ALSPAC bmi-forecasting

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2023-02-19T00:00:00-06:00

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1 Preface

This document is a working paper on preliminary analyses examining methods for BMI forecasting in the ALSPAC Cohort.

2 Brief Introduction to Analyses

Typically, youth follow an expected growth curve, with gains in weight and height progressing in a **predictable, but individualized** manner reflecting previous development. In some cases, deviations from expected growth signal mental health concern. Historically, conceptualizations of restrictive-spectrum eating disorders (specifically anorexia nervosa) has included weight-related diagnostic markers informed by population-based norms; however, a large and growing body of research supports *individualized* markers of weight status (i.e. weight suppression – the difference between current and highest past weight status – which can be operationalized as deviation from expected growth amongst youth) as a key predictor of both risk and recovery for restrictive EDs. At present, use of individualized measurements to screen for and treat restrictive EDs is not widespread.

The current analyses aim to define a model which predicts expected growth (along with an expected window of BMI) for an individual across adolescence, based on data obtained from their height and weight throughout childhood. We will use this predicted model to examine whether a drop from expected BMI z-score during adolescence is likely to predict or be accompanied by eating disordered behaviors in the ALSPAC Cohort.

3 Forecasting BMI

There are 7453 individuals with four or more bmi measurements in the dataset between ages 2-13 years.

When combining data with assessments of body weight after age 12.99, there were a total of 23385 observations of body weight from ages 13-20 in the dataset, across 6633 participants.

Below is a worked example of the steps involved in developing the BMIz forecasts:

3.1 Coding and Modeling BMIz from Growth Charts

First, inputs (height and weight or raw BMI values with child age) are converted to BMIz score, which is plotted across childhood along with the mean BMIz and 95% confidence band for this mean. In the current study, we are using data from ages 2-13 years as our prediction set.

After all available BMIz scores are input, prediction of future BMIz is forecast which accounts for recent measures of and variability in BMIz to forecast BMIz moving forward. Further, the overall number of observations and variance in previous BMIz to create a prediction window for future observations.

Three starting models are: Mean, Random Walk, and Random Walk + Mean (RWM). In the mean model, the prediction window for BMIz score is responsive to variance of the BMIz scores in the prediction set, the predicted BMIz score is set at the mean of previous values, and the prediction interval stays constant over time. In the Random Walk model, the predicted value begins at the most recent BMIz data point (closest to age 13), and the prediction window begins very narrow, but widens over time, which accounts for increased confidence in observations that are more proximal to the last measurement. The Mean + Random Walk model combines both models, with a predicted BMIz between the mean of previous values and the most recent, and some widening of the prediction window over time. An alternative model might specify that the highest BMIz scores – regardless of age – define prediction (potentially defining a more conceptually pure value of developmental weight suppression).

In the following example, Participant 1, 'Mara', has routine observations with BMI-Z mean of ~ -0.5 in childhood. Participant 2, 'Shannon' has routine observations with a BMI-Z of ~ 0.5, fewer assessment points, and slightly higher variability in BMIz. The Mean(Figure 3.1),

Random Walk(Figure 3.2), and RWM(Figure 3.3) models are presented below for visualization of expected BMIz over time after age 13 for these individuals.

