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Modelling life trajectories of body-mass index

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- The Household, Income and Labour Dynamics in Australia (HILDA) survey – housed at the Melbourne Institute, and accessible via the ADA Dataverse
- The 1970 British Cohort Study (BCS) – housed at the Centre for Longitudinal Studies (CLS), UCL Social Research Institute, and accessible via the UK Data Service
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2 Abstract

Body-mass index (BMI) tends to follow a typical trajectory over the life-course of an individual, increasing in early life while decreasing after middle age. To be able to reflect these trends in the OECD Strategic Public Health Planning for Non-Communicable Diseases (SPHeP-NCDs) model, this paper analyses longitudinal BMI data from 22 countries to build a mixed, autoregressive model predicting an individual's BMI based on their sex, age and previous BMI. The resulting model shows how young people are likely to see an increase in BMI year-on-year, even if they already have overweight or obesity. It also shows that that a healthy weight in childhood does not protect against future overweight, as BMI continues to increase well into adulthood even for children who start off with a healthy weight. The results of this analysis will be incorporated in the OECD SPHeP NCDs model, to better simulate the longer-term impact of interventions, in particular interventions targeting childhood obesity.

L'indice de masse corporelle (IMC) a tendance à suivre une trajectoire typique au cours de la vie d'un individu, augmentant au début de la vie et diminuant après l'âge moyen. Afin de pouvoir refléter ces tendances dans le modèle de l'OCDE pour la planification stratégique de la santé publique pour les maladies non transmissibles (SPHeP-NCDs), cet article analyse les données longitudinales de l'IMC dans 22 pays pour construire un modèle mixte autorégressif prédisant l'IMC d'un individu en fonction de son sexe, de son âge et de son IMC précédent. Le modèle qui en résulte montre comment les jeunes sont susceptibles de voir leur IMC augmenter d'année en année, même s'ils sont déjà en surpoids ou obèses. Il montre également qu'un poids sain pendant l'enfance ne protège pas contre le surpoids futur, car l'IMC continue d'augmenter à l'âge adulte, même pour les enfants qui commencent avec un poids sain. Les résultats de cette analyse seront intégrés au modèle SPHeP-NCDs de l'OCDE, afin de mieux simuler l'impact à long terme des interventions, notamment des interventions ciblant l'obésité infantile.

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3 Introduction

1. Body-mass index (BMI, measured as weight in kilograms divided by height in metres squared) is closely related to age. On average, BMI tends to increase over time until middle-age, after which it often decreases as people age (Villareal et al., 2005[1]). Moreover, BMI is known to be strongly linked to BMI at earlier age. For example, childhood obesity is a major predictor of obesity in adulthood: children with obesity are around five times more likely to be obese in adulthood than those who were not obese (Simmonds et al., 2016[2]). Due to these effects, BMI tends to follow a typical trajectory over the life-course of an individual.

2. Currently, the OECD Strategic Public Health Planning for Non-Communicable Diseases (SPHeP-NCDs) model does not accurately capture these longitudinal effects. BMI is modelled longitudinally using the "fixed quantile" approach (OECD, 2019[3]). This means that an individual is assigned a fixed position within the BMI distribution for that age, sex and country cohort (e.g. 790th highest BMI out of 900 men aged 40 in Italy). At a different point in time (e.g. same sex and country, but age+1), the individual keeps their relative position in the distribution of BMI, but their actual BMI can change based on the new BMI distribution for that age, sex and country. Because of this approach, people with a high BMI will always keep a high BMI, and the model does not capture differences in BMI trajectory based on age, previous BMI or sex.

3. To be able to model different BMI trajectories in the OECD SPHeP-NCDs model, an algorithm is needed to predict BMI year on year, based on previous BMI, age and sex. A number of studies describe average BMI trajectories by age for specific population groups (Lee et al., 2010[4]) (Koepsell, Littman and Forsberg, 2012[5]) (Clarke et al., 2009[6]). Other studies take into account prior BMI, primarily by looking at BMI trajectories for predefined weight categories, such as people with obesity (Wandai et al., 2020[7]) (Callo Quinte et al., 2019[8]), children with overweight (Ferraro, Thorpe and Wilkinson, 2003[9]) people with metabolically unhealthy obesity (Smith et al., 2019[10]), or children with a history of rapid weight gain (Lu, Pearce and Li, 2020[11])). Instead of using predefined groups, other studies analysed BMI data to identify latent subgroups with similar trajectories (Chen and Brogan, 2012[12]) (Yang et al., 2019[13]) (Mattsson et al., 2019[14]). However, no studies were found which directly used BMI and age to predict future BMI at the individual level.

4. This analysis explores the trajectory of BMI over the life course of an individual. Rather than looking at age-based average BMI for specific population groups, it identifies how BMI changes over time in an individual given its previous state. In other words, it looks to predict a person's BMI at age t based on their BMI at age $t-1$. The aim of this analysis is two-fold. Firstly, the analysis aims to shed light on the impact of current BMI on future BMI, which is important when thinking about the impact of childhood obesity as well as temporary interventions that lower BMI. Secondly, the results of this analysis are specifically designed to be used in the OECD SPHeP-NCDs model (OECD, 2020[15]) (OECD, 2019[3]).

5. Once incorporated, the model will more accurately capture the longer-term impact of interventions that affect BMI, by simulating realistic trajectories of BMI in the following years (see Box 1). This is particularly important for interventions that act on childhood obesity, for example some of the programmes evaluated as part of the Best Practices project. Instead of only looking at the impact on BMI during the evaluation period, future levels of overweight can be assessed.

