide[is.na(dta_d3_wide)] <- "Not_eating"

for (i in 5:ncol(dta_d4_wide))
  if (is.factor(dta_d4_wide[, i])) levels(dta_d4_wide[,
    i]) <- c(levels(dta_d4_wide[, i]), "Not_eating")

dta_d4_wide[is.na(dta_d4_wide)] <- "Not_eating"
```

Appendix B

Mplus code and output for Multilevel LCA models

```
Mplus VERSION 7.4
MUTHEN & MUTHEN
07/28/2018   9:55 AM

INPUT INSTRUCTIONS

TITLE:    3-class at level 1 (CW), 3-classes at level 2 (CB) random effects model
ordered polytomous variables for carb intake at each time slot over four
days of NDNS survey 2008/09 - 2015/16
variable 0 = not eating
1 = eating & carb provided < 50% calorie
2 = eating & carb provided >= 50% calorie

DATA:     File is H:\summer_project\Mplus\TimeSlots\NDNS_Tslots.dat;


VARIABLE: NAMES = id id_dy Age Sex H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;

USEVAR = H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;

auxiliary = Age Sex;

CATEGORICAL =  H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;
```

```
CLUSTER = id;

IDVARIABLE = id_dy;

BETWEEN = CB;

WITHIN = H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;

CLASSES = CB(3) CW(3);

MISSING are .;



ANALYSIS:
type = mixture twolevel;
starts = 50 25;
process = 8(starts);


MODEL:
%within%
%overall%
%between%
%overall%
CW ON CB;



Savedata:
file is H:\summer_project\Mplus\TimeSlots\Multilevel\NDNSslot_CW3CB3.txt;
save is cprob;
format is free;
```

```
3-class at level 1 (CW), 3-classes at level 2 (CB) random effects model
ordered polytomous variables for carb intake at each time slot over four
days of NDNS survey 2008/09 - 2015/16
variable 0 = not eating
1 = eating & carb provided < 50% calorie
2 = eating & carb provided >= 50% calorie

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                       24483

Number of dependent variables                                    7
Number of independent variables                                  0
Number of continuous latent variables                            0
Number of categorical latent variables                           2

Observed dependent variables

Binary and ordered categorical (ordinal)
H6_9        H9_12       H12_14      H14_17      H17_20      H20_22
H22_6

Observed auxiliary variables
AGE         SEX

Categorical latent variables
CB          CW

Variables with special functions

Cluster variable      ID
ID variable           ID_DY

Within variables
H6_9        H9_12       H12_14      H14_17      H17_20      H20_22
H22_6
```

```
Estimator                                                          MLR
Information matrix                                            OBSERVED
Optimization Specifications for the Quasi-Newton Algorithm for
Continuous Outcomes
Maximum number of iterations                                     100
Convergence criterion                                      0.100D-05
Optimization Specifications for the EM Algorithm
Maximum number of iterations                                     500
Convergence criteria
Loglikelihood change                                     0.100D-02
Relative loglikelihood change                            0.100D-05
Derivative                                               0.100D-02
Optimization Specifications for the M step of the EM Algorithm for
Categorical Latent variables
Number of M step iterations                                        1
M step convergence criterion                               0.100D-02
Basis for M step termination                               ITERATION
Optimization Specifications for the M step of the EM Algorithm for
Censored, Binary or Ordered Categorical (Ordinal), Unordered
Categorical (Nominal) and Count Outcomes
Number of M step iterations                                        1
M step convergence criterion                               0.100D-02
Basis for M step termination                               ITERATION
Maximum value for logit thresholds                                15
Minimum value for logit thresholds                               -15
Minimum expected cell size for chi-square                  0.100D-01
Maximum number of iterations for H1                              2000
Convergence criterion for H1                                0.100D-03
Optimization algorithm                                             EMA
Integration Specifications
Type                                                         STANDARD
Number of integration points                                      15
Dimensions of numerical integration                                0
Adaptive quadrature                                               ON
Random Starts Specifications
Number of initial stage random starts                             50
Number of final stage optimizations                               25
```

