from 0, the other estimated values (variances or covariances) must be modified given the same value for Cov(y_2,y_3). If the correlated measurement residual is positive, an initially negative covariance between the intercept and slope factor will be moved in the positive direction and an initially positive covariance between intercept and slope will be moved in the negative direction.

Example 7.1. Growth Curve Model with Observed Variables

A latent growth curve model as depicted in Figure 7.3 was estimated to investigate changes in body weight over 12 years (six waves of data separated by two years each) using the health and aging data set (N = 5,335). Body weight was measured by the body mass index (BMI), which is a ratio of weight to square of height (kg/m^2). Syntax and data sets used in the examples are available at the website for the book. The model set each intercept factor loading equal to 1 and the slope factor loadings equal to 0, 1, 2, 3, 4, and 5. Correlated measurement residuals were not included in the initial model. The model fit the data well according to the relative fit indices, with $\chi^2(16) = 623.877$, CFI = .990, SRMR = .031, RMSEA = .084. The mean of the intercept factor was 27.211, which is nearly identical to the observed mean of the same for the first wave (27.176). Although this value is significant, the test merely indicates the value is greater than zero, so its significance is usually a trivial matter. The mean of approximately 27 suggests that, at the beginning of the study, the average respondent was in the overweight category. The mean of the slope factor was .150, $p < .001$, indicating that there was a significant increase of approximately .15 points on the BMI score every two years.

An alternative coding scheme for time could have been used for the loadings, with 0, 2, 4, 6, 8, and 10. These values would have produced a slope half the magnitude, indicating a .150/2 = .075 increase in BMI per year. The standardized estimate of the slope mean was .337, suggesting a moderate-sized effect on average and an approximate increase of .3 standard deviation units on BMI per standard deviation increase in time. The variance of the intercept, 23.377, and the slope, .197, were both significant, $p < .001$, showing significant between-person variance of the initial BMI score and the slope. The latter result indicates that some individuals increase at greater or lesser rates over time. Figure 7.5 is a plot of predicted slopes from the model for a random sample of 20 cases.[7] The figure shows variability in the intercepts as well as slopes. A heavier type line is drawn for the average slope and suggests a slight linear increase in BMI over time. The average intercept and slope values in this plot differ slightly from the predicted values from the equation because of the particular sample of cases. The covariance between the intercept and slope factors, −.057, was nonsignificant, with the standardized value (correlation) equal to −.026. Although not different from what would be expected by chance, the slight negative correlation would suggest that higher baseline BMI tended to be associated with less increase in BMI over time.

To illustrate the impact on model parameters, a second model replicated the first but added autocorrelations among adjacent time points of measurement residuals (ε_1 with ε_2, ε_2 with ε_3, etc.). This model had a considerably better fit, with $\chi^2(11) = 187.542$, CFI = .997, SRMR = .031, RMSEA = .055. The estimates of the average intercept and slope were virtually unchanged, 27.214 and .151, but there were substantial changes in the estimates of variances and covariances. The intercept variance was 22.783, $p < .001$, the slope variance was .110, $p < .001$, and the covariance between the intercept and slope factors was .150, $p < .001$. The covariance, which was not significant in the first model, indicated a positive correlation (.095) between BMI at baseline and changes in BMI over time after