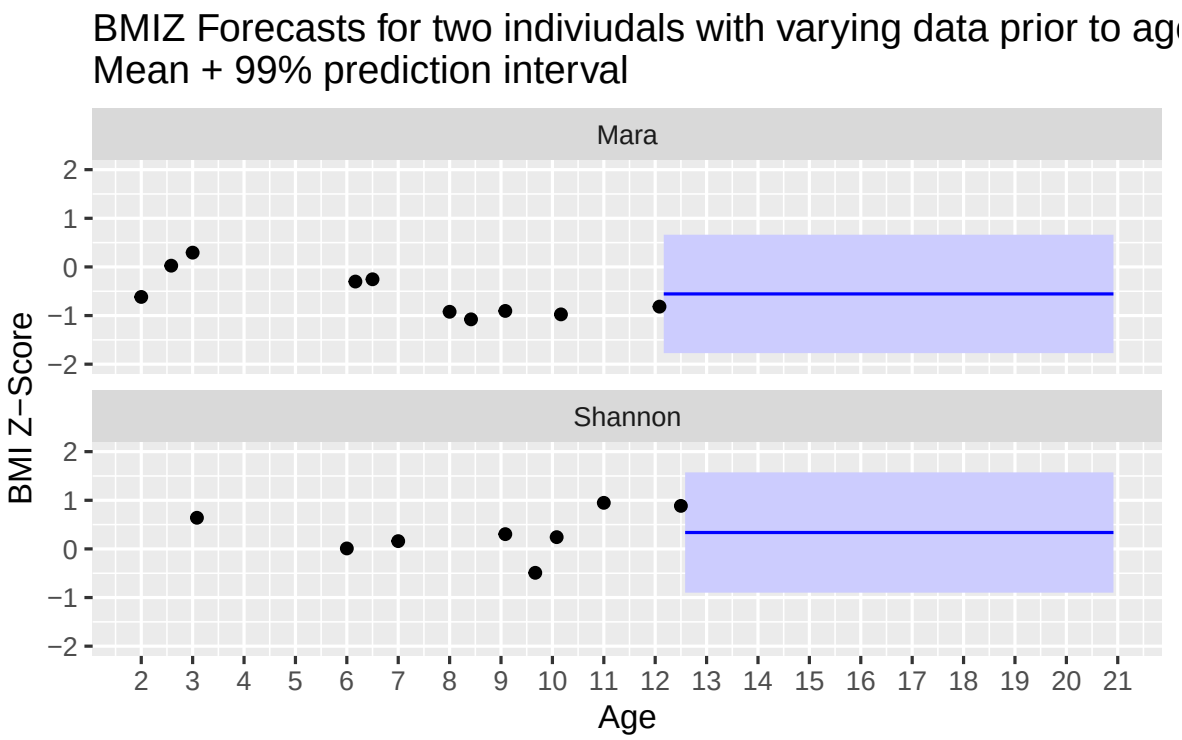

Figure 3.1: Example BMIz Prediction - Mean model

3.1.1 Comparison with observed values

The below graphs back translate these BMI-Z forecasts to actual BMI numbers over time, using the example of the RWM model with a 95% confidence interval. In Figure 3.4 we see that Participant 1 has some a datapoint at age 15.5 which falls below the predicted window.