6. The incorporation of the results of this analysis in the OECD SPHeP-NCDs model is important to note as it drives a number of methodological decisions. The most important one is related to the choice of the main explanatory variables, which is limited to sex and age to enhance cross-country comparability and cope with data limitations (e.g. ethnicity is not commonly reported in datasets). The analyses are carried out assuming that the population in the datasets used for the analyses on BMI, the population in the OECD SPHeP-NCDs model and the real population have the same prevalence for any variable that is not included in the model. Importantly, since interventions modelled in the microsimulation do not change the relative prevalence of subgroups, this assumption does not affect the model results.

Box 1. Incorporating BMI trajectories in the OECD SPHeP-NCDs model

The main output of this analysis is a formula predicting BMI based on BMI in the year prior, age and sex. This formula will be used in the OECD SPHeP-NCDs model to assign BMI values to the individuals in its simulated population. While the exact methodology to incorporate the formula in the model will be subject to testing and calibration, it is expected that the historic distribution of BMI for young people will be retained, after which the formula will predict the course of BMI over time for each individual as they age. Interventions that "shock" BMI (e.g. a policy that results in a sudden reduction in BMI for some individuals) will be modelled according to the evidence in the literature (e.g. a 5% reduction in BMI the first year, after which it goes back up to a 2% reduction in the second year). After the effect of the shock stabilises, the individual will continue on the trajectory associated with their BMI at the end of the intervention effect.

4 Methods

Data

7. To analyse changes in BMI over time in individuals, longitudinal data was used. Data from four sources covering a total of 22 countries was combined for this analysis (see Box 2 for more information). The 22 countries included in the analyses are Australia, Austria, Belgium, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Israel[1], Italy, Luxembourg, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Since the countries cover different parts of the life trajectory, and because not all countries in the OECD SPHeP NCDs model are represented in the data, no country-specific analyses were done.

8. The four databases were cleaned, standardised and merged into a single dataset. Since the three surveys all had different designs with regards to cohort selection and follow-up time, BMI data was linearly interpolated between observations to create a standardised format. This means that if BMI at age 10 was 15, and at age 16 it was 21, then observations were created where BMI=16 at age=11, BMI=17 at age=12 etc. Since the average number of observations per trajectory was about three, it was not possible to explore accurately non-linear patterns for extrapolation. To minimise the impact of the linearity assumption, only observations that were 12 years or less apart were included (12 years being the longest interval between consecutive waves in the UK database). For this same reason, if two sets of consecutive waves were available that were themselves not consecutive (e.g. wave 1 and 2, and 5 and 6), only the first set of consecutive waves was included.

Box 2. Description of data sources

1970 British Cohort Study (BCS70)

The 1970 British Cohort Study (BCS70) follows the lives of more than 17,000 people born in England, Scotland and Wales in a single week of 1970. Subsequently, data was collected at 5 to 12 years intervals, with the latest in 2016 at age 46.

For this study, the waves collected at ages 10, 16, 26, 34 and 46 were included, as these are roughly equally spaced (intervals between 6 and 12 years) and contained height and weight data. It was decided to use data collected at age 10 instead of 5 years-old – despite the smaller interval with the next wave than in the rest of the study – as BMI becomes more accurate for older children (Mei et al., 2002[16]) . For each transition (e.g. from age 10 to 16), the sample contained between 4,403 and 6,451 individuals

[1] The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

with consecutive BMI data. In total, 2,131 individuals had BMI data for all five waves and were therefore included in all four transitions.

National Longitudinal Study of Adolescent to Adult Health (Add Health)

The analysis for the United States was based on data from the National Longitudinal Study of Adolescent to Adult Health (Add Health). This longitudinal study started with a nationally representative sample of United States adolescents in grades 7 through 12 (ages 12 to 21) during the 1994-1995 school year. This cohort was then followed into young adulthood through four in-home interviews, the most recent one conducted in 2008 when the sample was aged 25 to 34.

For this analysis, waves 1, 3 and 4 were used. These waves are roughly equally spaced (six to seven years apart, in 1995, 2001 and 2008). Wave 2 was conducted only one year after wave 1, and was therefore left out of the analysis. For this same reason, only transitions between wave 1 and 3, and 3 and 4 were included, as the time interval for students who only participated in wave 1 and 4 was too large. The number of people observed at extreme ages (age 12 and 13, and at age 32, 33 and 34) was small and therefore excluded from the analysis to prevent outliers. The analysis sample contained 4,464 individuals with BMI data for wave 1 and 3, and 4,787 individuals with BMI data for wave 3 and 4. Of these, 3,803 individuals had BMI data for all three waves.

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

The Survey of Health, Ageing and Retirement in Europe (SHARE) database contains longitudinal data on people aged 50 years and older for the 27 European Union countries, Switzerland and Israel. Countries joined the project at different times, which means that some countries do not have data for the earlier waves. The target population of the survey was all persons aged 50 years and over, and the data therefore covers different ages in the same wave. Collection takes place roughly every two years, with wave 1 conducted in 2004/5 and wave 7 in 2017/18.

Six waves were included in this study, since wave 3 used a special survey that did not include the data required. In total, 20 countries had the relevant data. All transitions were included in the analysis, since only 0.1% of transitions exceeded the maximum time of 12 years. However, a minimum time period was used to balance the data with the other datasets and to avoid measuring short-term fluctuations. Only participants with BMI measured over at least 6 years were included in the analysis (55% of all participants), reflecting the time gaps in the other datasets. This meant that Croatia was not included, as this country only started participating in SHARE in wave 6. In the final analysis, 40,528 participants were included and 19 countries.