```
Number of initial stage iterations                          10
Initial stage convergence criterion                  0.100D+01
Random starts scale                                  0.500D+01
Random seed for generating random starts                     0
Parameterization                                         LOGIT
Link                                                     LOGIT
Cholesky                                                   OFF

Input data file(s)
H:\summer_project\Mplus\TimeSlots\NDNS_Tslots.dat
Input data format  FREE


SUMMARY OF DATA

Number of missing data patterns             1
Number of y missing data patterns           0
Number of u missing data patterns           1
Number of clusters                       6155



COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value   0.100


UNIVARIATE PROPORTIONS AND COUNTS FOR CATEGORICAL VARIABLES

H6_9
Category 1     0.313         7655.000
Category 2     0.184         4500.000
Category 3     0.504        12328.000
H9_12
Category 1     0.222         5447.000
Category 2     0.295         7227.000
Category 3     0.482        11809.000
H12_14
```

```
Category 1    0.195          4783.000
Category 2    0.454         11112.000
Category 3    0.351          8588.000
H14_17
Category 1    0.283          6926.000
Category 2    0.338          8277.000
Category 3    0.379          9280.000
H17_20
Category 1    0.124          3043.000
Category 2    0.582         14240.000
Category 3    0.294          7200.000
H20_22
Category 1    0.356          8722.000
Category 2    0.363          8898.000
Category 3    0.280          6863.000
H22_6
Category 1    0.666         16295.000
Category 2    0.169          4144.000
Category 3    0.165          4044.000


RANDOM STARTS RESULTS RANKED FROM THE BEST TO THE WORST LOGLIKELIHOOD VALUES

Final stage loglikelihood values at local maxima, seeds, and initial stage
start numbers:

-166348.815  153942           31
-166348.815  573096           20
-166348.815  253358           2
-166348.816  318230           46
-166348.816  246261           38
-166348.873  285380           1
-166348.908  903420           5
-166349.394  120506           45
-166349.394  966014           37
-166349.394  207896           25
-166349.395  195873           6
-166349.513  68985            17
```

```
-166349.514  366706          29
-166352.737  76974           16
-166357.057  127215          9
-166482.723  533738          11
-166495.844  645664          39
-166668.918  372176          23


THE BEST LOGLIKELIHOOD VALUE HAS BEEN REPLICATED.  RERUN WITH AT LEAST TWICE THE
RANDOM STARTS TO CHECK THAT THE BEST LOGLIKELIHOOD IS STILL OBTAINED AND REPLICATED.


THE MODEL ESTIMATION TERMINATED NORMALLY



MODEL FIT INFORMATION

Number of Free Parameters                      134

Loglikelihood

H0 Value                      -166348.815
H0 Scaling Correction Factor      1.8182
for MLR

Information Criteria

Akaike (AIC)                   332965.630
Bayesian (BIC)                 334051.799
Sample-Size Adjusted BIC       333625.950
(n* = (n + 2) / 24)



MODEL RESULTS USE THE LATENT CLASS VARIABLE ORDER

CB  CW
```

```
Latent Class Variable Patterns

CB        CW
Class     Class

1         1
1         2
1         3
2         1
2         2
2         3
3         1
3         2
3         3


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASS PATTERNS
BASED ON ESTIMATED POSTERIOR PROBABILITIES

Latent Class
Pattern

1  1       4050.97975          0.16546
1  2       1561.55249          0.06378
1  3       1286.46696          0.05255
2  1       2746.94031          0.11220
2  2       3011.00217          0.12298
2  3       1341.59686          0.05480
3  1       2748.25320          0.11225
3  2       4770.55950          0.19485
3  3       2965.64876          0.12113


FINAL CLASS COUNTS AND PROPORTIONS FOR EACH LATENT CLASS VARIABLE
BASED ON ESTIMATED POSTERIOR PROBABILITIES

Latent Class
```

```
Variable    Class

CB             1      6898.99902          0.28179
               2      7099.53906          0.28998
               3     10484.46094          0.42823
CW             1      9546.17285          0.38991
               2      9343.11426          0.38162
               3      5593.71240          0.22847