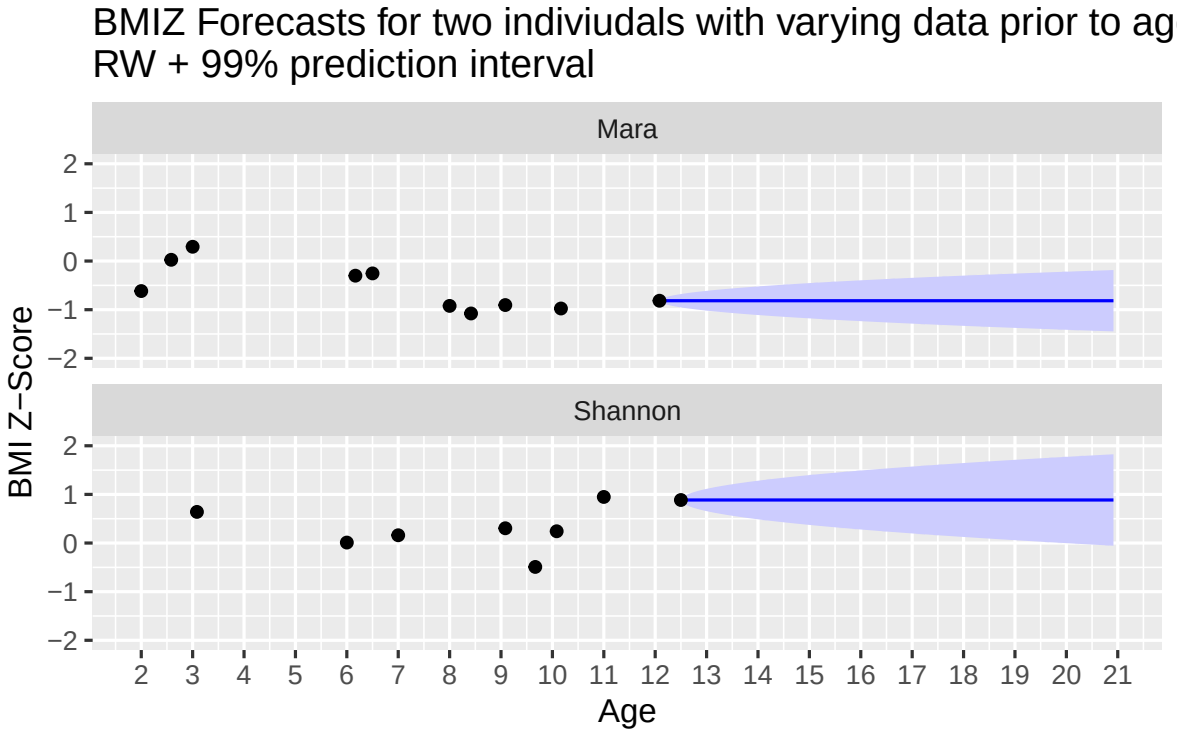

Figure 3.2: Example BMIz Prediction - RW Model

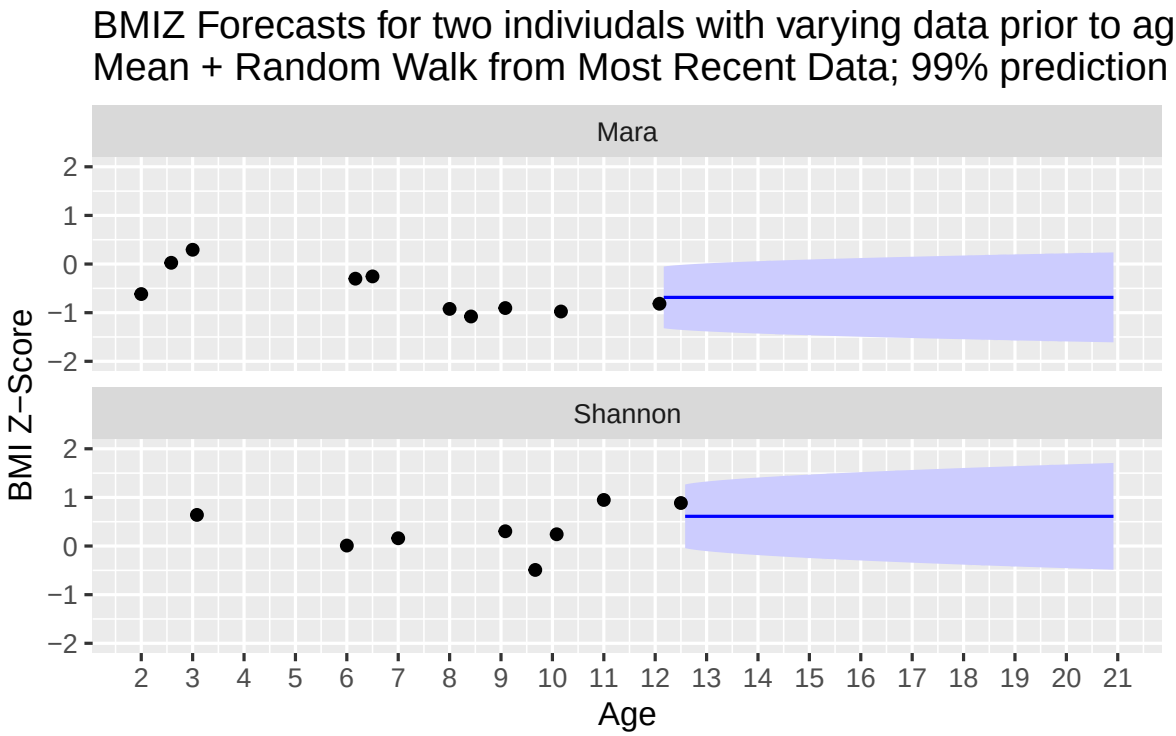

Figure 3.3: Example BMIz Prediction - RWM Model

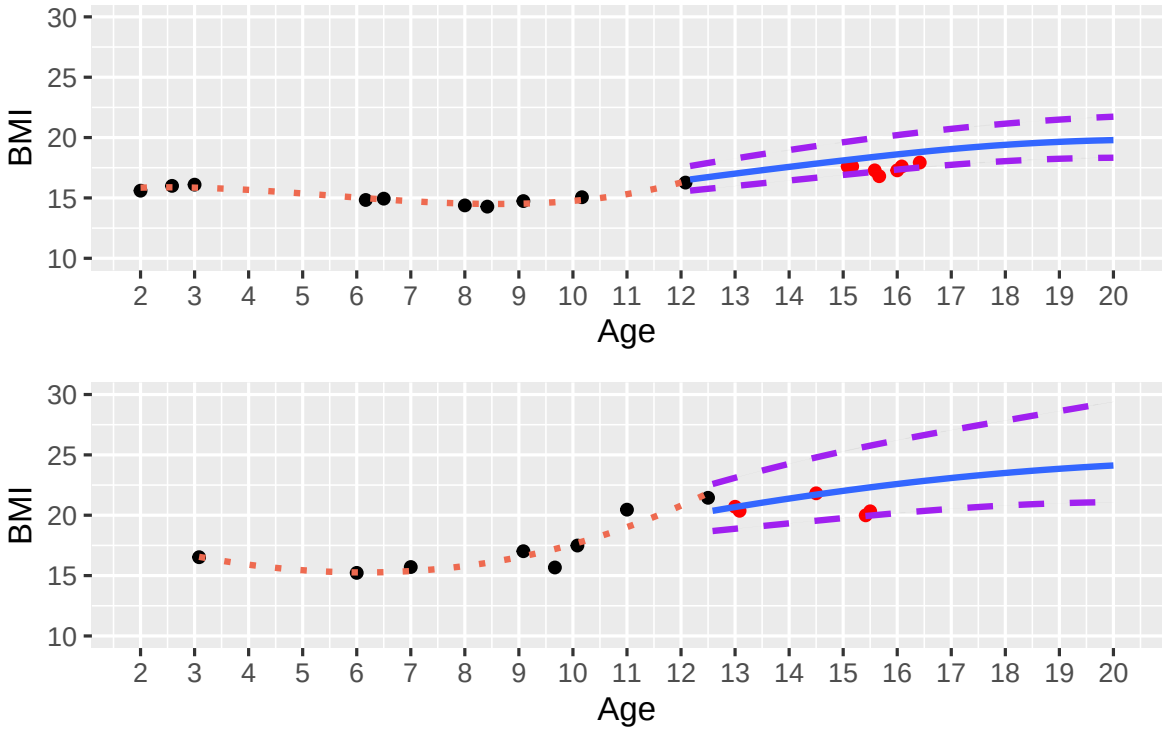

Figure 3.4: Example BMIz Prediction - M1 Model

4 Prediction

Below we present examples of comparing expected vs. predicted BMIz values at age 13 and from ages 13-16 in the ALSPAC Cohort

4.1 Age 13

There were 4245 individuals (2176 females and 2069 males) with at least one BMI measurement at age 13, including 388 individuals who provided two measurements during this time period. For those who provided more than one measurement, the older measurement was used.

4.1.1 Percent falling below and above predicted ranges based on model at age 13

Table 4.1: Weight Status Groups at Age 13 by Model

Sex	Model	n below	% below	n above	% above
female	Mean	257	11.81%	85	3.91%
female	RW	663	30.47%	431	19.81%
female	RWM	418	19.21%	183	8.41%
female	AbsVal >1	324	14.89%	517	23.76%
male	Mean	205	9.91%	104	5.03%
male	RW	577	27.89%	416	20.11%
male	RWM	345	16.67%	195	9.42%
male	AbsVal >1	305	14.74%	1060	26.24%

As seen in Table 4.1, the mean model was the most conservative, with approximately 15% of both boys and girls falling outside of the prediction window during age 13. The random walk model had the largest margin of error in prediction, with almost 50% of bmiz datapoints falling outside of the predicted window. In all models, falling below the BMIz prediction window was more likely than falling above the BMIz prediction window. In other words, when measured during this year, decreases in one's BMIz score were more common as compared to increases in one's BMIz score relative to historical BMIz, and this finding was consistent across boys and girls.

4.1.2 Low and High Weight Groups based on Mean Prediction Model

For the following analyses, we focus in on the Mean model (99% prediction interval) as our primary comparison group. Looking at low weight groups, the majority of individuals who fell outside of their expected window did not reach underweight status (BMIz < -1), and the majority of those who were underweight during their 13th year did not have a major BMIz reduction (see Figure 4.1)

