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CHAPTER 5

A CRITICAL EXAMINATION OF THE DEMOGRAPHIC AND PSYCHOLOGICAL IMPLICATIONS OF MASS PREPARATION THEORY

"Today, mass preparation means that individuals can satiate their desires immediately, and as a result, the impatient eat more."
- David M. Cutler et al.

5.1 Introduction

The obesity epidemic has generated a tremendous amount of speculation regarding its etiology. Some explanations focus on structural changes in U.S. society, such as the increased reliance on modern technologies for food production, work and entertainment (French, Story and Jeffery 2001; Koplan and Deitz 1999; Philipson and Posner 2003). Other explanations cite societal trends that have coincided with the rise in obesity, such the marketing of high calorie foods and engagement in passive leisure activities, both of which have reached all time highs in the U.S. (Brownell 2002; French et al. 2001). Still other explanations focus narrowly on specific determinants, such as the "supersized" portions available at a number of restaurants (Simms and Martell 2003).

Although these arguments vary in their specific content, they all share the view that secular changes (i.e., period effects) have caused the obesity epidemic. As shown in Chapter 2, this assumption is correct—period effects are primarily responsible for the obesity epidemic despite indications that more recent birth cohorts have experienced increased risks of obesity. However, while many of these arguments are intuitively appealing, most lack the rigor of scientific, empirically verifiable theoretical propositions. In the absence of formal theories about the obesity epidemic, interesting speculation is destined to remain just that—speculation.

Fortunately, there are a handful of exceptions. One of the more cogent theories of the obesity epidemic was recently exposited by Cutler, Glaeser and Shapiro (2003), who argue that technological innovations in industrial food processing have dramatically reduced the time costs of food preparation. Cutler et al. illustrate their "mass preparation theory" nicely in the following statement:

> People could always make almost any form of food that is currently available, if they were willing to spend the time to do so. For example, ambitious cooks could make snack-size cream filled cakes … but it took time. Technological innovations since 1970 mean that preparation can now be done in restaurants and factories, exploiting technology and returns to scale. Snack-size cream-filled cakes are now widely available for less than a dollar (P. 105).

While improved industrial processing has lowered the monetary costs of food, Cutler et al. (2003) argue that this has had much less impact on increased consumption than reduced time costs. Cutler et al. support this argument by noting that the time required to prepare food has fallen at a much faster rate than the monetary costs of food purchases. Between 1965 and 1995, the amount of time needed to prepare food at home fell by 29 percent per calorie. Over roughly the same period, the relative monetary cost of food also fell, but only by three percent.

With the rapid diminishment of time costs as a disincentive for overindulgence, people must rely on other disincentives such as future health and appearance. According to standard economic models, people are rational actors who weigh these disincentives fully in their cost-benefit calculations. However, Cutler et al. (2003) argue that eating is not always the result of rational decision-making. Indeed, because food offers short-term psychological and physiological rewards such as comfort and satiety, it can override a consumer's rational long-term interests—including both the quality and duration of life. Consequently, persons with "self-control problems" (p. 113) are vulnerable to hyperbolic discounting. That is, the instant availability of food causes some people to make irrational consumption choices that used to be prevented by relatively short time delays necessitated by food preparation. In other words, "mass preparation means that individuals can satiate their desires immediately, and as a result, the impatient eat more" (p. 113).

Obesity Trends—A Function of Calorie Intake or Energy Expenditure?

Mass preparation theory rests upon the assertion that increased calorie intake—not reduced physical activity—is responsible for the small calorie imbalance (about 125 calories per day) that has led to rapid increases in BMI and obesity prevalence. To support this claim, Cutler et al. (2003) cite data from food recall studies and time use diaries. According to recall data from the 1977-78 and 1994-96 Continuing Survey of Food Intake, daily calorie intake increased over this period by 268 calories among males and 143 calories among females. Almost all of this increase was accounted for by increased calories from snacks, which nearly doubled. This increase was caused by more frequent snacking rather than a change in the amount of calories consumed per snack. Moreover, calories consumed during meals did not change substantially and, in the case of dinner, actually decreased. Given this evidence, Cutler et al. reject the possibility that the obesity epidemic could have been caused by increased portion sizes or more frequent patronage of fast food restaurants.

While Cutler et al. (2003) make an intriguing argument, it is based upon a questionable assumption and selective reading of the evidence. Cutler et al. note that food diary studies likely suffer from underreporting bias. That is, people consume more food than they report to survey researchers. Cutler et al. also concede that "Underreporting is not necessarily a problem for our analysis, if the extent of underreporting is constant over time, but as surveys have improved, underreporting has likely fallen" (p. 101). This concession makes the assumption of constant reporting bias dubious. If underreporting has declined even by a small amount, as Cutler et al. surmise, it could easily account for the small increase observed in calorie intake.

In addition to this questionable assumption, Cutler et al. (2003) are selective in their reading of the evidence. As noted in Chapter 1, the evidence is mixed on calorie intake trends in recent decades. Of course, some scholars (e.g., Koplan and Dietz 1999) concur with the argument that calorie intake has increased somewhat. But Weinsier et al. (1998) cite data from U.S., French and British studies showing that obesity prevalence has increased despite reductions in calorie and fat intake. On balance, the evidence appears to suggest that calorie intake over the past 25 years has changed little in one direction or the other (Blair and Nichaman 2002; Franklin 2001; Lakdawalla and Philipson 2002). To their credit, Cutler et al. (2003) admit that "detailed data on dietary habits and [physical] activities do not exist" (p. 100). For this very reason, the small calorie changes reported in the Continuing Survey of Food Intake should be viewed with a healthy dose of skepticism.

In addition to food recall data, Cutler et al. (2003) also cite data on time use over the period 1965-95 (see Robinson and Godbey 1997) and calculate indices of energy expenditure to support their argument that changes in physical activity are not responsible for the obesity epidemic. According to these data, television viewing increased by an average of 40 minutes per day between 1965 and 1975, but subsequently increased by only 22 minutes. However, increased television viewing was compensated for by more time spent in various physical activities. Given these small changes, Cutler et al. argue that Americans have not altered their patterns of physical activity substantially in recent decades. This is reflected in their index of energy expenditure, which declined between 1965 and 1975 but, in their words, "has remained quite stable since then" (p. 103). To bolster their argument, Cutler et al. also cite data indicating that the fraction of the U.S. population employed in physically demanding occupations declined by just 3 percent from 1980 to 1990. Similarly, the fraction of the U.S. population that drove to work increased by just 3 percent over this period.

There are a few important reasons to question this argument. First, these self-reported time use data appear to underestimate the amount of time spent watching television. According to the estimates cited by Cutler et al. (2003), the average American adult aged 18-64 watched 17.6 hours of television per week in 1995. In stark contrast, Nielsen data from 1999 showed that Americans aged 12 and over watched an average of 28 hours of television per week (Nielsen Media Research 2000). This suggests that American adults may underreport their time spent viewing television by as much as 60 percent. Of course, some of this difference may be caused by the different age range in the Nielsen study and its later date. Therefore, I conservatively assume that the downward bias in television reporting among adults is actually just 40 percent and has remained constant since 1965. (Because social stigmas are likely attached to excessive television viewing among adults, underreporting may have increased in recent years at excessive viewing has become more common. But for the sake of argument, I assume constancy).

Working from these conservative assumptions, television viewing actually increased by about 31 minutes per day between 1975 and 1995, not the 22 minutes reported by Cutler et al.

Second, there is little indication in the literature that increased leisure-time physical activity has counterbalanced increased television viewing and other passive leisure activities, as Cutler et al. (2003) suggest. According to data from the Behavioral Risk Factor Surveillance System (BRFSS) and the National Health Interview Survey (NHIS), the proportion of Americans who participated regularly in leisure-time physical activity changed little from the mid-1980s to the mid-1990s (U.S. Dept. of Health and Human Services 1996b). Indeed, the data provided by Cutler et al. indicate that the time spent in all forms of active recreation increased by a mere four minutes per day from 1985 to 1995, which is the most relevant time period to consider since it was during this span that obesity risks truly began to accelerate. These data also indicate that the amount of time spent sleeping or napping increased by 16 minutes per day from 1985 to 1995 and, as noted, television viewing increased substantially.

Curiously, this decline in physical activity is reflected in the energy expenditure indexes provided by Cutler et al. (2003). While Cutler et al. interpret their energy expenditure indexes as falling from 1965 to 1975 and remaining “quite stable” thereafter (p. 103), a close inspection reveals that energy expenditure actually increased slightly between 1975 and 1985 and then fell again between 1985 and 1995. Because the latter time period is most relevant to the study of the obesity epidemic, it is important to consider this decline in physical activity as seriously as the data will permit. According to these indexes, energy expenditure declined by 14 percent among men and 16 percent among women between 1985 and 1995. Clearly, a decline of this magnitude could have contributed to the obesity epidemic.

Third, while Cutler et al. (2003) cite data on the modest quantitative changes in the proportion of Americans engaged in physically demanding occupations and motorized commuting, they say nothing about possible changes in the *qualitative* nature of these activities. Have jobs and their associated commuting requirements remained essentially unchanged during the past few decades? It seems unlikely. The rigors of physically demanding jobs (e.g., construction work) may have eased to some extent as technologies (e.g., nail guns) have improved and become more widely available. Even sedentary occupations may have become more so in recent years. To illustrate, e-mail has reduced the need to unseat oneself to converse with colleagues, reducing the physical activity requirements of sedentary positions. Moreover, although the proportion of Americans who drive to work has not changed substantially, average commute times have increased somewhat as people tend to live farther from work and must contend with more congested roads. Census data indicate that average commute times increased from 21.7 minutes in 1980 (U.S. Census Bureau 2004) to 25.5 minutes in 2000—although some of the increase in 2000 was caused by a change in survey instrumentation (Reschovsky 2004). Perhaps more importantly, the share of Americans that make very long commutes (i.e., 90 minutes or more) increased substantially, from 1.6 percent in 1990 to 2.8 percent in 2000.

Empirical Implications of Mass Preparation Theory

Cutler et al. (2003) acknowledge the limitations of their data and indicate that they "cannot be certain that [increased snacking] completely explains the rise in obesity" (p. 104). The previous discussion provides a number of reasons to suspect that it does not. Nevertheless, for the moment I will accept this premise as valid in order to review the four main empirical implications of mass preparation theory outlined by Cutler et al. These implications are:

1. The reduced time costs of food preparation should encourage people to consume a diverse set of foods over a wide range of times during the day.