Household, Income and Labour Dynamics in Australia (HILDA)

The Household, Income and Labour Dynamics in Australia (HILDA) survey was started in 2001 and follows 17,000 Australians, asking them every year about their economic and personal wellbeing, labour market dynamics and family life. In Wave 1 data was collected from 13 969 individuals aged 15 and over. During the data collection for wave 11 data a sample top-up of 5 477 individuals was added. At the time of writing, data collected from 2001 through 2019 (Waves 1-19) were available for analysis.

BMI was available from wave 6 onwards, and therefore the data sample covered 13 years (2006 to 2019). This period is close to the maximum of 12 years and therefore no maximum time period was applied. However, a minimum time period of 6 years was introduced to prevent short term fluctuations and balance the data with the other datasets, leaving 63% of the sample.

Source: https://cls.ucl.ac.uk/cls-studies/1970-british-cohort-study/; https://addhealth.cpc.unc.edu/; http://www.share-project.org/; https://melbourneinstitute.unimelb.edu.au/hilda

Analysis

9. Since BMI observations from different waves are clustered within individuals, a mixed model was used with a random intercept for individuals (see Box 3). Random intercepts for country or database were not included because they skewed the results, likely because the databases/countries covered distinct parts of the life course, and were therefore strongly (in some cases fully) correlated with age. Random slopes were not explored as the number of observations per individual was too small in most cases (Wright, 2017[17]). The mixed models were tested by comparing them to normal linear models using on the likelihood-ratio test.

Box 3. Mixed models

Mixed models (also called hierarchical or multi-level models) are widely used to deal with longitudinal data where repeated observations are made over time for the same individuals. They have also been used to model life course trajectories, e.g. by (Britton et al., 2015[18]) (Lu, Pearce and Li, 2020[19]) (Smith et al., 2019[10]).

In general, mixed models are used to deal with observations that are not fully independent, but are instead clustered. For example:

- Smoking status (observation) of patients (level 1), who are sampled from specific doctor's offices (level 2)
- BMI measurements (observation) over time (level 1), which are sampled from specific individuals (level 2)

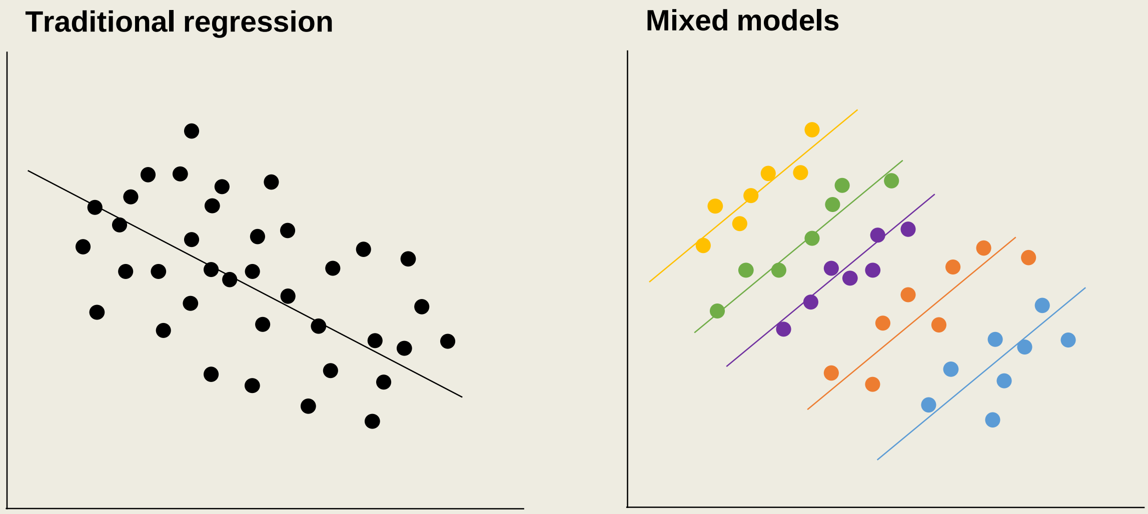
In the first case, patients from the same doctor's office may be more similar than patients from different doctors. In the second case, BMI measurements from an individual at different time points are not independent of each other, as they come from the same person.

To deal with this, mixed models include fixed and random effects. The fixed effects are same for the entire dataset, and can be interpreted similar to a traditional regression. The random effects are specific to the group (level 2). This means that the BMI of individual x is predicted by a standard regression formula, plus a random effect specific to individual x. Random effects can be applied to the intercept and/or the slope of the model. Simply put, a random intercept model means that the fixed effect of the predictors is the same for all individuals, but that the starting point (the intercept with the y-axis) is different (see the example in Figure 1). In this case, the random effect is not correlated with predictor variables, but a constant for individual X. A random slope model also allows the effect of predictors on BMI (the slope of the regression line) to vary by individual.

Mixed models take into account the trajectory of BMI within an individual, which ensures correct interpretation of the data (see Figure 1). Moreover, they prevent individuals with a large number of BMI measurements to be overrepresented in the model, as only one curve is fit per person, regardless of the number of BMI measurements. A disadvantage is that the random effects are specific to the individual, and can therefore not be used outside the original dataset. Since the individuals in the database are not the same as those generated in the microsimulation model, only the fixed part of the model can be used in the microsimulation.

Figure 1. Mixed models versus traditional regression

Illustrative example of how traditional regression and mixed models can produce different results for the same data



Note: Illustrative example showing a mixed model with random intercepts; the colours represent different individuals for whom measurements were recorded over time. Note that this is an extreme scenario where the global trend is in an opposite direction from the individual ones. This extreme scenario was chosen to highlight the importance of taking into account random effects – not because it is expected that the BMI trajectories display this kind of pattern.
Source: OECD analysis.