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASS PATTERNS
BASED ON THEIR MOST LIKELY LATENT CLASS PATTERN

Class Counts and Proportions

Latent Class
Pattern

1  1            4262          0.17408
1  2            1406          0.05743
1  3            1178          0.04812
2  1            2807          0.11465
2  2            2946          0.12033
2  3            1260          0.05146
3  1            2745          0.11212
3  2            5315          0.21709
3  3            2564          0.10473


FINAL CLASS COUNTS AND PROPORTIONS FOR EACH LATENT CLASS VARIABLE
BASED ON THEIR MOST LIKELY LATENT CLASS PATTERN

Latent Class
Variable    Class

CB             1            6846          0.27962
               2            7013          0.28644
               3           10624          0.43393
```

```
CW              1           9814          0.40085
                2           9667          0.39485
                3           5002          0.20431


CLASSIFICATION QUALITY

Entropy                          0.630


Average Latent Class Probabilities for Most Likely Latent Class Pattern (Row)
by Latent Class Pattern (Column)

Latent Class Variable Patterns

Latent Class         CB         CW
Pattern No.       Class      Class

1             1          1
2             1          2
3             1          3
4             2          1
5             2          2
6             2          3
7             3          1
8             3          2
9             3          3

1        2        3        4        5        6        7        8        9

1   0.720    0.091    0.073    0.016    0.032    0.004    0.005    0.033    0.025
2   0.183    0.609    0.098    0.005    0.002    0.030    0.040    0.005    0.027
3   0.211    0.084    0.629    0.008    0.005    0.007    0.011    0.036    0.009
4   0.019    0.004    0.002    0.692    0.184    0.051    0.011    0.034    0.003
5   0.042    0.001    0.001    0.158    0.709    0.045    0.001    0.035    0.009
6   0.012    0.037    0.013    0.065    0.084    0.702    0.042    0.003    0.042
7   0.011    0.029    0.004    0.012    0.002    0.022    0.641    0.126    0.153
8   0.026    0.003    0.009    0.025    0.024    0.001    0.115    0.675    0.123
```

```
9   0.046    0.024    0.004    0.003    0.010    0.018    0.079    0.174    0.642



MODEL RESULTS

Two-Tailed
Estimate       S.E.  Est./S.E.    P-Value

Within Level

Latent Class Pattern 1 1

Thresholds
H6_9$1            -0.718      0.218     -3.294      0.001
H6_9$2             0.973      0.299      3.258      0.001
H9_12$1           -2.516      0.463     -5.433      0.000
H9_12$2            0.675      0.132      5.118      0.000
H12_14$1          -1.025      0.145     -7.057      0.000
H12_14$2           1.240      0.116     10.725      0.000
H14_17$1          -1.566      0.149    -10.520      0.000
H14_17$2           1.090      0.100     10.909      0.000
H17_20$1          -1.998      0.125    -16.000      0.000
H17_20$2           1.549      0.100     15.556      0.000
H20_22$1          -0.933      0.085    -10.914      0.000
H20_22$2           1.829      0.103     17.770      0.000
H22_6$1            0.253      0.083      3.046      0.002
H22_6$2            2.308      0.117     19.691      0.000

Latent Class Pattern 1 2

Thresholds
H6_9$1            -4.021      1.788     -2.249      0.025
H6_9$2            -0.115      0.259     -0.445      0.656
H9_12$1            0.167      0.373      0.448      0.654
H9_12$2            2.142      0.586      3.657      0.000
H12_14$1          -3.210      1.518     -2.115      0.034
H12_14$2           0.858      0.167      5.124      0.000
```

```
H14_17$1             0.044      0.384      0.114      0.909
H14_17$2             1.617      0.293      5.509      0.000
H17_20$1            -2.109      0.390     -5.409      0.000
H17_20$2             1.399      0.196      7.126      0.000
H20_22$1            -0.367      0.174     -2.109      0.035
H20_22$2             2.347      0.382      6.151      0.000
H22_6$1              0.754      0.259      2.912      0.004
H22_6$2              2.542      0.264      9.646      0.000