2. Consumption should increase least for food products that generally do not require industrial processing (e.g., fruit).

3. Countries more open to mass preparation technologies should have experienced faster rates of obesity increase.

4. Demographic groups that benefited the most from industrial improvements in food processing should have experienced the fastest gains in BMI.

Cutler et al. (2003) cite the increased frequency of snacking as evidence to support the first implication that mass preparation should encourage the consumption of a diverse set of foods throughout the day. They test the second implication that consumption should increase least for food products requiring little processing by regressing the percent change in calories consumed for various food items from 1970-99 on the percent of revenue that went to farmers for those items (an indicator of the amount of industrial processing required for various foods). Through this analysis, Cutler et al. demonstrate that consumption increased most over this period for foods that tend to require substantial industrial processing. Cutler et al. also utilize regression analyses to examine the third implication that countries more open to mass preparation technologies should have experienced faster rates of obesity increase. However, because multinational data on the extent of industrial food preparation are not available, they rely upon data on price controls and other market restrictions (e.g., food statutes) to serve as proxies (i.e., nation-states with more restrictive economies tend to limit incursions from the U.S. agricultural sector). These analyses indicate that nation-states with more restrictive economies are generally less obese than countries more open to U.S. technologies and products.

Evidence in favor of these implications of mass preparation theory is compelling. For the purposes of the present investigation, I will presume that Cutler et al. (2003) are correct in their reading of the evidence on these three points. However, I would like to take a more careful look at the fourth implication of mass preparation theory—namely that demographic groups that benefited the most from industrial improvements in food processing should have experienced the fastest gains in BMI. Cutler et al. identify eight demographic groups based on gender, marital status, employment and age, and show that meal preparation and cleanup times decreased much more for women (particularly married women who were not employed outside of the household) than men over the past few decades. According to the theory, declines in the amount of time spent preparing meals should lead to increased BMI because of the lowered costs of food preparation. Stated otherwise, "obesity should increase the most among groups who formerly made most of their food in the house and should have increased the least among groups that already ate out more" (p. 109).

To test this theory, Cutler et al. (2003) regress BMI changes from 1971-75 to 1988-94 for these eight demographic groups on changes in the amount of time spent preparing food.[1] Results of this model support the demographic implications of mass preparation theory. Changes in the amount of time spent in food preparation explained about 63 percent of the increase in BMI. For each 15 minute reduction in food preparation, BMI increased by about 0.27 units.

[1] Cutler et al. also regress BMI changes on the initial amount of individual and household time spent in food preparation in 1965. Results of these models indicate that individual time spent in food preparation is more important to BMI change than household time.

Again, the evidence seems compelling. However, there is also reason to question both the logic of the theory on this point and the evidence used to support it. Regarding the theory, why should mass preparation necessarily lead to a greater reduction in the time costs of *eating* for persons who formerly spent a lot of time preparing food than for persons who were preoccupied with activities outside of the home? Cookie jars and refrigerators existed in 1965, just as they do today. Homemakers had to spend much more time on food preparation in 1965, of course, but this in itself should not preclude overeating. In fact, one could argue food preparation should encourage overconsumption, since it requires confinement to the kitchen for a considerable portion of each day. Also, because meal preparation and cleanup can be moderately strenuous, reductions in this physical activity may have led to a decline in total energy expenditure among homemakers, explaining (in part) why BMI increased for this group. Moreover, as convenience stores, vending machines and fast food restaurants have spread across the nation, people engaged in activities outside of the home should have more opportunities to eat without the time expense required by traditional restaurants.

Curiously, Cutler et al. (2003) use the example of a "hungry worker" who might be tempted to eat cookies if the vending machine is 10 feet away, but could be dissuaded by the time expense involved in walking to the corner store or baking the cookies himself (pp. 113-114). This would seem to corroborate my point that mass preparation has likely increased eating opportunities for persons away from home at least as much it has for homemakers. Evidently, Cutler et al. assume that because homemakers spent much time in meal preparation and cleanup, they did not have opportunities to eat unless they baked the goods themselves immediately prior to consumption. It would seem that they have forgotten about food storage units found in the kitchens of 1965 (such as refrigerators and cookie jars), which could be viewed as particularly convenient and cost-effective forms of vending machines.

Perhaps more troubling than the logic of the theory is the evidence used to support it. I have no qualms about the data themselves—Cutler et al. (2003) use data from the 1971-75 and 1988-94 National Health and Nutrition Examination Surveys (NHANES). Also, Cutler et al. rightly note that demographic changes in the U.S. cannot be responsible for the obesity epidemic, which (according to their analyses) account for just around 10 percent of BMI change between 1971-75 and 1988-94. However, while demographic change may not be responsible for the obesity epidemic, it could certainly explain a substantial portion of BMI change *within* the eight groups that Cutler et al. identify. For instance, the mean age of single females has risen over the past few decades as women tend to marry later in life. As shown in Chapter 2, BMI and age are positively associated through late middle age, which could account for some of the BMI change that Cutler et al. observe among single females. Unfortunately, there is no indication that Cutler et al. age-adjust within any of the demographic groups that they studied. Moreover, they do not control for changes in educational status, racial identification or birth cohort membership, all of which were shown to be independent contributors to BMI and obesity in Chapter 2. Given these important oversights, the conclusions Cutler et al. reach about BMI change within demographic groups are potentially faulty. Consequently, they will be revisited later in this investigation.

Impatience and Obesity

As discussed, Cutler et al. (2003) argue that improvements in food processing have made a wide variety of prepackaged food items available to the American consumer, making it possible to instantly gratify food desires. Therefore, mass preparation has predisposed persons with “self-control” problems to excessive weight gain in recent decades. Stated otherwise, impatient persons (i.e., hyperbolic discounters) are more susceptible to overeating in the food-rich environment in the U.S. and, as a consequence, are more likely than patient persons to gain weight.

Cutler et al. (2003) are not the only voices in the economic literature to associate impatience with overeating. Frederick, Loewenstein and O’Donoghue (2002) have observed that “visceral influences” such as hunger can interfere with the process of rational decision-making and encourage self-destructive behaviors:

> Visceral influences have important implications for intertemporal choice because, by increasing the attractiveness of certain goods or activities, they can give rise to behaviors that look extremely impatient or even impulsive. Indeed, for every visceral influence, it is easy to think of one or more associated problems of self-control—hunger and dieting, sexual desire and various “heat-of-the-moment” behaviors, craving and drug addiction, and so on (P. 372).

In the psychological literature, impatience and irritability combine to form one of two main constructs in the type-A behavior pattern (TABP) (Spence, Helmreich and Pred 1987). The other main construct in TABP is achievement striving, which measures the tendency to work industriously in pursuit of one’s goals (Conte et al. 2001). As the economic literature would suggest, impatience-irritability is associated with several health problems, including stress, sleep disorders and headaches (Barling and Charbonneau 1992; Conte et al. 2001). Although research has consistently shown that impatience-irritability is related to health issues with psychological roots (e.g., stress), recent analyses of data from the Coronary Artery Risk Development in Young Adults (CARDIA) study failed to detect a significant association between body mass and impatience (Yan et al. 2003). Moreover, achievement striving was strongly related to physical activity in this study, suggesting that this subcomponent of TABP is potentially important in weight management.

Cutler et al. (2003) argue that people with self-control problems consume an excessive amount of food "particularly when the time costs of food preparation fall" (p. 113). This implies that impatience should affect the likelihood of weight change differently among persons in the various demographic groups. That is, impatient individuals in groups that have experienced large reductions in the time costs of food preparation and cleanup should be more susceptible to overeating (and weight gain) than impatient individuals in groups without such large reductions. Given that adult women spent between 27 and 69 fewer minutes in food preparation and cleanup per day in 1995 than in 1965 (depending on marital status and employment) but adult men of all sorts experienced virtually no change in the time costs of food preparation over this period, it should be expected that impatient women were much more susceptible to weight gain than impatient men.

Cutler et al. (2003) do not provide an empirical test of their model of self-control problems to corroborate their view that impatience is fundamentally related to BMI change in the U.S. today. In addition, they do not recognize that impatience is a subcomponent of TABP, nor do they acknowledge the possibility that achievement striving could account for any observed association between impatience and changes in BMI. Before accepting their premises, it is important that research establish a solid link between impatience and BMI change. To date, evidence on this point is in short supply.

Research Questions

The preceding discussion of mass preparation theory begs three important research questions:

1. Have period changes in BMI increased most rapidly for demographic groups that have experienced the largest reductions in the amount of time spent in food preparation and cleanup?

2a. Does impatience affect changes in body mass, net of achievement striving?

2b. Are the effects of impatience stronger for women than men?

To answer the first question, age-period-cohort (APC) analyses were conducted using National Health Interview Survey (NHIS) data from 1976-2002. These analyses were stratified by gender, marital status and occupational activity to determine the extent to which period effects varied across four of the demographic groups identified by Cutler et al. (2003)—adult males, single (adult) females, married females in the labor force and married females not currently in the labor force. Note that Cutler et al. also divided adult males into three groups based on marital status and occupational activity, but they were collapsed into a single group for APC analyses because men in these groups experienced virtually no change between 1965 and 1995 in terms of meal preparation and cleanup time.[2] Single females spent 27 fewer minutes per day in meal preparation and cleanup in 1995 than 1965. The corresponding declines in meal preparation and cleanup time for married females in the labor force and married females not

[2] Cutler et al. (2003) also examined changes in BMI and time spent in meal preparation among elderly men and women. These groups were not analyzed in this study, in part due to an apparent error in reporting the amount of time spent in meal preparation and cleanup among elderly females in 1965 (i.e., 10.4 minutes per day). This figure is clearly too low, as elderly men spent 26.3 minutes per day on meal preparation and cleanup in 1965 and elderly females spent over an hour per day on these tasks in 1995.

currently in the labor force were 43 and 69 minutes, respectively. If the implications of mass preparation hold true, period effects should be strongest for married females not currently in the labor force, followed sequentially by (1) married females in the labor force, (2) single females and (3) adult males.

Questions 2a and 2b were explored through a preliminary set of structural equation models that made use of data from the 1957 and 1993 waves of the Wisconsin Longitudinal Study (WLS). These models investigated whether impatience-irritability affected BMI in 1993 independently of achievement striving, educational attainment and baseline measures of relative body mass, occupational aspirations and educational plans. Because mass preparation theory implies that the effects of impatience should be much stronger for women, these models were stratified by gender.