10. The mixed model was defined as an autoregressive model, where the outcome variable at time t (BMI_t) is based on the same variable at time t-1 (BMI_{t-1}). Autoregressive models are often used to forecast processes that change over time, and where the predicted variable is correlated with that same variable at a previous time point (e.g. temperature, stocks). Since a person's BMI is closely correlated with their BMI the year before, this method was used here. Because BMI from the year immediately prior is used as a predictor, rather than two or more years back, it is called a first-order autoregressive model. The analysis was limited to first-order models to allow BMI predictions for individuals from the first year on.

11. Independent variables tested included sex, BMI_{t-1}, and age_{t-1}. To give the trajectory more flexibility to change direction over time and across BMI values, squared and cubed values were also included: BMI_{t-1}^2, age_{t-1}^2, BMI_{t-1}^3 and age_{t-1}^3. Including these terms allows the effect of a predictor on the outcome to take a non-linear shape (e.g. a curve that goes up and then down rather than a straight line). An interaction term between BMI_{t-1} and age was included to capture age-specific effects of BMI_{t-1} on BMI_t. An interaction term between sex and BMI_{t-1} was also tested. Since this term was significant, the analysis was split by sex to fully account for all sex-specific effects.

5 Results

Descriptive statistics

12. Three data sources have an average of roughly three BMI measurements per participant, while the HILDA dataset has over ten measurements per participant (see Table 1). The Add Health and BCS70 databases cover childhood to early adulthood, while SHARE covers the later part of life. The HILDA database covers the entire life course. Women are slightly overrepresented in three data sources.

Table 1. Descriptive statistics of the three contributing data sources

	Add Health	BCS70	SHARE	HILDA	Combined dataset
Participants (n)	4,503	10,317	40,528	16,505	**71,853**
BMI measurements (n)	12,187	31,728	136,402	168,028	**348,345**
BMI measurements per participant, average (n)	2.7	3.1	3.4	10.2	**4.8**
Sex (% women)	53%	58%	56%	53%	**55%**
Age (mean)	22.2	25.5	67.1	46.5	**51.8**
Age (min-max)	14 - 31	10 - 46	50 - 90	15 - 101	**10 - 101**
BMI (mean)	25.8	24.2	27.0	26.9	**26.7**
BMI (min-max)	12 - 61.9	9.9 - 70	12.6 - 77.8	9.6 - 79.4	**9.6 - 79.4**
% overweight	48%	43%	64%	59%	**59%**
% obese	22%	18%	22%	24%	**23%**

Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

13. Looking for attrition, in the SHARE data there are few differences between people with only two BMI measurements (the minimum to be included in the study) and people who had more than two (see Table 2). In the Add Health, HILDA and BCS70 studies women are more likely to have more than two observations, as were people with a lower BMI. The difference in sex is particularly pronounced in the BCS70 database: of those with only two observations 38% was female, compared to 66% of individuals with more than two observations. While the mixed model ensures that all individuals are equally weighted regardless of the number of BMI observations, this difference in attrition may mean that longitudinal BMI trajectories for men and individuals with a higher BMI are less well captured.

Table 2. Attrition comparison

		Two BMI measurements	More than two BMI measurements
Add Health	% women	52%	54%
	Mean BMI	24.3	22.5
BCS70	% women	38%	66%

	Mean BMI	20.9	19.3
SHARE	% women	56%	56%
	Mean BMI	26.9	26.9
HILDA	% women	52%	54%
	Mean BMI	26.4	26.9

Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

Predictive performance

14. In the predictive model, all dependent variables (BMI_{t-1}, age_{t-1}, BMI_{t-1}^2, age_{t-1}^2, BMI_{t-1}^3, and age_{t-1}^3) were significant for both sexes (all p<0.001), as was the interaction term between BMI_{t-1} and age_{t-1}. A mixed model with a random intercept for individuals was preferred for both sexes over a linear model based on the likelihood-ratio test (p < 0.0000) (see 7Annex A for Stata outputs). The predictions from the model appear have a very strong fit with the observed data when using a metric such as R-squared, but this is partially due to the strong correlation of previous BMI with future BMI (Box 4).

Box 4. Calculating an R-squared for mixed models

One of the most commonly used measures of goodness of fit for regression models is R-squared, which, ranging from 0 to 1, represents the proportion of variance in the dependent variable (here BMI) that is explained by the independent variables in the model. A value of 1 means that any variability in the dependent variable is fully explained by the model.

For mixed models however R-squared is not readily available, as there are multiple sources of variance: for the fixed effects and for any random effects. There have been various suggestions as to how to calculate analogue R-squared metrics for mixed models. The Snijders/Bosker approach produces two R-squared values: one for the variance within each individual (level 1) and one for the variance between individuals (level 2). For the predictive model in this study, the level 1 R-squared was 98% and the level 2 R-squared was 99%.

These very high values for R-squared are to be expected for an autoregressive model: BMI across the population varies a lot (e.g. a random individual can have a BMI of 18 or 38) but once prior BMI is included in the prediction, a lot of the variance is removed (e.g. if the individual's BMI was 18 in one year, then it will likely be somewhere in the range of 17 to 19 the next year – it is very unlikely to suddenly be 38).