Latent Class Pattern 1 3

Thresholds
H6_9$1             -15.000      0.000    999.000    999.000
H6_9$2               2.357      0.783      3.011      0.003
H9_12$1             -1.433      0.372     -3.850      0.000
H9_12$2             -0.604      0.279     -2.166      0.030
H12_14$1            -1.988      0.257     -7.749      0.000
H12_14$2             0.524      0.125      4.209      0.000
H14_17$1            -1.027      0.232     -4.436      0.000
H14_17$2             0.274      0.131      2.087      0.037
H17_20$1            -2.665      0.310     -8.605      0.000
H17_20$2             0.707      0.112      6.322      0.000
H20_22$1            -0.527      0.152     -3.462      0.001
H20_22$2             0.702      0.138      5.102      0.000
H22_6$1              1.119      0.185      6.062      0.000
H22_6$2              1.748      0.183      9.544      0.000

Latent Class Pattern 2 1

Thresholds
H6_9$1               1.663      0.199      8.370      0.000
H6_9$2               1.839      0.198      9.274      0.000
H9_12$1             -2.150      0.281     -7.643      0.000
H9_12$2             -0.869      0.140     -6.190      0.000
H12_14$1            -1.978      0.191    -10.349      0.000
H12_14$2             0.323      0.078      4.139      0.000
H14_17$1             0.237      0.183      1.293      0.196
H14_17$2             0.782      0.123      6.352      0.000
```

```
H17_20$1          -2.936      0.428     -6.853      0.000
H17_20$2           0.632      0.081      7.807      0.000
H20_22$1           0.028      0.142      0.194      0.846
H20_22$2           0.868      0.086     10.145      0.000
H22_6$1            0.658      0.109      6.010      0.000
H22_6$2            1.326      0.100     13.215      0.000

Latent Class Pattern 2 2

Thresholds
H6_9$1             1.640      0.171      9.619      0.000
H6_9$2             1.906      0.179     10.678      0.000
H9_12$1           -1.954      0.347     -5.636      0.000
H9_12$2           -0.360      0.127     -2.842      0.004
H12_14$1          -0.016      0.189     -0.084      0.933
H12_14$2           0.948      0.135      7.029      0.000
H14_17$1          -1.906      0.301     -6.327      0.000
H14_17$2           0.371      0.080      4.614      0.000
H17_20$1          -0.812      0.116     -7.030      0.000
H17_20$2           0.910      0.089     10.259      0.000
H20_22$1          -0.742      0.089     -8.318      0.000
H20_22$2           0.998      0.085     11.705      0.000
H22_6$1            0.298      0.083      3.608      0.000
H22_6$2            1.337      0.099     13.475      0.000

Latent Class Pattern 2 3

Thresholds
H6_9$1            -1.072      0.500     -2.144      0.032
H6_9$2            -0.309      0.346     -0.892      0.372
H9_12$1            2.441      1.044      2.339      0.019
H9_12$2            3.599      1.983      1.815      0.069
H12_14$1          -1.029      0.211     -4.880      0.000
H12_14$2           0.603      0.123      4.913      0.000
H14_17$1          -0.010      0.243     -0.041      0.967
H14_17$2           0.784      0.157      4.977      0.000
H17_20$1          -0.953      0.203     -4.684      0.000
H17_20$2           0.779      0.135      5.784      0.000
```

```
H20_22$1          -0.105      0.210     -0.500      0.617
H20_22$2           1.203      0.135      8.914      0.000
H22_6$1            0.582      0.299      1.950      0.051
H22_6$2            1.370      0.206      6.653      0.000