Figure 5.1 presents a theoretical path diagram of a covariance structure model linking impatience and achievement striving to BMI. For the moment, focus on the structural aspect of the path diagram (measurement will be discussed shortly). Because persons with lofty career and educational ambitions are likely to pursue post-secondary education and score high on TABP inventories (particularly achievement striving), adolescent measures of occupational aspirations and educational plans are theorized to directly affect educational attainment, impatience-irritability, and achievement striving in mid-life. In turn, educational attainment, impatience-irritability and achievement striving are theorized to affect BMI in 1993 directly, net of body mass at baseline. Chapter 2 showed the strong effects of educational attainment on BMI, so it was included as a control variable to account for the possibility that psychological variables might affect BMI only by dint of their association with education.

In addition, "economic discipline" (i.e., the ratio of household savings to household income) was included as a measure of patience. In "The Economics of Impatience," Fehr (2002) indicates that rational long-term decisions (such as saving sufficient income for retirement or sustaining a healthy diet) require the deferment of gratification, which is compromised by the fact that people often prefer smaller, immediate rewards over larger, future rewards. That is, people often prefer to have their desires satisfied *now*, even if such a time preference does not maximize long term outcomes. The allure of immediate rewards leads to a "divergence between intention and action" in which people understand the importance of long-term goals (e.g., savings or weight-loss) yet tend not to act accordingly (p. 271). Therefore, there is reason to suspect that persons who exhibit impatient economic behaviors will also exhibit impatient behaviors with regard to diet and exercise, which of course promote elevated body mass. Persons with impatient psychological profiles are expected to show less economic discipline, which in turn is expected to affect BMI in 1993 directly.

5.2 Materials, Methods and Results for Research Question 1

Study population

NHIS is a repeated cross-sectional household survey of the noninstitutionalized civilian population in the U.S. (National Center for Health Statistics 2004). Its primary functions are to monitor the prevalence and distribution of disease and disability in the U.S. and assess patterns of health care utilization. Every week, interviewers from the U.S. Census Bureau gather information from "responsible family members" residing in randomly chosen households across the nation (Adams, Hendershot and Marano 1999:2). Response rates to NHIS are outstanding.

On average, Census personnel complete interviews at about 94 percent of the households selected (Adams et al. 1999). This study merged NHIS data from 1976-2002 into a single database consisting of approximately 1.7 million adults aged 18 and over. For readers interested in additional details on NHIS, please refer to Chapter 2 and Adams et al.

Measures in NHIS

As discussed in Chapter 3, the age-period-survey (APS) adjustment was developed to provide a measure of body mass index ((BMI = weight(kg)/height(m^2)) in NHIS that corresponded to BMI values recorded in NHANES examination data. Age was subtracted from period (i.e., year of study) to identify birth cohorts, which ranged from 1877 to 1984. Cohorts were arranged into five-year groups, with the exception of the initial cohort (1877 to 1899) which covered a broader range of years to ensure a sufficient number of subjects. After constructing birth cohorts, age was collapsed into three-year intervals (e.g., 18-21) and a final category of 84 and over. Because each wave of NHIS was relatively large, periods were left in single year increments. To estimate the unique effect of each age group, birth cohort and time period, indicator variables were constructed based on these categorizations.

Measures of sex, marital status and occupational activity were extracted from NHIS to stratify APC models into four demographic groups—adult males, single (adult) females, married females in the labor force and married females not currently in the labor force. The categories "married, spouse in household" and "never married" were employed to identify respondents who were either married or single at the time of the survey. Also, the category "working" identified persons currently in the labor force and the categories "keeping house," "school" and "other" were combined to identify persons not currently in the labor force. Although questions for both of these items changed in the 1997 NHIS redesign, the categories “married, spouse in household” and “working” were constant from 1976 to 2002. Also, whereas the percentage of respondents falling into some categories (e.g., keeping house) varied noticeably before and after 1997, the various categories employed here were relatively stable despite the redesign.

In addition to these measures, race and education were extracted from NHIS to serve as control variables in APC models. In each year from 1976-2002, NHIS included a racial identification variable that categorized respondents as White, Black or other. Consistent with Chapter 2, racial identification was recoded as either Black or non-Black. Also, education was recoded into less than high school (0-11 years of education), high school (12 years of education), some college (13-15 years of education) and college or more (16 or more years of education). Indicator variables were subsequently created for race and each educational category.

Statistical Analyses of NHIS Data

Data management and analyses were conducted with SAS 9.1 (2003) and SPSS 8.0 (1997). Ordinary least-squares (OLS) regression analyses were used to estimate APC models of BMI for demographic groups within the U.S. population. APC models were stratified by the four groups identified previously (i.e., adult males, single females, married females in the labor force and married females not currently in the labor force) and included education and racial identification as control variables. Survey weights provided by NHIS were used to adjust for response probabilities and sampling design. Given the very large sample size and arbitrary nature of choosing referent categories in indicator variable regression analyses, estimating the statistical uncertainty of individual parameter estimates was not a primary consideration. For most parameter estimates, SAS reported p-values of less than 0.0001 for two-sided t tests in OLS regression models. SAS indicated that the parameter estimates in the initial specification of models for some groups (e.g., single females) were threatened by a linear dependency between the period 1993 and other variables. To address this problem, 1993 and 1994 were combined into a single variable, 1993.5. This effectively resolved the linear dependency but, notably, did not lead to substantially different results, indicating that the parameters were robustly estimated. For more information on resolving identification problems, please refer back to Chapter 2.

Instead of focusing on individual parameter estimates, this study utilized its large sample and long period of observation to estimate the functional form of age, period and cohort effects in the U.S. This was accomplished by regressing the unstandardized OLS estimates of BMI differences for each age group, time period and birth cohort on centered values of age, period and cohort, respectively. Centered values were employed to minimize the threat of collinearity in polynomial models (Klienbaum et al. 1998).

Linear, quadratic and cubic models were explored to find the functional form that most closely matched the patterns of parameter estimates. Two-sided t tests were used to assess null hypotheses that linear, quadratic and cubic β coefficients were equal to zero. Coefficients with T statistics falling outside the 97.5th percentile of either tail of t distributions with n-1 degrees of freedom were retained in the regression equations used to model the functional form of APC parameter estimates. Because polynomials were added one at a time, two-sided t tests were equivalent to partial F tests (Klienbaum et al. 1998). That is, statistically significant polynomials necessarily led to significantly improved model fit.

Results of APC Models of BMI

Recall that mass preparation theory predicts that period effects should be strongest for married females not currently in the labor force, followed sequentially by (1) married females in the labor force, (2) single females and (3) adult males. Consistent with these predictions, APC models showed that adult males exhibited the smallest period change in BMI among the four demographic groups considered (see Figure 5.2). A quadratic model fit the parameter estimates for period effects extraordinarily well for men ($R^2 \approx 1.0$), indicating that BMI rose at an exponential pace between 1976 and 2002 (see Appendix E, Part 5).[3] Net of age, birth cohort membership, educational attainment and racial identification, men averaged 3.3 BMI units heavier in 2002 than in 1976.

However, contrary to expectations, period effects among the three groups of women were rank-ordered in the *opposite* direction of that predicted by the theory. Among women, married females not currently in the labor force exhibited the weakest period effects (see Figure 5.2); a quadratic model fit the parameter estimates extraordinarily well for this group ($R^2 \approx 1.0$; see Appendix E, Part 8). Compared to 1976, married females not in the labor force were, on average, 3.8 BMI units heavier in 2002—a change of only 0.5 BMI units more than adult males.

Married females currently in the labor force experienced faster period change in BMI than males or married females not currently in the labor force, but slower change than single females, who experienced the fastest change of any group (see Figure 5.2). Among married, working females and single females, the best-fitting regression models included negative cubic

[3] Interested readers should consult Appendix E for details on the regression models used to summarize period change, as well as to review age and cohort effects for these groups.

terms ($R^2 \approx 1.0$ in each case; see Appendix E, Part 6 and Part 7). This suggests that increasing levels of BMI will eventually asymptote for married females in the labor force and single females. Nevertheless, BMI increased substantially between 1976 and 2002 for both groups. Married females currently in the labor force averaged 4.5 BMI units heaver in 2002 than in 1976. In sharp contrast to the predictions of mass preparation theory, BMI among single females increased by an average of 5.4 units between 1976 and 2002—fully 1.6 units more than married females not in the labor force.

5.3 Materials, Methods and Results for Research Questions 2a and 2b

Study population

The WLS is a random sample of 10,317 persons who graduated from a public, private or parochial high school in Wisconsin in 1957 (Sewell et al. 2004). The initial wave of the WLS collected information on academic ability, socioeconomic background, attitudes toward higher education, educational and occupational aspirations, and a handful of contextual factors (Hauser 2005). Subsequent waves in 1964, 1975, 1992-93 and 2003-05 collected data from WLS respondents (or their parents) on a wide range of issues that are essential to studies of the life course, including educational and occupational histories, indicators of socioeconomic status, military service, marital status, family characteristics, social participation, psychological well-being, health behaviors and health outcomes (Hauser 2005; Sewell et al. 2004). Although the WLS is not nationally representative, its respondents resemble over two-thirds of Americans who are now entering retirement age in terms of academic achievement and ethnic background (Hauser 2005). This study merged data from the 1957 and 1992-93 waves of the WLS. After accounting for random selection into the subsample of 3,027 for the relative body mass coding project, attrition and various forms of non-response, 1,121 respondents were available for analysis. Readers interested in learning more about the WLS should consult Sewell et al. (2004) and Hauser (2005).

Measures in the WLS

The scale developed in Chapter 4 was included as a baseline (i.e., 1957) measure of relative body mass (RBM). Accounting for measurement error does not substantially alter the effect of RBM in 1957 on BMI in 1993, but RBM was nevertheless treated as a latent variable for illustrative purposes. Other baseline measures included occupational aspirations and educational plans, which were assessed via recodes of items from the original 1957 questionnaire. Reported occupational aspirations were assigned three digit Census codes and then recoded to match Duncan's socioeconomic status index (SEI), which ranks occupations in terms of their income and educational levels (Duncan 1961). The three digit WLS measure of SEI was multiplied by a factor of 0.01 to provide similar scaling to the other variables in the covariance structure models. An indicator variable was created to measure educational plans, where 1 equaled "plans to attend college" and 0 equaled "does not plan to attend college." Individuals with plans to attend post-secondary vocational, business or trade schools were assigned to the latter category.