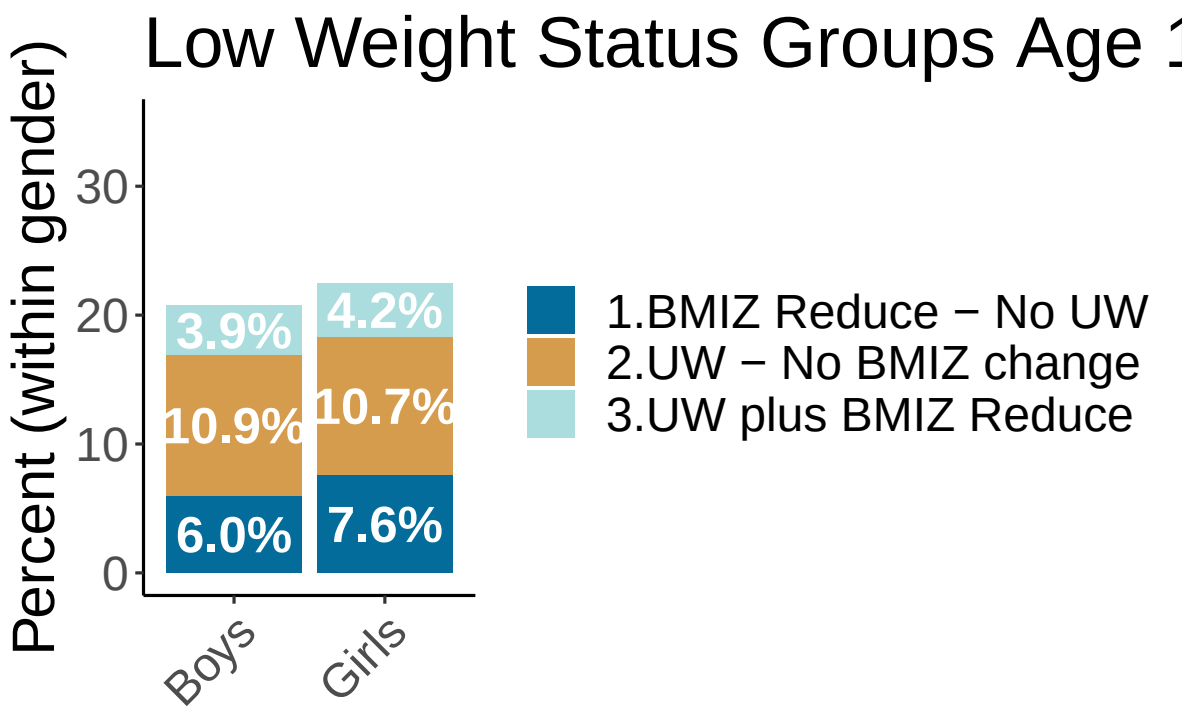

Figure 4.1: Low Weight Status Groups at Age 13

Regarding high weight status, Figure 4.2 shows the proportion of individuals who had an elevation of BMIz score, those who had a BMIz score of > 1 at their 13yo assessment time point, and those who had both a BMI elevation and a BMIz score of > 1. Again, the majority of individuals who had a BMIz score elevation (relative to their predicted mean BMIz value) were not overweight at the age 13 assessment point, and the majority of individuals who were overweight at the age 13 assessment point did not have a BMI elevation relative to their prior expected BMIz value.

Together, this initial information suggests that underweight and overweight status, which are commonly used to screen youth for intervention, are not synonymous with (and may be largely distinct from) identifying youth who have a deviation from their own historical body weight trends.

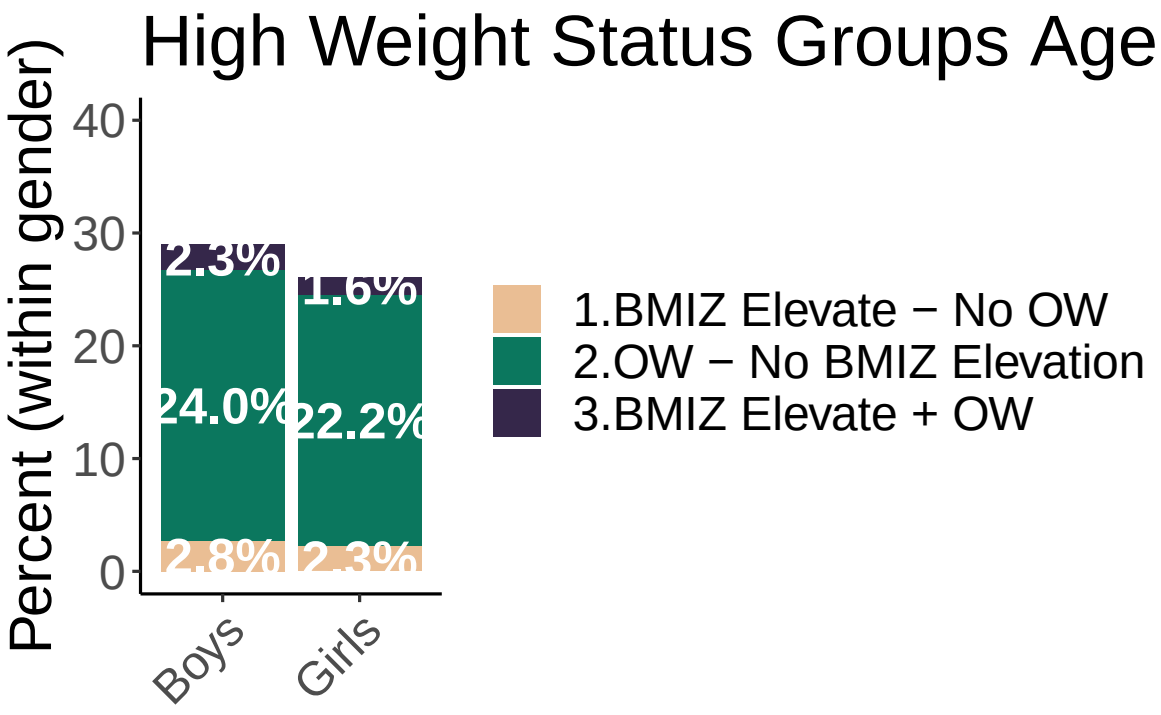

Figure 4.2: High Weight Status Groups at Age 13

4.1.3 Eating Disorder Behaviors at Age 14 across age 13 Low Weight Groups

Next we combine the dataset with these new groups (whether individuals had a bmi z reduction and whether they were underweight) to examine rates of ED behaviors at age 14 across groups.