Source: (Nakagawa and Schielzeth, 2013[20]) (Kwok et al., 2008[21]) (Selya et al., 2012[22]) (Snijders and Bosker, 1994[23])

15. Since the microsimulation model will use only the fixed effects from the mixed model to predict BMI trajectories, the performance of a fixed-only model was compared to the full mixed model. Across a range of performance measures, the fixed-only model performs well, producing only slightly larger errors (see Table 3). The mean absolute error of the fixed-only model was 0.57 BMI points (2.1% of the observed BMI) for men and 0.63 BMI points (2.4%) for women, compared to 0.56 BMI points (2.1%) and 0.61 (2.3%) BMI points for men and women respectively using both the random and the fixed part of the model. While there were some outliers creating high minimum and maximum errors, removing the highest and lowest 5% the errors were much smaller.

Table 3. Predictive performance of the mixed autoregressive model

		Men		Women	
		Random + fixed	*Fixed only*	*Random + fixed*	*Fixed only*
Error in BMI points	*Min - Max*	-36.04 - 40.62	-36.24 - 40.42	-36.97 - 38.53	-36.8 - 38.97
	1% - 99%	-3.19 - 3.17	-3.19 - 3.20	-3.64 - 3.62	-3.65 - 3.65
	5% - 95%	-1.30 - 1.33	-1.31 - 1.35	-1.39 - 1.46	-1.41 - 1.50
	Mean	0.00	0.00	0.00	0.00
	Mean absolute	0.56	0.57	0.61	0.63
Error in percentage	*Min - Max*	-150.2% - 62.6%	-151% - 62.3%	-173.6% - 60.9%	-172.8% - 61.5%
	1% - 99%	-12.5% - 10.6%	-12.6% - 10.7%	-14.3% - 11.9%	-14.4% - 12.0%
	5% - 95%	-5.0% - 4.6%	-5.1% - 4.6%	-5.5% - 5.1%	-5.6% - 5.2%
	Mean	-0.1%	-0.1%	-0.2%	-0.2%
	Mean absolute	2.1%	2.1%	2.3%	2.4%

Note: The "Random + fixed" model uses the mixed autoregression model to make predictions; the "Fixed only" model is based only on the fixed effects of the mixed autoregressive model.
Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

16. Using only the fixed part of the model (i.e. the part that will be used in the OECD SPHeP-NCDs model), prediction errors were calculated for different subgroups. The mean absolute percentage error was generally largest for people with obesity and for people aged under 20 or over 80 (see Table 4). The greater inaccuracy may be due to the fact that there are fewer observations in these subgroups, and therefore less data to train the model.

Table 4. Predictive performance for subgroups

Mean absolute percentage error (%) by sex, weight and age group, based on the fixed part of the model only

	Men			Women		
Age group	*Healthy weight*	*Overweight*	*Obese*	*Healthy weight*	*Overweight*	*Obese*
0-19	1.9%	2.7%	4.1%	1.9%	2.8%	4.4%
20-39	2.5%	2.2%	2.5%	2.6%	2.4%	2.8%
40-59	2.6%	2.0%	2.5%	2.6%	2.3%	2.8%
60-79	1.9%	1.6%	2.2%	2.1%	1.8%	2.4%
80+	2.4%	2.0%	2.7%	2.9%	2.4%	2.9%

Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

BMI trajectories

17. To visually compare the predicted BMI trajectories with the observed averages in the original data, 12 cohorts of individuals were selected from the dataset for both men and women. These cohorts were defined based on their age (15, 35, 55, and 75) and their BMI category at this time (healthy weight, overweight, obese). The average observed BMI for each cohort over the next ten years was extracted. This analysis was limited to ten years for each cohort because loss-to-follow up beyond this horizon made the averages unstable or absent. The observed average BMI of each cohort was compared to the BMI predicted by the model using the cohort's average BMI and age at the start of the ten-year period.