Endogenous variables included 1993 measures of BMI, educational attainment, achievement striving and impatience-irritability. BMI was calculated from self-reported measures of weight in pounds and height in inches. Educational attainment was measured as the number of years of post-secondary education (recall that all WLS respondents are high school graduates). Achievement striving was measured via four likert scale items in the WLS mail survey. All four of these items were reverse coded so that larger integers corresponded to higher values of achievement striving.

1. Item 19e. I enjoy making plans for the future and working to make them a reality.
2. Item 19s. I am an active person in carrying out the plans I set for myself.
3. Item 20a. Even when things seem hopeless, I keep on fighting to reach my goals.
4. Item 20d. I stick to my goals and projects even in the face of great difficulties.

In their original design, items 19e and 19s were intended to measure purpose in life—one of six dimensions in Ryff's scale of psychological well-being (1989). Items 20a and 20d were constructed by Brandtstädter and Renner (1990) to measure tenacious goal pursuit (TGP), which they contrast to flexible goal adjustment (FGA) as distinct strategies of goal attainment. Although designed for other purposes, all four of these items have face validity as measures of achievement striving.

Likewise, impatience-irritability was measured by four items in the WLS. Two of these items measured impatience in a likert scale format. Item 20c was reverse coded so that larger integers reflected higher levels of impatience.

1. Item 20b. If I don't get something I want, I take it with patience.
2. Item 20c. It is very difficult for me to accept a setback or defeat.

These items were developed by Brandtstädter and Renner (1990) to measure flexible goal adjustment (FGA). I surmise that persons with inflexible goal orientations are less patient than those who are capable of adjusting goals as new scenarios and challenges arise. Indeed, item 20b asks respondents whether they react patiently when their desires are frustrated.

The other two items inquired about the number of days during the past week that WLS respondents felt irritable.

3. Item 18u. On how many days during the past week did you feel irritable, or likely to fight or argue?
4. Item 18v. On how many days during the past week did you feel like telling someone off?

Nadine Marks designed these items to measure hostility in the 1993 WLS mail survey; subsequent research has shown that they reliably achieve this purpose (see Marks 1996). Hostility is arguably quite similar to irritability as a psychological construct, as suggested by Item 18u which asks respondents specifically about feelings of irritability. Although items 18u and 18v were moderately skewed, transformations did not materially alter the results. Consequently, they were left in their original metrics to simplify the interpretation of factor loadings.

In addition to psychological items, economic discipline was measured as the ratio of household savings to household income. Household savings was measured via the question "About how much is the total value or your/you and your spouse's savings?" The quantity 0.01 was added to household savings to avoid logging zero, which is mathematically impossible. Household income was measured as the total income for the respondent's household in the past 12 months, which was a composite of a series of questions in the WLS. The ratio of household savings to household income seriously violated the assumption of univariate normality (skew = 20.26; kurtosis = 521.11), necessitating transformation of the variable. Through a log-transformation that included a start value (i.e., economic discipline = ln(0.25+(household savings/household income))), this problem was rectified.

Of course, many things can affect the ratio of household savings to household income (e.g., medical emergencies), but in this study it was assumed that the larger the numerator relative to the denominator, the more disciplined (i.e., patient) the individual with regard to economic decisions. Household measures of savings and income were preferred over personal measures of savings and income due to gender inequities with regard to these variables. That is, although women often earned less than their husbands in 1993, they nevertheless tended to have considerable say over decisions regarding household finances. In this way, the ratio of household savings to household income is assumed to reflect upon the economic discipline of the individual, regardless of gender.

Statistical Analyses of WLS Data

Data management and analyses were conducted with SAS 9.1 (2003) and LISREL 8.72 (2005). The structural component of covariance structure models was estimated via maximum likelihood in LISREL through the following equation:

$$\eta = B\eta + \Gamma\xi + \zeta,$$

where η is a vector of unobserved endogenous variables, B is a matrix of effects between endogenous variables, Γ is a matrix of effects between exogenous variables (i.e., ξ) and endogenous variables, ξ is a vector of unobserved exogenous variables, and ζ is a vector of disturbances for unobserved endogenous variables (Jöreskog and Sörbom 1996).

Measurement components of covariance structure models were also estimated in LISREL 8.72 via the following set of equations:

$$y = \Lambda_y \eta + \varepsilon$$

$$x = \Lambda_x \xi + \delta,$$

where y is a vector of endogenous observed variables, Λ_y is a matrix of the effects of endogenous latent variables (i.e., η) on endogenous observed variables (i.e., y), ε is a vector of measurement errors for y variables, x is a vector of exogenous observed variables, Λ_x is a matrix of the effects of exogenous latent variables (i.e., ξ) on exogenous observed variables (i.e., x) and δ is a vector of measurement errors for x variables (Jöreskog and Sörbom 1996).

To reiterate, research question 2a asked, "Does impatience affect changes in body mass, net of achievement striving?" This question was evaluated separately for men and women through gender-stratified covariance structure analyses of the theoretical model shown in Figure 5.1.[4] Changes in the fit of the theoretical model relative to a saturated model was evaluated by χ^2/df ratios as well as the Bayesian Information Criterion (BIC), which was calculated according the formula advocated by Raferty (1995) for model comparisons.

$$\mathrm{BIC} = \chi^2 - (df * (\ln(n))$$

After estimating the theoretical model, modification indices provided by LISREL 8.72 were used to identify parameters (e.g., error covariances) that could improve model fit if freely estimated. Through a systematic process of freeing individual parameters with "large" modification indices (i.e., about 8 or higher), estimating models, and reevaluating model fit, final preferred models

[4] Note that the LISREL default of symmetric and free for the Φ matrix was not altered in this model. However, to preserve the visual clarity of Figure 5.1 (and subsequent figures of covariance structure models), covariances between ξ variables were not included. Interested readers may consult Appendix F for a complete list of parameter estimates.

were developed for each group. Parameter estimates with T values of +/- 1.96 or more were considered to be significantly different from zero.

Research question 2b asked, “Are the effects of impatience stronger for women than men?” This question was evaluated by imposing a series of equality constraints on the best-fitting covariance structure models for men and women that were identified in the single-group LISREL analyses. As a first step, the factor loadings between impatience-irritability and Items 18v, 20b and 20c were constrained to be equal for men and women in a two-group LISREL model (see Figure 5.1). With equivalent factor structures in place, equality constraints were imposed on the structural paths involving direct or indirect relationships between impatience and BMI—i.e., the effects of (1) impatience-irritability on economic discipline, (2) impatience-irritability on BMI in 1993 and (3) economic discipline on BMI in 1993. Through a process of backward model selection, the best-fitting two-group LISREL model was identified. Importantly, because mass preparation theory argues that the effects of impatience should be greater for groups that experienced large reductions in the time costs of food preparation (i.e., women) than for groups that did not experience such large reductions (i.e., men), it follows that the imposition of equality constraints on these structural coefficients should cause model fit to deteriorate significantly. If model fit does not deteriorate, then there is no basis to conclude that men and women differ with regard to the effects of impatience on changes in body mass, contrary to the implications of mass preparation theory.

Results of Covariance Structure Models Linking Impatience to BMI

Descriptive statistics for continuous variables used in covariance structure models are presented in Table 5.1.[5] Exogenous variables were all normally distributed with similar means and standard deviations. With the exception of Item 18u and Item 18v, endogenous variables were also normally distributed. BMI in 1993 exhibited a somewhat leptokurtic (kurtosis = 3.45) and positively skewed (skew = 1.23) distribution, but this was not perceived as a sufficient deviation from normality to warrant transformations. Log transformations of Item 18u and Item 18v reduced skew and kurtosis considerably, but did not substantially alter results, so the original metrics were preserved to facilitate interpretation of factor loadings. However, as discussed, it was necessary to log-transform the ratio of household savings to household income, which seriously violated the assumptions of normality (skew = 20.26; kurtosis = 521.11) prior to transformation.

Estimating the theoretical path diagram shown in Figure 5.1 caused model fit to improve dramatically relative to saturated models. The theoretical model caused χ^2 to increase by 280.96 ($p < 0.01$) among males ($n = 492$) and 318.80 ($p < 0.01$) among females ($n = 629$), indicating significant differences between the actual covariance matrices and those implied by the theoretical model (see Model 2 and Model 5 in Table 5.2). Importantly, however, the theoretical model also released 142 degrees of freedom, resulting in non-significant χ^2/df ratios for males (1.98) and females (2.25). That is, *per degree of freedom*, the theoretical model did not cause significant deterioration in fit. Moreover, the theoretical model led to drastic improvement in

[5] Note that college plans is a dichotomous variable. Approximately 37 percent of WLS respondents in this sample of 1,121 indicated that they intended to attend college after graduation from high school in 1957.

BIC for both males and females (e.g., BIC declined by 599.22 among males), demonstrating that the disparities between the actual covariance matrices and those implied by the theoretical model were (1) not substantial and (2) more than compensated for by the superior parsimony of theoretical model.

Despite these improvements, modification indices revealed that model fit could be enhanced further by allowing LISREL to estimate certain parameters that were constrained to equal zero in the theoretical model. The majority of these parameters were correlated errors between either (1) relative body mass coders or (2) adjacent survey items in the WLS (see Model 3 and Model 6 in Table 5.2). For instance, significant error covariances were detected between coder 1 and coder 6 in Model 3 for males ($\Theta\delta_{1,6} = -0.22$; $T = -4.23$) and coder 2 and coder 6 in Model 6 for females ($\Theta\delta_{2,6} = 0.16$; $T = 3.72$), indicating that the latent variable for relative body mass in 1957 did not capture all of the systematic agreement (or disagreement) unique to these pairs of coders. Also, errors for items 20b and 20c were strongly correlated in both Model 3 ($\Theta\varepsilon_{3,4} = 0.20$; $T = 4.82$) and Model 6 ($\Theta\varepsilon_{3,4} = 0.26$; $T = 7.30$), indicating that impatience-irritability did not capture all of the covariation between these items among either male or female WLS respondents. Converse and Presser (1986) observe that mail surveys occasionally suffer from "acquiescence response sets" (p. 38), in which subjects respond to a block of agree-disagree questions as if it were a single item. This form of response bias may account for correlated errors found among items 20a-20d in the WLS mail survey. Readers interested in reviewing the other error covariances shown in Table 5.2 should consult Appendix F.