With regards to maladpative exercise, girls in the underweight group were overall less likely to engage in maladaptive exercise at age 14 as compared to those who were not underweight and without a BMIz reduction. The other groups did not differ in rates of maldaptive exercise compared to the 'No Low Weight' Group (see Table 4.2 and Figure 4.3)

Table 4.2: Age 13 weight status vs. Age 14 Maladaptive Exercise

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.258	0.093	-24.305	0.000
low_wt_category1.BMIZ Reduce - No UW	-0.078	0.316	-0.245	0.806
low_wt_category2.UW - No BMIZ change	-0.671	0.338	-1.987	0.047
low_wt_category3.UW plus BMIZ Reduce	0.014	0.408	0.035	0.972

Regarding Purging behavior, rates were low at this age (see Figure 4.4), with low cell sizes (n < 5) in several groups at age 14, leading to low power for these comparisons.

Fasting was a more common behavior, particularly amongst girls. Those in the underweight group reported the lowest levels of fasting, which was significantly lower than those who did not have a weight reduction and were not underweight at age 14 (Table 4.3). The highest levels were amongst girls who experienced a BMIz reduction but were not underweight (Figure 4.5), though this was not significantly higher than those who did not have a weight reduction.

Table 4.3: Age 13 weight status vs. Age 14 Fasting - Female

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.291	0.094	-24.413	0.000
low_wt_category1.BMIZ Reduce - No UW	0.411	0.270	1.523	0.128
low_wt_category2.UW - No BMIZ change	-1.868	0.589	-3.170	0.002
low_wt_category3.UW plus BMIZ Reduce	-0.859	0.597	-1.438	0.150