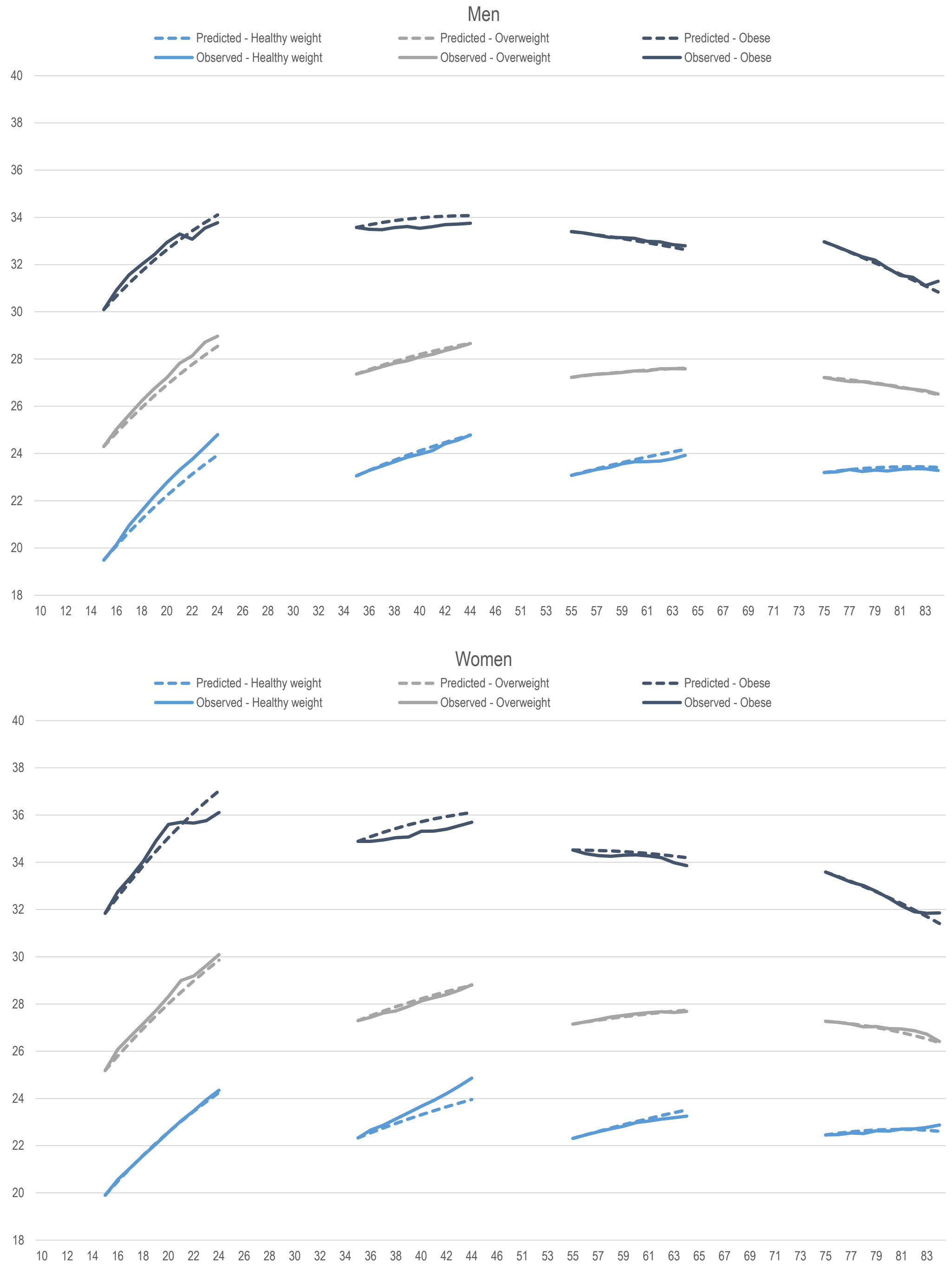
18. The graphs show that the predicted trajectories for each cohort approximately follow the observed average (Figure 2). At the extremities the predictions fit the observed values less well – most notable for the group with obesity at age 15. This groups is based on a smaller number of individuals, especially

towards the end of the ten-year period, and the cohort average is therefore more subject to noise. Nevertheless, the model predicts the right trend in BMI for all cohorts.

19. The cohort of 15-year-old children saw the greatest increase in BMI over the following ten years, for all weight categories. Most people at age 35 saw their BMI increase over the next ten years, except for men who already had obesity, for whom BMI stayed largely stable. Both men and women aged 55 were likely to experience a drop in their BMI if they had obesity, but an increase if they had a healthy weight. From age 75 BMI decreased for people who were overweight or obese, but remained roughly stable for people with a healthy weight.

Figure 2. Predicted BMI trajectory for people with healthy weight, overweight and obesity at age 15, 35, 55 and 75

Observed group average BMI (solid) and predicted BMI (dotted) for men and women who were at a healthy weight, overweight or obese at age 15, 35, 55 and 75



Note: Predicted BMI takes the average BMI at age 15, 35, 55 and 75 for each weight group, and predicts the progression of BMI from there over time for those people. This is slightly different from the population average (solid line). Overweight and obesity are defined as having a BMI equal to or greater than 25 and 30, respectively, except for children under the age of 18 where the WHO age-specific cut-off values were used (de Onis et al., 2007[24]).
Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

20. Using the model, it is possible to predict future BMI for each age and BMI combination. Figure 3 (men) and Figure 4 (women) show the change in BMI that is predicted based on age and current BMI. Red values indicate an increase in BMI, while blue values represent an expected decrease. Looking at these heatmaps, high-level trends can be observed.

21. For both men and women, young people are likely to see an increase in BMI year-on-year, even if they already had overweight or obesity. This suggest that childhood overweight is not only likely to persist, but may even worsen over time.

22. Older people are likely to see a decrease in BMI, unless they have a very low BMI already (approximately 20 or less), in which case BMI tends to increase. The decrease in BMI for people with overweight and obesity happens earlier for men than for women. The greatest decreases can be seen in people with the highest BMI.

Figure 3. Annual change in BMI, by prior BMI and age - Men

Change in BMI (points) per year, by age and BMI in the year prior

	Previous BMI																											
Previous age	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
10	0.9	0.9	0.8	0.8	0.8	0.8	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6	0.6
11	0.9	0.8	0.8	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6
12	0.8	0.8	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.5
13	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.5
14	0.8	0.8	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.4
15	0.8	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.4	0.4
16	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4
17	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.3
18	0.7	0.7	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.3	0.3
19	0.7	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3
20	0.7	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.2
21	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2
22	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.2	0.2
23	0.6	0.6	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2
24	0.6	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.1
25	0.6	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1
26	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1
27	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1
28	0.6	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.0
29	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.0
30	0.5	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0
31	0.5	0.5	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0
32	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0
33	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	-0.1
34	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1
35	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1
36	0.5	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1
37	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1
38	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1
39	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1
40	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.2
41	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2
42	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2
43	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.2	-0.2
44	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2
45	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2
46	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2
47	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2
48	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3
49	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3
50	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3
51	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3
52	0.5	0.4	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3
53	0.5	0.4	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3
54	0.5	0.4	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3
55	0.5	0.4	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3
56	0.5	0.4	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3
57	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3
58	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.4
59	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.4
60	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4
61	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4
62	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4
63	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4
64	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4
65	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4
66	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4
67	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4
68	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.5
69	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5
70	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5
71	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5
72	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5
73	0.5	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5
74	0.5	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5
75	0.5	0.5	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5
76	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.6
77	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6
78	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6
79	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6
80	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6
81	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6
82	0.5	0.4	0.4	0.3	0.2	0.2	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.7
83	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7
84	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7
85	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.7	-0.7
86	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7	-0.7
87	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7	-0.8
88	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7	-0.7	-0.8
89	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7	-0.8	-0.8
90	0.4	0.3	0.3	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7	-0.7	-0.8	-0.8
													Overweight					Obesity										