In addition to correlated errors, modification indices revealed significant, negative associations between the disturbances for impatience-irritability and achievement striving among both men ($\Psi_{1,2}$ = -0.11; T = -3.66) and women ($\Psi_{1,2}$ = -0.21; T = -4.72). Net of other variables affecting TABP subcomponents, respondents who scored high on one subcomponent of TABP (i.e., impatience-irritability) tended to score somewhat lower on the other (i.e., achievement striving). Modification indices also revealed that occupational aspirations among adolescent girls directly affected their economic discipline later in life ($\Gamma_{3,2}$ = 0.09; T = 3.53). (This finding will be discussed in more detail shortly). By estimating the error covariances and structural parameters shown in Table 5.2, model fit improved considerably. Among males, χ^2 dropped from 280.96 to 183.93 (or by 16.17 for each degree of freedom used); BIC also dropped by 59.84 units, showing the superiority of Model 3 to Model 2. Similarly, among females χ^2 dropped from 318.80 to 146.12 (or by 21.59 for each degree of freedom used); BIC also dropped by 121.13 units, showing the superiority of Model 6 to Model 5.

Figure 5.3 shows the preferred model for males (i.e., Model 3), sans the added parameter estimates and covariances between exogenous ξ variables (e.g., occupational aspirations and educational plans), which were omitted to preserve a modicum of visual elegance.[6] Factor loadings for relative body mass, impatience-irritability and achievement striving in Model 3 were all positive (i.e., in the expected direction) and highly significant (see the Λy and Λx matrices in Appendix F, Part 1 for individual T values). However, while the measurement models conformed to theoretical expectations, the structural coefficients in Model 3 often did not. Net of relative body mass (RBM) in 1957 and other covariates (e.g., educational attainment),

[6] Readers may consult Appendix F, Part 1 for a complete list of parameter estimates for Model 3, which are given in unstandardized and completely standardized form. Appendix F also includes the correlation matrices and standard deviations used to estimate these models, allowing interested researchers to replicate and extend these results.

impatience-irritability did not significantly affect the BMI of men in 1993 ($B_{5,1} = 0.37$; $T = 1.44$), although the direction of this effect was consistent with theory. Similarly, neither economic discipline ($B_{5,3} = -0.07$; $T = -0.33$) nor achievement striving ($B_{5,2} = -0.36$; $T = -1.03$) significantly affected BMI, although, again, theory anticipated the direction of these effects. Only education ($B_{5,4} = -0.14$; $T = -2.72$) and relative body mass in 1957 ($\Gamma_{5,1} = 0.87$; $T = 8.24$) directly affected BMI in 1993, suggesting that TABP subconstructs are of limited value in understanding body mass change among males.

However, through their influence on educational attainment, the occupational aspirations and educational plans of boys in 1957 indirectly affected their BMI as men in 1993. Boys who planned to attend college at age 18 had, on average, 2.46 years more education ($T = 8.19$) at age 54 than boys who did not. Because BMI in 1993 decreased by an average of 0.14 units with each additional year of educational attainment ($T = -2.72$), boys who planned to attend college averaged 0.34 BMI units less at age 54 than boys without such plans (i.e., $\Gamma_{4,3}*B_{5,4} = 2.46*-0.14 = -0.34$). With each unit increase in occupational aspirations (normed to Duncan's SEI, which ranged from 0.7-9.6) educational attainment increased by 0.34 years ($T = 6.41$). Therefore, boys scoring 5 units higher on occupational aspirations averaged 0.24 BMI units lower in 1993 (i.e., $\Gamma_{4,2}*5*B_{5,4} = 0.34*5*-0.14 = -0.24$). Incidentally, occupational aspirations also significantly affected achievement striving ($\Gamma_{2,2} = 0.04$; $T = 2.65$), but did not affect impatience-irritability, contrary to theoretical expectations. Educational plans did not affect either achievement striving or impatience-irritability, also contrary to expectations.

Figure 5.4 shows the preferred model for females (i.e., Model 6). Note that, again, some parameters in this model (e.g., error covariances) were omitted to preserve the visual clarity of the diagram.[7] As found among males, the factor loadings for relative body mass, impatience-irritability and achievement striving in Model 6 were all positive and statistically significant (see the Λy and Λx matrices in Appendix F, Part 2 for individual T values). Unlike Model 3, however, Model 6 provided some support for mass preparation theory. Although impatience-irritability did not directly affect BMI ($B_{5,1} = -0.07$; $T = -0.33$), women with more economic discipline reported significantly lower BMI in 1993 ($B_{5,3} = -0.55$; $T = -2.54$), net of relative body mass in 1957 ($\Gamma_{5,1} = 0.95$; $T = 7.80$) and other covariates in the model (e.g., achievement striving). To illustrate the effect of economic discipline on BMI, a thirty percent increase in economic discipline (normed to the logged ratio of household savings to household income) led to an average BMI decline of 0.17 units. Consequently, impatience-irritability indirectly affected BMI through its influence on economic discipline ($B_{3,1} = -0.07$; $T = -2.08$). One interpretation of this somewhat complex indirect effect follows: A four unit increase in impatience-irritability (normed to Item 18u, an eight-point scale) led to an average decline of 27.2 percent in economic discipline, which in turn produced an average increase of 0.15 BMI units. In other words, women scoring four points higher on impatience-irritability averaged 0.15 BMI units lower in 1993 due to the effect of impatience-irritability on economic discipline.

Although these results provide nominal support for question 2a, the effects of impatience-irritability and economic discipline on BMI were rather weak. In contrast, achievement striving had a robust, direct effect on women's BMI in 1993 (see Figure 5.4). With each unit increase in achievement striving (normed to Item 19e, a six point scale), BMI declined by over one unit ($B_{5,2} = -1.02$; $T = -3.20$). Model 6 also demonstrated that women's achievement striving was

[7] Please refer to Appendix F, Part 2 for a complete list of parameter estimates for Model 6.

influenced by their educational plans during adolescence ($\Gamma_{2,3} = 0.20$; $T = 2.26$). Consequently, educational plans affected BMI indirectly, via their effect on achievement striving. Girls with college plans at age 18 were, on average, 0.20 BMI units lighter at age 54 than girls without such plans (i.e., $\Gamma_{2,3} * B_{5,2} = 0.20 * -1.02 = -0.20$). Although educational plans and occupational aspirations were strongly related to educational attainment, this effect was not transmitted to BMI in 1993 due to the insignificant effect of education on BMI ($B_{5,4} = -0.07$; $T = -0.89$). However, occupational aspirations indirectly affected BMI through their significant, direct effect on economic discipline ($\Gamma_{2,2} = 0.09$; $T = 3.53$). An interpretation of this indirect effect follows: A four unit increase in occupational aspirations (normed to Duncan's SEI scale, which ranged from 0.7-9.6) resulted, on average, in a 37.6 percent increase in economic discipline, which in turn led to a 0.21 unit reduction in BMI. That is, girls who scored four points higher on occupational aspirations at age 18 averaged 0.21 BMI units less at age 54 because of their generally higher level of economic discipline in adulthood.

Results of Two-Group LISREL Models

The preferred models for males and females (i.e., Models 3 and 6, respectively) were combined to form the baseline model in two-group LISREL analyses (see Model 7 in Table 5.2). The χ^2 value of 330.05 for Model 7 is the sum of the χ^2 values for Model 3 ($\chi^2 = 183.93$) and Model 6 ($\chi^2 = 146.12$), showing that Model 7 is simply the simultaneous estimation of the preferred models. (Note also that the *df* in Model 7 is simply the sum of *df* in Models 3 and 6). Although the χ^2 value of 330.05 was significant at 270 degrees of freedom ($p < 0.01$), the fit of the baseline model was excellent. The χ^2/df ratio of 1.22 indicated that, per degree of freedom, there were not significant discrepancies between the actual covariance matrices and those implied by Model 7. Also, the low BIC value of -1565.88 demonstrated that Model 7 parsimoniously explained most of the covariation between variables in the model.

In Model 8, the factor loadings between impatience-irritability and Items 18v, 20b and 20c (i.e., $\Lambda y_{2,1}$, $\Lambda y_{3,1}$, and $\Lambda y_{4,1}$) were held constant for men and women (see Table 5.2). Imposing these equality constraints across groups caused χ^2 to increase by a significant amount, per degree of freedom released ($\Delta \chi^2/df = 3.94$; $p < 0.05$). This loss of fit was likely the result of somewhat weaker factor loadings for women than men on the impatience-irritability items. However, relative to Model 7, BIC declined by 9.24 units in Model 8, suggesting that this loss of model fit was (1) acceptably small and (2) more than compensated for by improved model parsimony.

With equivalent factor structures in place, the effect of impatience-irritability on BMI in 1993 (i.e., $B_{5,1}$) was held constant for men and women (see Model 9 in Table 5.2). Imposition of this equality constraint improved the parsimony of Model 9 relative to Model 8, without significant deterioration in fit ($\Delta \chi^2/df = 2.46$; Δ BIC = -4.56). This demonstrated that men and women did not differ significantly with regard to the effect of impatience-irritability on BMI. Next, the effect of economic discipline on BMI in 1993 (i.e., $B_{5,3}$) was held constant (see Model 10 in Table 5.2). This equality constraint improved the fit of Model 10 relative to Model 8 ($\Delta \chi^2/df = 3.16$; Δ BIC = -3.86), showing that the effect of economic discipline on BMI was not significantly different for men and women. Finally, the effect of impatience-irritability on economic discipline (i.e., $B_{3,1}$) was held constant (see Model 11 in Table 5.2). This equality constraint improved the fit of Model 11 relative to Model 8 ($\Delta \chi^2/df = 1.83$; Δ BIC = -5.19), indicating that men and women did not differ with regard to the effect of impatience-irritability on economic discipline.

Because all three of these structural constraints improved model fit, they were subsequently combined into a single model and estimated simultaneously (see Model 12 in Table 5.2). When estimated together, these equality constraints resulted in a non-significant increase in the χ^2/df ratio relative to Model 8 ($\Delta\chi^2/df = 2.42$) and considerable improvement in overall model fit (Δ BIC = -13.82). Therefore, Model 12 became the preferred two-group model showing that, in response to question 2b, the effects of impatience on BMI are *not* significantly different for men and women.