Latent Class Pattern 3 1

Thresholds
H6_9$1            -4.593      1.699     -2.703      0.007
H6_9$2            -2.975      0.428     -6.957      0.000
H9_12$1           -0.322      0.207     -1.553      0.120
H9_12$2            0.398      0.363      1.095      0.274
H12_14$1          -5.060      3.668     -1.380      0.168
H12_14$2           0.307      0.100      3.080      0.002
H14_17$1           0.186      0.530      0.351      0.726
H14_17$2           0.317      0.245      1.295      0.195
H17_20$1          -4.019      0.957     -4.199      0.000
H17_20$2           0.747      0.093      7.987      0.000
H20_22$1          -0.233      0.132     -1.767      0.077
H20_22$2           0.607      0.109      5.571      0.000
H22_6$1            1.304      0.146      8.918      0.000
H22_6$2            1.850      0.160     11.579      0.000

Latent Class Pattern 3 2

Thresholds
H6_9$1            -1.232      0.195     -6.305      0.000
H6_9$2            -0.858      0.169     -5.068      0.000
H9_12$1           -4.377      1.937     -2.260      0.024
H9_12$2           -1.488      0.316     -4.717      0.000
H12_14$1          -1.727      0.227     -7.611      0.000
H12_14$2           0.302      0.082      3.666      0.000
H14_17$1          -1.834      0.237     -7.730      0.000
H14_17$2          -0.294      0.186     -1.582      0.114
H17_20$1          -2.588      0.487     -5.313      0.000
H17_20$2           0.631      0.062     10.187      0.000
H20_22$1          -0.920      0.078    -11.852      0.000
H20_22$2           0.462      0.073      6.308      0.000
```

```
H22_6$1            0.640      0.119      5.361      0.000
H22_6$2            1.162      0.129      9.039      0.000

Latent Class Pattern 3 3

Thresholds
H6_9$1            -4.941      5.813     -0.850      0.395
H6_9$2            -2.680      0.887     -3.024      0.002
H9_12$1           -0.765      0.640     -1.195      0.232
H9_12$2            1.164      0.920      1.265      0.206
H12_14$1          -1.415      0.439     -3.226      0.001
H12_14$2           0.566      0.085      6.626      0.000
H14_17$1          -2.052      0.650     -3.158      0.002
H14_17$2           0.612      0.210      2.909      0.004
H17_20$1          -1.627      0.427     -3.810      0.000
H17_20$2           0.713      0.103      6.935      0.000
H20_22$1          -0.850      0.329     -2.585      0.010
H20_22$2           0.685      0.134      5.104      0.000
H22_6$1            1.237      0.195      6.349      0.000
H22_6$2            1.893      0.179     10.582      0.000

Between Level

Categorical Latent Variables

Within Level

Intercepts
CW#1              -0.076      0.366     -0.208      0.835
CW#2               0.475      0.309      1.539      0.124

Between Level

CW#1       ON
CB#1               1.223      0.473      2.585      0.010
CB#2               0.793      0.441      1.796      0.073

CW#2       ON
```

```
CB#1               -0.282      0.535     -0.526      0.599
CB#2                0.333      0.455      0.733      0.464

Means
CB#1               -0.417      0.100     -4.178      0.000
CB#2               -0.386      0.067     -5.770      0.000


QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix            0.428E-04
(ratio of smallest to largest eigenvalue)


SAVEDATA INFORMATION


Save file
H:\summer_project\Mplus\TimeSlots\Multilevel\NDNSslot_CW3CB3.txt

Order of variables

H6_9
H9_12
H12_14
H14_17
H17_20
H20_22
H22_6
ID_DY
AGE
SEX
CPROB1
CPROB2
CPROB3
CPROB4
CPROB5
CPROB6
```

```
CPROB7
CPROB8
CPROB9
CB
CW
MLCJOINT
ID

Save file format           Free

Save file record length    10000


DIAGRAM INFORMATION

Mplus diagrams are currently not available for Mixture analysis.
No diagram output was produced.