Note: Overweight and obesity are defined as having a BMI equal to or greater than 25 and 30, respectively, except for children under the age of 18 where the WHO age-specific cut-off values were used (de Onis et al., 2007[24]). Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

Figure 4. Annual change in BMI, by prior BMI and age - Women

Change in BMI (points) per year, by age and BMI in the year prior

Previous age \ Previous BMI	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
10	0.9	0.9	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
11	0.9	0.8	0.8	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
12	0.9	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.9	0.8	0.8	0.8
13	0.8	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
14	0.8	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.8	0.7	0.7
15	0.8	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
16	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6
17	0.7	0.7	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
18	0.7	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
19	0.7	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.5	0.5
20	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
21	0.6	0.6	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
22	0.6	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.4
23	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4
24	0.6	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
25	0.6	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3
26	0.6	0.5	0.5	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.3
27	0.5	0.5	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3
28	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
29	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2
30	0.5	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2
31	0.5	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2
32	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2
33	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1
34	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1
35	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1
36	0.5	0.4	0.4	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1
37	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1
38	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0
39	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0
40	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
41	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0
42	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0
43	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0
44	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0
45	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	-0.1
46	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1
47	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1
48	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1
49	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1
50	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1
51	0.5	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1
52	0.5	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1
53	0.5	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1
54	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2
55	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2
56	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2
57	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2
58	0.5	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2
59	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2
60	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2
61	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2
62	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2
63	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3
64	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3
65	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3
66	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3
67	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3
68	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3
69	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.3
70	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4
71	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4
72	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4
73	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.4	-0.4
74	0.6	0.5	0.4	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4
75	0.6	0.5	0.4	0.4	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4
76	0.6	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5
77	0.6	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5
78	0.6	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5
79	0.5	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.0	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5
80	0.5	0.5	0.4	0.3	0.3	0.2	0.1	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6
81	0.5	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6
82	0.5	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6
83	0.5	0.4	0.3	0.3	0.2	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6
84	0.5	0.4	0.3	0.3	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7
85	0.5	0.4	0.3	0.2	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.5	-0.6	-0.6	-0.7
86	0.5	0.4	0.3	0.2	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.6	-0.6	-0.7	-0.7
87	0.4	0.4	0.3	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.5	-0.6	-0.6	-0.7	-0.8
88	0.4	0.3	0.3	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.5	-0.6	-0.6	-0.7	-0.7	-0.8
89	0.4	0.3	0.2	0.2	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.5	-0.6	-0.6	-0.7	-0.7	-0.8	-0.8
90	0.4	0.3	0.2	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.3	-0.4	-0.4	-0.4	-0.5	-0.5	-0.5	-0.6	-0.6	-0.6	-0.7	-0.7	-0.8	-0.9
													Overweight					Obesity										

Note: Overweight and obesity are defined as having a BMI equal to or greater than 25 and 30, respectively, except for children under the age of 18 where the WHO age-specific cut-off values were used (de Onis et al., 2007[24]).
Source: OECD analysis on British Cohort Study 1970, Add Health, SHARE and HILDA data.

6 Discussion

23. The results show that early in life, BMI increases year-on-year for people in all weight categories. This means that childhood overweight not only persists into adulthood, but is likely to worsen over time. This effect is important to incorporate in the OECD SPHeP-NCDs model, to accurately model policies addressing high BMI in childhood and their long-term impact on obesity prevalence in adults.

24. As people age, they will, on average, see a decrease in their BMI. Interventions targeting the elderly population should take into account this baseline reduction in BMI and not ascribe it solely to the intervention's effect. However, this trend needs to be interpreted with caution. Aging is associated with a reduction in fat-free mass and muscle mass – both of which reduce the weight of an individual (and consequently BMI) but are harmful for overall health (Inelmen et al., 2003[25]). For this reason, other measures such as waist circumference index should be used where possible.

25. This analysis is subject to a number of limitations. Data limitations meant that some assumptions had to be made. To model BMI across all ages, rather than for the distinct age groups included in the survey data, BMI data was linearly extrapolated between observations. To minimise the impact of this assumption, only observations that were 12 years or less apart were included. As a large proportion of participants had three or fewer observations, no random slope could be used, as random slopes can be unreliable with less than six time points and are particularly likely to be poor with three or four time points (Wright, 2017[17]).

26. Databases that could be included were limited to those that collected BMI data for a general population over a length of time (>5 years), and where microdata was accessible to the OECD for analysis. As the included databases cover specific countries and age ranges, it is possible that the results are not fully representative for other country-age combinations (e.g. for older adults in the US and the UK, who are not covered in the data).

27. The aim of this analysis was to develop a method to predict BMI trajectories based on prior BMI, age and sex, to be used in the OECD SPHeP-NCDs microsimulation model. Since the microsimulation model does not include other variables that may affect BMI (such as education, income, or ethnicity), these were not included as confounders in the analysis. Instead, it was assumed that on these characteristics the simulated population is similar to the one in the dataset. Since interventions modelled in the microsimulation do not change the relative prevalence of subgroups, this assumption does not affect the model results. Nevertheless, for correct interpretation of the results shown here it is important to note that these trajectories are a combination of confounding external factors and any "intrinsic" progression of BMI.