The factor loadings and structural coefficients for Model 12 are presented in Figure 5.5 (males) and Figure 5.6 (females). First, it is important to note that the imposition of equality constraints did not lead to substantively different conclusions for men or women with regard to other variables in the model, although some parameter estimates changed slightly. Second, note that the factor loadings for impatience-irritability are, of course, equal for men and women. Consistent with the single-group models, these factor loadings were highly significant in the two-group model ($T \geq 5.85$). Third and most importantly, note that while the *direction* of the effects for impatience-irritability on BMI ($B_{5,1} = 0.18$; $T = 1.16$), economic discipline on BMI ($B_{5,3} = -0.27$; $T = -1.87$) and impatience-irritability on economic discipline ($B_{3,1} = -0.06$; $T = -1.94$) were all consistent with theoretical expectations, the results themselves were not statistically significant. This finding casts doubt on the results of single-group models showing that impatience is a (weak) cause of body mass change among women.

5.4 Summary and Conclusions

Results of APC analyses and covariance structure models generally did not support the predictions of mass preparation theory. To review, the three research questions identified at the outset of this investigation were:

1. Have period changes in BMI increased most rapidly for demographic groups that have experienced the largest reductions in the amount of time spent in food preparation and cleanup?

2a. Does impatience affect changes in body mass, net of achievement striving?

2b. Is the effect of impatience stronger for women than men?

Mass preparation theory anticipates that research should provide affirmative responses to each of these questions but, in general, my investigation did not. With regard to the first question, APC models of NHIS data showed that period changes in BMI were indeed smaller for men than women, as predicted by the theory. However, period effects differed little between men and married women not currently in the labor force, despite the fact that these groups differed most with regard to changes in the time costs of food preparation. Mass preparation theory was also contradicted by the rank-order of period effects for groups of women, which were in precisely the *opposite* order of that implied by the theory. Single women exhibited the fastest period change in BMI even though they experienced much smaller reductions in the time costs of food preparation than either group of married women. Also, married women not currently in the labor force exhibited the weakest period effects (among women), even though they experienced by far the largest reduction in the time costs of meal preparation and cleanup.

In addition to these contradictions, APC analyses raised another troubling question for advocates of mass preparation theory. What accounts for the strong period effects among men?

For the moment, ignore the rank-ordering of period effects among groups of women and assume that mass preparation theory correctly accounts for average differences in BMI change between men and women. In that case, changes in the amount of time spent preparing food could conceivably explain the 0.5-2.1 unit difference in BMI between men and various groups of women in 2002. However, the time costs of food preparation cannot explain the 3.3 unit increase in BMI observed among men between 1976 and 2002, since men did not change much in this regard. Of course, mass preparation *could* lead to increased calorie intake among men by creating new opportunities to eat while they are "on the go." However, Cutler et al (2003) argue that "men already ate out more" (p. 109) and clearly emphasize that the reduced time costs of food preparation have altered eating patterns over the past few decades which have, in turn, caused BMI to increase. Since men did not experience meaningful reductions in the time costs of food preparation, there is nothing in mass preparation theory to account for their increased BMI.

Consequently, BMI change among men likely represents a conservative estimate of residual variation in the period effects observed among women. That is, of the 3.8-5.4 unit increase in BMI observed among groups of women between 1976 and 2002, mass preparation cannot account for 3.3 units, or between 61-87 percent of BMI change. Of course, these calculations are optimistic because they ignore the rank-order of period effects among women, which imply that changes in the time costs of food preparation explain even less variation in BMI change.

With regard to question 2a, covariance structure models of WLS data showed that women with more economic discipline tended to have lower BMIs in 1993, net of achievement striving, educational attainment and the baseline measure of body mass. This result is important because it supports the idea that people who make patient economic decisions are less impulsive with regard to their dietary choices. That said, it is also important to recognize that economic discipline affected BMI only weakly among women and not at all among men. Moreover, in clear violation of theoretical expectations, impatience-irritability did not directly affect BMI among either men or women. Although impatient and irritable women exhibited less economic discipline and, consequently, higher BMIs than more patient women, this indirect effect of impatience-irritability on BMI was also fairly weak. On balance, covariance structure models provided scant evidence that impatience is fundamentally related to changes in body mass.

With regard to question 2b, covariance structure models failed to detect evidence that the effects of impatience were stronger for women than men. When the structural effects linking measures of impatience to BMI were held constant for men and women, the fit of covariance structure models did not deteriorate, but rather improved. This finding presents another challenge for Cutler et al. (2003), who argue that "people with self-control problems may find themselves overconsuming food, particularly when the time costs of food preparation fall" (p. 113). The time costs of food preparation fell much more for women than men, and yet women with "self-control problems" (i.e., impatient women) did not differ from impatient men with regard to changes in body mass.

Importantly, covariance structure models showed that achievement striving was a strong predictor of BMI among women. This indicates that TABP is potentially important in the etiology of obesity. However, results of this investigation suggest that lack of motivation, not impatience, is the primary psychological mechanism related to TABP that encourages weight gain. The public health and psychological literature support the notion that motivational factors are related to health behaviors affecting body mass. In a sample of 3,308 adults, Yan et al. (2003) recently found that achievement striving is positively associated with physical activity. Similarly, studies of adolescents and young adults have shown that motivational readiness and intrinsic motivation are related to exercise behaviors (Ferrer-Caja and Weiss 2000; Lee et al. 2001). Williams et al. (1996) linked autonomous motivation (similar to intrinsic motivation) among obese participants in a low-calorie weight loss program to regular attendance of meetings, successful treatment and subsequent maintenance of weight loss. Other studies (e.g., Armitage 2004; Milne, Orbell and Sheeran 2002) in the psychological literature have found that motivation is not sufficient to influence exercise and other health behaviors, but that it is a necessary precursor to the development of volitional strategies. In other words, motivation may affect health behaviors indirectly through the formation of behavioral intentions, which could account for the associations observed in this study between achievement striving and BMI.

This investigation also affirmed the results of Chapter 4 and several epidemiological studies that have shown that adolescent body mass is strongly linked to adult BMI. Moreover, this investigation showed that indicators of motivation in adolescence (e.g., occupational aspirations) affected BMI in adulthood through their influence on educational attainment and achievement striving. Although these indirect effects were not very strong, they lend further credence to the idea that motivational factors are important to the etiology of obesity.

A key advantage to the APC analyses in this study was the ability to control for factors that threatened to influence BMI changes within demographic groups (e.g., age and educational attainment). Other strengths of the APC analyses were the same as those discussed in Chapter

2—namely a large nationally representative sample, micro-level data and refined measures of age, period and cohort. A potentially important limitation of APC analyses is that NHIS offers a peculiar mix of proxy, partial-self and self-reported height and weight. Although reporting status and other biases were carefully accounted for through the age-period-survey adjustment, BMI corrections are less desirable than direct anthropometric measures of height and weight. Another limitation of APC analyses is the inability to account for Hispanic ethnicity, which may have affected BMI change within certain demographic groups.

The WLS provided several important strengths for the covariance structure analyses, including longitudinal data spanning 36 years, multiple measures of TABP subcomponents, and two distinct measures of impatience (i.e., impatience-irritability and economic discipline). In addition, by incorporating latent constructs for relative body mass at baseline, impatience-irritability and achievement striving, structural coefficients were maximized by accounting for errors in measurement. However, there were also a few important limitations to these analyses. First and perhaps foremost, selection into the 1993 sample may have been related to impatience (as is true with virtually any longitudinal study). That is, impatient persons may have been less likely than others to participate in the 1993 wave of the WLS (particularly the mail survey) or respond to all of the questions. The selection of impatient WLS subjects out of the sample could have attenuated the relationship between impatience-irritability and BMI. Second, while statistically significant, the factor loadings for the impatience items were relatively weak in all of the models, indicating that the impatience-irritability construct was weighted toward the irritability items. Although a large body of literature treats impatience and irritability as part of the same TABP subcomponent, it is nevertheless possible that they differ with regard to their effects on obesity. If irritability is less important than impatience in the etiology of obesity, then these analyses may have underestimated the effects of impatience-irritability on BMI. Third, the statistical power of the covariance structure analyses were compromised by the baseline measure of body mass, which was based on a random subsample of 3,027 out of 10,316 WLS subjects. If all WLS subjects are assigned RBM scores in the future, it would be worthwhile to replicate these analyses.

This investigation found several reasons to question the claims of mass preparation theory. Nevertheless, the development of this theory stands as one of the most important research contributions to date on the obesity epidemic. The clear assumptions and empirical implications of mass preparation theory facilitated a critical assessment—precisely what is needed in the current environment where non-falsifiable speculation abounds. Also, the notion that psychological characteristics may predispose certain persons to weight gain in the obesogenic environment in the U.S. continues to hold intuitive appeal, and was supported (although not in the way mass preparation theory would predict) by the effects of achievement striving on changes in body mass among women.

Future research should continue to investigate the interplay between individual psychology and the broader social environment as a potential explanation for the obesity epidemic. The psychological literature has shown that constructs such as self-efficacy (Wdowik et al. 2001) and implementation intentions (Armitage 2004) may be important in the etiology of obesity. Promising constructs from the psychological literature (including motivation) should be integrated into theoretical models of BMI change that incorporate constructs from other disciplines such as sociology, economics and the health sciences. This could help determine which psychological constructs are most germane to the study of obesity and also elucidate the pathways by which macro-level (e.g., mass preparation) and meso-level variables (e.g., community disadvantage) influence weight change in the U.S. today. The urgent need to develop formal, integrated theories of the obesity epidemic that are amenable to empirical examination will be explored further in the final chapter of this dissertation.