Beginning Time:  09:55:10
Ending Time:  10:02:01
Elapsed Time:  00:06:51



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```

Appendix C

Example of a food diary for one day

Day EXAMPLE			**Day:** Thursday	**Date:** March 31^{st}
Time	**Where? With whom? TV on? Table?**	**What**	**Brand Name**	**Amount eaten**
How to describe what you had and how much you had can be found on pages 20-25				
		6am to 9am		
7.30am	Kitchen	Orange juice, unsweetened, UHT	Tesco	Large glass
	Family	Tea	Tesco	Mug
	No TV	Milk, fresh semi skimmed	Tesco	A little
	At table	Sugar white	Silverspoon	2 level teaspoons
		Weetabix		2
		Milk as above		Drowned
		Sugar as above		2 heaped teaspoons
		Toast wholemeal, large loaf	Hovis	2 thin slices
		Butter unsalted	Anchor	thick spread on both
		Strawberry Jam	Co-op	1 teaspoon on one slice
		9am to 12 noon		
11am	School playground	Coca cola diet	Coca Cola	330ml can
	With friends	Potato crisps, Salt and Vinegar	Walkers	25g packet from a multipack
12noon	School corridor	Water from water cooler		small plastic cup
	Alone	Mars Bar		1 kingsize
		12 noon to 2pm		
12.45pm	School canteen	Sandwich, from home		
	With friends	White bread, large loaf	Kingsmill	2 med slices
	At table	Spread	Flora Light	thin spread on both slices
		Ham unsmoked	Tescos	1 slice
		Cheddar cheese		2 medium slices
		Branston Pickle		1 teaspoon
		Apple with skin from home		1 (left core)
		Ribena Light, Ready to Drink, Blackcurrant, from canteen		220ml carton
		Kitkat from home		2 fingers
1.50pm	School corridor			
	Alone	Chewing gum	Orbit Sugar Free	1 piece

FIGURE C.1: NATIONAL DIET AND NUTRITION SURVEY – Food and Drink Diary Example, from 6 am to 2 pm.

Day EXAMPLE			Day: Thursday	Date: March 31st
Time	Where? With whom? TV on? Table?	What	Brand Name	Amount eaten
		2pm to 5pm		
3.45pm	Bus Alone	 Wine gums	 Maynards	 140g packet
4.30pm	Home, sitting room, With family TV on Not at table	 Tea (as above) Chocolate Hob Nobs	 Mcvitites	 mug 3
		5pm to 8pm		
6.30pm	Friend's kitchen With friends No TV At table	Chicken in tomato sauce made by friend's mum Tomato fresh Sweetcorn tinned Peach yoghurt low fat Lemon squash No Added Sugar	See recipe Mullerlight Sainsbury's	3 tablespoons 3 slices 1 dessertspoon 200g pot medium glass
		8pm to 10pm		
8pm	Home, sitting room Alone TV on, Not at table	Satsuma Cream Crackers (no spread)	 Jacob's	1 4
9.30pm	Kitchen Alone No TV, At table	 Thick cut, frozen chips fried in vegetable oil Brown sauce	 McCains HP	 small portion 1 dessertspoon
		10pm to 6am		
10.30pm	Bedroom Alone TV on Not at table	Hot chocolate drink made with water	Cadbury's	Mug (made with 4 tsp powder)
2am	Bedroom (in bed) Alone No TV	Water tap		$\frac{1}{2}$ small glass

FIGURE C.2: NATIONAL DIET AND NUTRITION SURVEY – Food and Drink Diary Example, from 2 pm to 6 am.

Write in recipes or ingredients of made up dishes or take-away dishes			
NAME OF DISH: *Chicken in tomato Sauce*		***Serves:*** *4 people*	
Ingredients	***Amount***	***Ingredients***	***Amount***
Pieces of chicken	*3 pieces*	*Olive oil*	*2 tbsp*
Sauce made with:			
Tinned tomatoes	*1 tin*		
Green pepper	*1 medium*		
Onion	*1 small*		
Brief description of cooking method Chicken pieces fried in olive oil, then mixed in with tomato and vegetable sauce.			

FIGURE C.3: NATIONAL DIET AND NUTRITION SURVEY – Food and Drink Diary Example, home made food recipes.