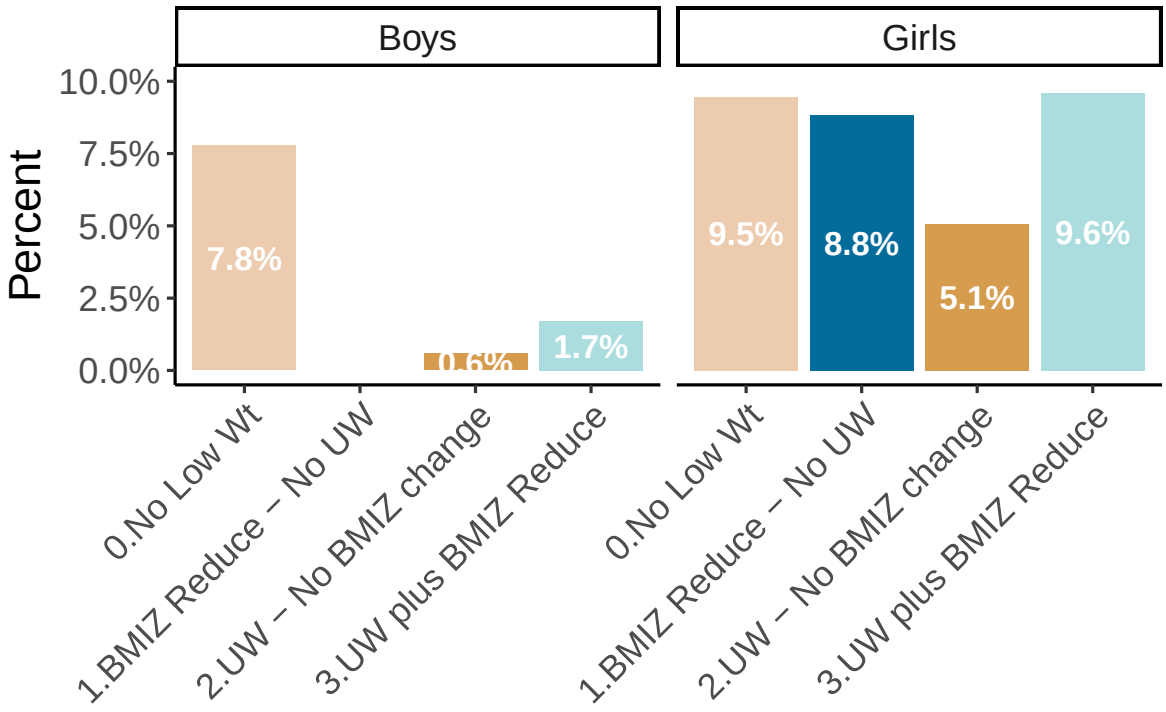

Figure 4.3: Maladpative Exercise at Age 14 based on Age 13 weight Groups

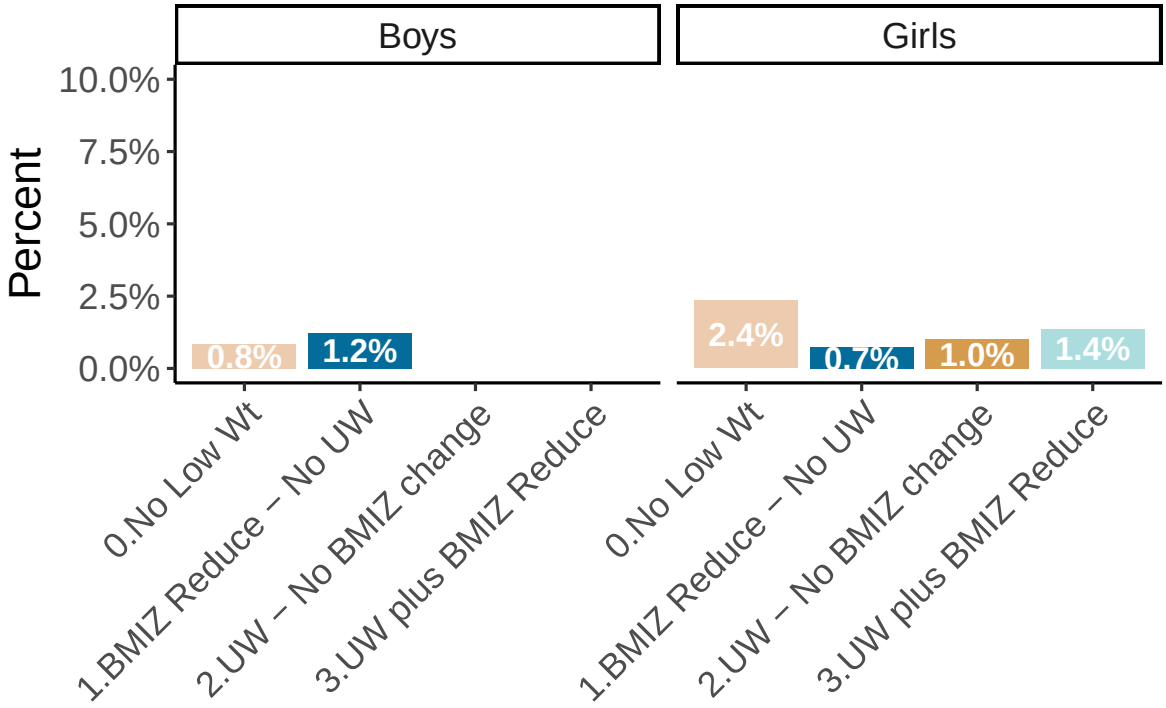

Figure 4.4: Rates of Purging at Age 14 based on Age 13 weight Groups - Female

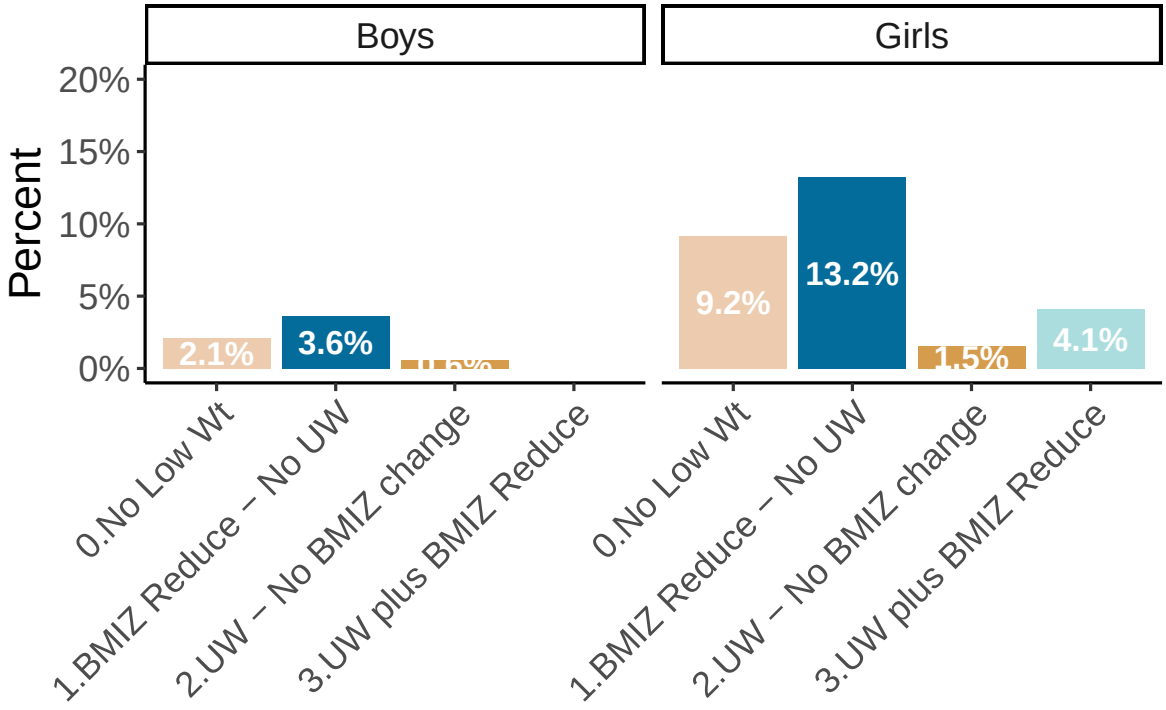

Figure 4.5: Age 13 weight status vs. Age 14 Fasting

When taken together, both girls and boys who had a BMIz reduction (but were not underweight) reported the highest frequency of compensatory behaviors relative to their peers (Figure 4.6), though these were not statistically significant differences relative to those who did not have a BMIz reduction or underweight status at age 13. Both girls and boys where were underweight where this weight was stable; however, did have a lower incidence of compensatory behaviors relative to their non-underweight peers (Table 4.4 and Table 4.5).