Table 5.1. Descriptive Statistics for Continuous Variables Used in Covariance Structure Models, Wisconsin Longitudinal Study (n = 1,121)

	Mean Score	Standard Deviation	Range	Skewness	Kurtosis
Exogenous Variables (1957)					
Duncan SEI	5.14	2.15	0.7-9.6	0.08	-0.64
Coder 1 (♂,33)†	5.98	1.92	1-11	-0.06	-0.60
Coder 2 (♂,26)	6.57	1.46	3-11	-0.04	-0.39
Coder 3 (♀,28)	6.98	1.53	2-11	-0.45	0.18
Coder 4 (♀,28)	6.15	1.73	2-11	0.32	-0.53
Coder 5 (♀,25)	6.00	1.83	1-11	-0.10	-0.38
Coder 6 (♂,30)	6.99	1.34	2-10	-0.46	0.57
College Plans‡					
Endogenous Variables (1993)					
Item 18u	0.68	1.13	0-7	2.68	9.45
Item 18v§	0.73	1.22	0-7	2.55	7.74
Item 20b	2.41	0.89	1-5	0.59	-0.25
Item 20c	2.82	1.04	1-5	0.30	-0.90
Item 19e	5.03	1.12	1-6	-1.41	2.04
Item 19s	4.98	0.99	1-6	-1.12	1.44
Item 20a	4.03	0.76	1-5	-0.65	0.65
Item 20d	3.89	0.75	1-5	-0.72	0.96
Years of College	2.33	3.01	0-16.5	1.21	0.94
Savings-to-Income Ratio	-0.24	0.87	-1.4-4.4	0.75	0.52
BMI 1993	26.75	4.72	14-55	1.23	3.45

† Gender and age of coder in parentheses

‡ Dichotomous variable

§ Log transformations of Items 18u and 18v reduced skew and kurtosis, but did not substantially alter LISREL results. The original metrics were retained to facilitate interpretation.

Table 5.2. Summary Statistics Used to Compare Linear Covariance Structure Models Linking Impatience and Achievement Motivation to BMI in the Wisconsin Longitudinal Study

Model	χ^2	*df*	χ^2/df	$\Delta\chi^2/df$	BIC	Δ BIC
Males (n = 492)						
1. Saturated Model	0.00	0	•	•	0.00	•
2. Theoretical Model	280.96	142	1.98	1.98	-599.22	-599.22
3. Model 2 + $\Theta\delta_{1,6}$; $\Theta\delta_{5,6}$; $\Theta\varepsilon_{3,4}$; $\Theta\varepsilon_{3,7}$; $\Theta\varepsilon_{7,8}$; $\Psi_{1,2}$†	183.93	136	1.35	-16.17	-659.06	-59.84
Females (n = 629)						
4. Saturated Model	0.00	0	•	•	0.00	•
5. Theoretical Model	318.80	142	2.25	2.25	-596.27	-596.27
6. Model 5 + $\Gamma_{3,2}$; $\Theta\delta_{2,3}$; $\Theta\delta_{2,6}$; $\Theta\varepsilon_{3,4}$; $\Theta\varepsilon_{3,7}$; $\Theta\varepsilon_{7,8}$; $\Theta\varepsilon_{8,10}$; $\Psi_{1,2}$†	146.12	134	1.09	-21.59	-717.39	-121.13
Two-Group Models (n = 1,121)						
7. Baseline Model (Model 3 for Males and Model 6 for Females)	330.05	270	1.22	1.22	-1565.88	-1565.88
8. Model 7 + Equality Constraints Across Groups (EQ) for $\Lambda y_{2,1}$; $\Lambda y_{3,1}$; $\Lambda y_{4,1}$	341.88	273	1.25	3.94	-1575.12	-9.24
9. Model 8 + EQ $B_{5,1}$	344.34	274	1.26	2.46	-1579.68	-4.56
10. Model 8 + EQ $B_{5,3}$	345.04	274	1.26	3.16	-1578.98	-3.86
11. Model 8 + EQ $B_{3,1}$	343.71	274	1.25	1.83	-1580.31	-5.19
12. Model 8 + EQ $B_{5,1}$; $B_{5,3}$; $B_{3,1}$†	349.13	276	1.26	2.42	-1588.94	-13.82

• Not calculable

† Variable names given in parentheses: $B_{3,1(\text{economic discipline.impatience-irritability})}$; $B_{5,1(\text{BMI.impatience-irritability})}$; $B_{5,3(\text{BMI.economic discipline})}$; $\Gamma_{3,2(\text{economic discipline.occupational aspirations})}$; $\Theta\delta_{1,6(\text{coder1.coder6})}$; $\Theta\delta_{2,3(\text{coder2.coder3})}$; $\Theta\delta_{2,6(\text{coder2.coder6})}$; $\Theta\delta_{5,6(\text{coder5.coder6})}$; $\Theta\varepsilon_{3,4(\text{item20b.item20c})}$; $\Theta\varepsilon_{3,7(\text{item20b.item20a})}$; $\Theta\varepsilon_{7,8(\text{item20a.item20d})}$; $\Theta\varepsilon_{8,10(\text{item20d.educational attainment})}$; $\Lambda y_{2,1(\text{item18v.impatience-irritability})}$; $\Lambda y_{3,1(\text{item20b. impatience-irritability})}$; $\Lambda y_{4,1(\text{item20c.impatience-irritability})}$; $\Psi_{1,2(\text{irritability-impatience.achievement striving})}$

Figure 5.1. Theoretical Path Diagram of a Covariance Structure Model Linking Measures of Impatience and Achievement Striving to BMI

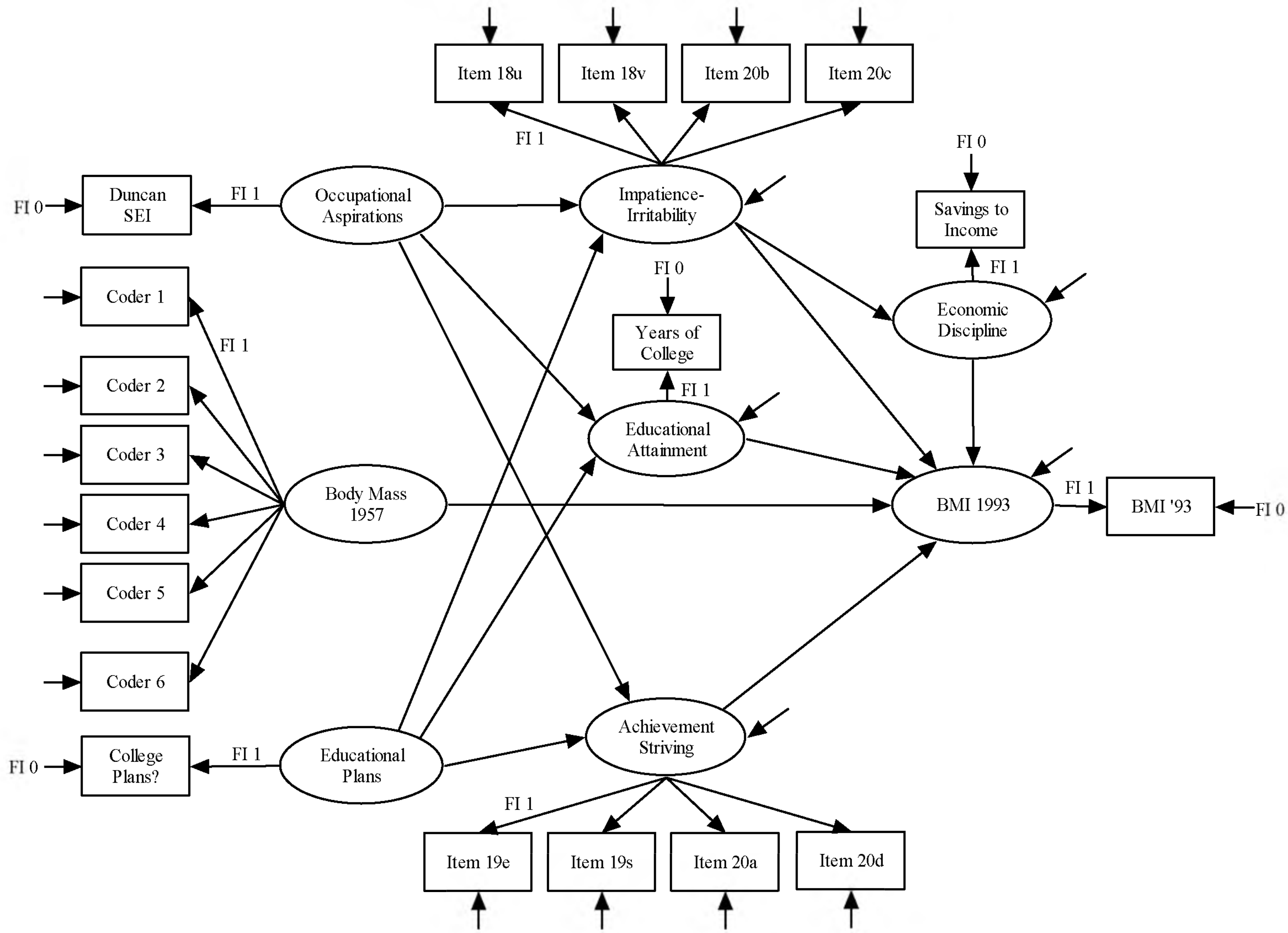


Figure 5.2. Period Effects in APC Models of BMI for Selected Demographic Groups Identified by Cutler et al. (2003), NHIS 1976-2002