28. To be able to incorporate the results in the microsimulation, the analysis was designed to produce a simple arithmetic formula to predict BMI. For this reason, more complex methods such as random forest or neural networks were not used – even if their predictive power can be greater in some cases.

29. The prediction model functions less well at the extreme ends of the spectrum – at very high BMI combined with a very young or old age. This is at least partially due to a smaller number of observations in these extreme groups. Moreover, the autoregressive nature of the model means that estimates become less accurate over a longer time period: a small overestimation of BMI gets amplified year on year, as BMI the year after is overestimated based on an already overestimated BMI (and vice versa for any underestimation). For this reason, the predictions are best used on a short time frame (e.g. 5 to 10 years)

and not for the entire life course starting from childhood BMI. Finally, it should be noted that the model described in this paper is meant to be used at the individual level, and in a microsimulation environment. Population-level predictions of overweight and obesity prevalence depend on many factors not represented in this model.

7 Conclusion

30. Body-mass index tends to follow a typical trajectory over the life-course of an individual – increasing during adolescence and early adulthood, and decreasing later on in life. However, these trajectories vary by sex and prior BMI. Using a mixed, autoregressive model based on longitudinal BMI data from 22 countries, future BMI can be predicted based on sex, age and prior BMI. Incorporating these results into the OECD SPHeP-NCDs model will improve the accuracy of interventions targeting BMI, especially those focused on childhood obesity.

Annex A. Stata results for the mixed-level autoregressive model

Main variables

```
sex

                  Type: Numeric (int)
                 Label: gender

                 Range: [1,2]                       Units: 1
         Unique values: 2                       Missing .: 10,245/826,033

            Tabulation: Freq.   Numeric  Label
                      357,273         1  male
                      458,515         2  female
                       10,245         .

age

                  Type: Numeric (float)

                 Range: [10,101]                    Units: 1
         Unique values: 92                      Missing .: 0/826,033

                  Mean: 49.5805
             Std. dev.:  21.111

           Percentiles:     10%       25%       50%       75%       90%
                             19        30        55        67        75

bmi_ipolate

                  Type: Numeric (double)

                 Range: [9.6,79.4]                  Units: 0
         Unique values: 377,146                 Missing .: 0/826,033

                  Mean: 26.4741
             Std. dev.: 5.23183

           Percentiles:     10%       25%       50%       75%       90%
                        20.4018     23.03   25.9259      29.3   33.0887
```

Note: All variables in the model are derived from the ones presented above – through a time lag of one year ($_{t-1}$), and/or squared (^{2}) or cubed (^{3})

Men

```
Mixed-effects ML regression                     Number of obs     =    325,016
Group variable: id                              Number of groups  =     32,250
                                                Obs per group:
                                                              min =          1
                                                              avg =       10.1
                                                              max =         36
                                                Wald chi2(7)      =   5.83e+06
Log likelihood = -479094.95                     Prob > chi2       =     0.0000
```

bmi_ipolate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
bmi_ipolate_tm1	.8587353	.0097558	88.02	0.000	.8396142	.8778564
c.bmi_ipolate_tm1#c.age_tm1	-.0004347	.0000241	-18.02	0.000	-.000482	-.0003874
bmi_ipolate_tm1_2	.005485	.0003132	17.51	0.000	.0048711	.0060989
age_tm1	-.0398682	.0018322	-21.76	0.000	-.0434593	-.0362772
age_tm1_2	.0008461	.000043	19.68	0.000	.0007619	.0009304
age_tm1_3	-4.99e-06	2.84e-07	-17.59	0.000	-5.54e-06	-4.43e-06
bmi_ipolate_tm1_3	-.0000682	3.19e-06	-21.40	0.000	-.0000745	-.000062
_cons	2.334513	.0908978	25.68	0.000	2.156357	2.51267

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
id: Identity				
var(_cons)	.0085661	.0011721	.0065511	.0112009
var(Residual)	1.108362	.0029522	1.102591	1.114164

LR test vs. linear model: chibar2(01) = 61.39   Prob >= chibar2 = 0.0000

Women

```
Mixed-effects ML regression                     Number of obs     =    419,480
Group variable: id                              Number of groups  =     39,046
                                                Obs per group:
                                                              min =          1
                                                              avg =       10.7
                                                              max =         36
                                                Wald chi2(7)      =   7.77e+06
Log likelihood = -665407.87                     Prob > chi2       =     0.0000
```

bmi_ipolate	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
bmi_ipolate_tm1	.8152701	.0083116	98.09	0.000	.7989796	.8315606
c.bmi_ipolate_tm1#c.age_tm1	-.0005802	.0000199	-29.15	0.000	-.0006193	-.0005412
bmi_ipolate_tm1_2	.0072768	.0002641	27.55	0.000	.0067592	.0077945
age_tm1	-.0481229	.0016689	-28.83	0.000	-.0513939	-.0448518
age_tm1_2	.0011094	.0000392	28.31	0.000	.0010326	.0011863
age_tm1_3	-6.80e-06	2.60e-07	-26.12	0.000	-7.31e-06	-6.29e-06
bmi_ipolate_tm1_3	-.0000852	2.67e-06	-31.90	0.000	-.0000905	-.00008
_cons	2.729348	.0798351	34.19	0.000	2.572874	2.885822

Random-effects parameters	Estimate	Std. err.	[95% conf.	interval]
id: Identity				
var(_cons)	.0176618	.0013942	.01513	.0206172
var(Residual)	1.381141	.0032442	1.374797	1.387514

```
LR test vs. linear model: chibar2(01) = 200.33          Prob >= chibar2 = 0.0000
```

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