Table 4.4: Age 13 weight status vs. Age 14 Compensatory Behaviors - Female

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.637	0.074	-22.059	0.000
low_wt_category1.BMIZ Reduce - No UW	0.054	0.241	0.223	0.823
low_wt_category2.UW - No BMIZ change	-0.917	0.287	-3.193	0.001
low_wt_category3.UW plus BMIZ Reduce	-0.293	0.364	-0.805	0.421

Table 4.5: Age 13 weight status vs. Age 14 Compensatory Behaviors - male

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.264	0.101	-22.392	0.000
low_wt_category1.BMIZ Reduce - No UW	0.428	0.340	1.258	0.208
low_wt_category2.UW - No BMIZ change	-2.161	0.718	-3.008	0.003
low_wt_category3.UW plus BMIZ Reduce	-1.797	1.014	-1.772	0.076

4.1.4 Continuous assessment of weight and weight suppression

In addition to setting dichotomous groups based on BMIz changes, we can also evaluate BMIz changes continuously. That is, we can identify deviation from eBMIz or eBMI based on the point predictions of different models (Mean, Random Walk (most recent BMIz), M1, Highest Ever BMIz) and examine whether the magnitude of these deviations at age 13, along with absolute weight status (BMIz), associates with ED behaviors at age 14.

Consider running continuous models – which continuous models to run?

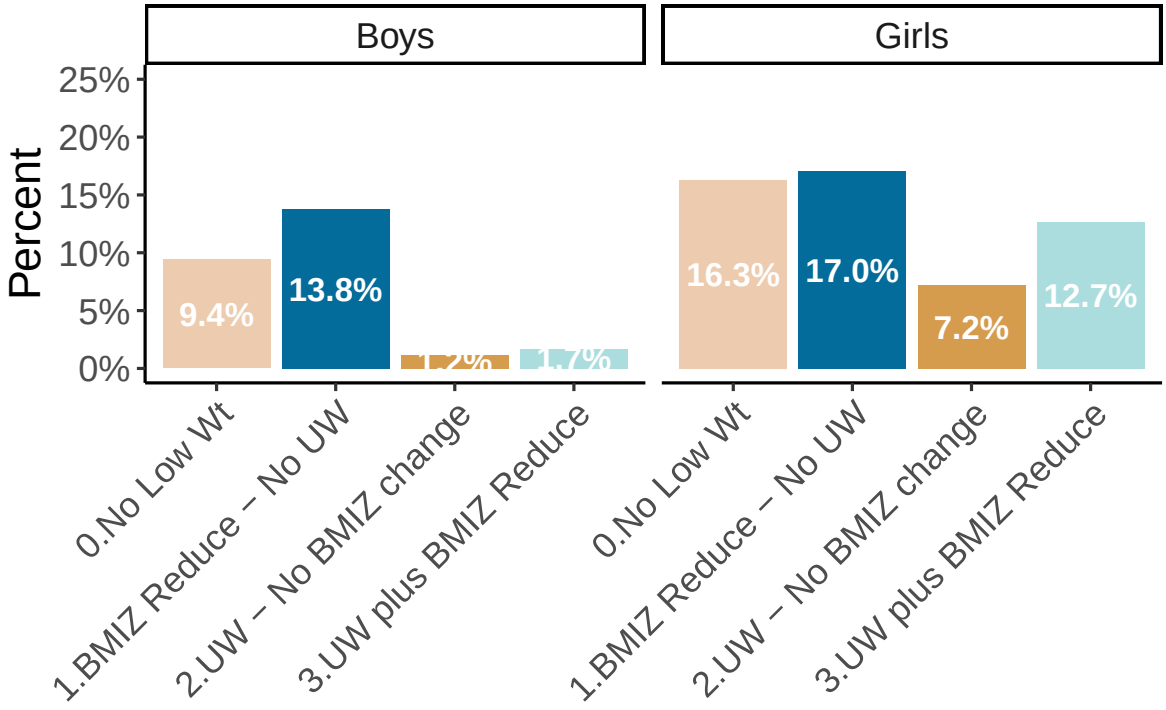

Figure 4.6: Age 13 weight status vs. Age 14 Compensatory Behavior Engagement

4.2 Age 13-16

As age 14 represents early onset of many ED beahviors, we replicated analyses above predicting out to age 16. For these analyses, we first defined