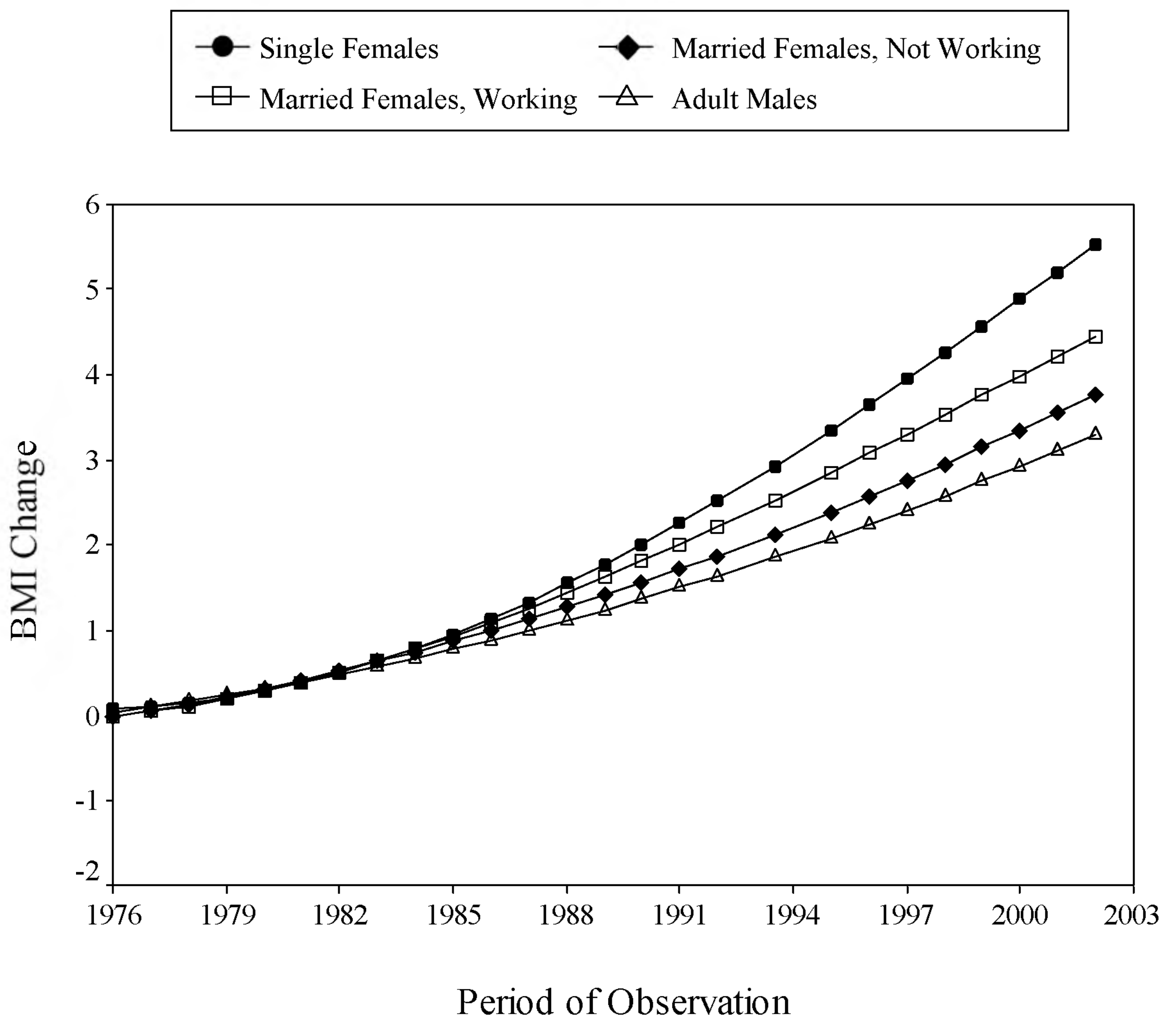
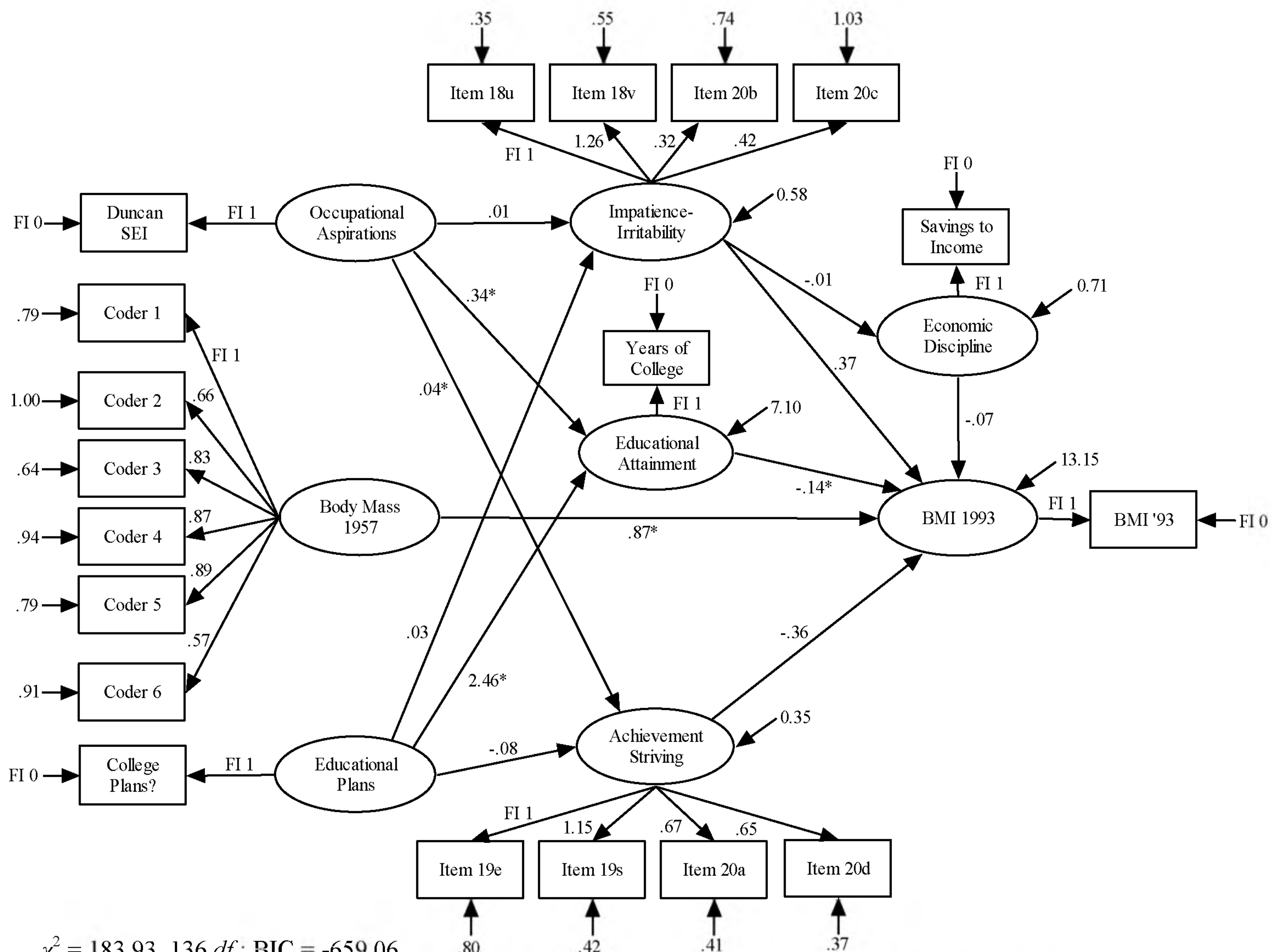


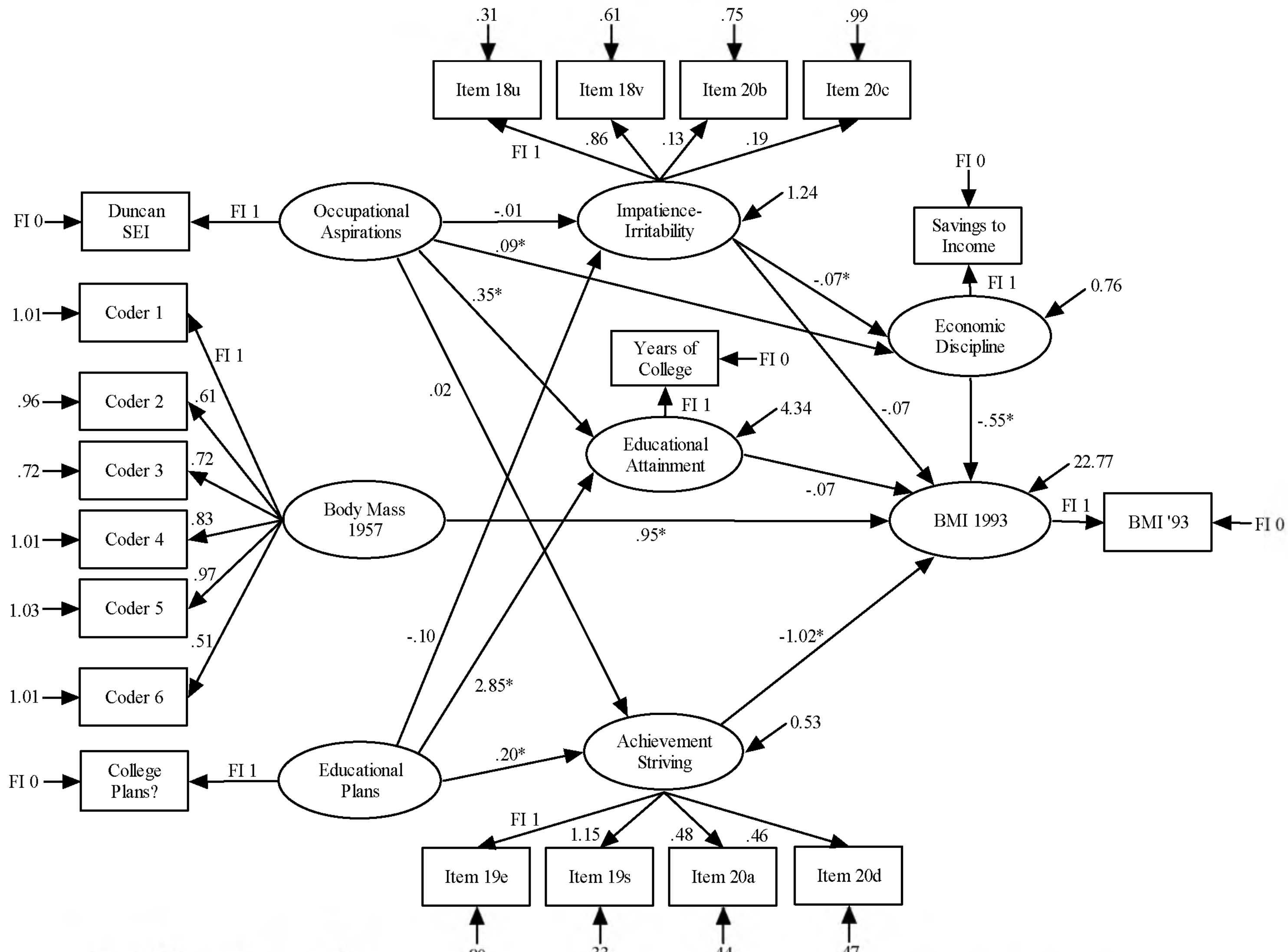
Figure 5.3. Path Diagram and Unstandardized Coefficients in the Linear Model (Model 3) Linking Impatience and Achievement Striving to BMI, Male WLS Subjects (n = 492), 1957 and 1993



$\chi^2 = 183.93$, 136 df; BIC = -659.06

* $p \leq 0.05$ for structural coefficients ($p \leq 0.05$ for all disturbances, factor loadings and error variances)

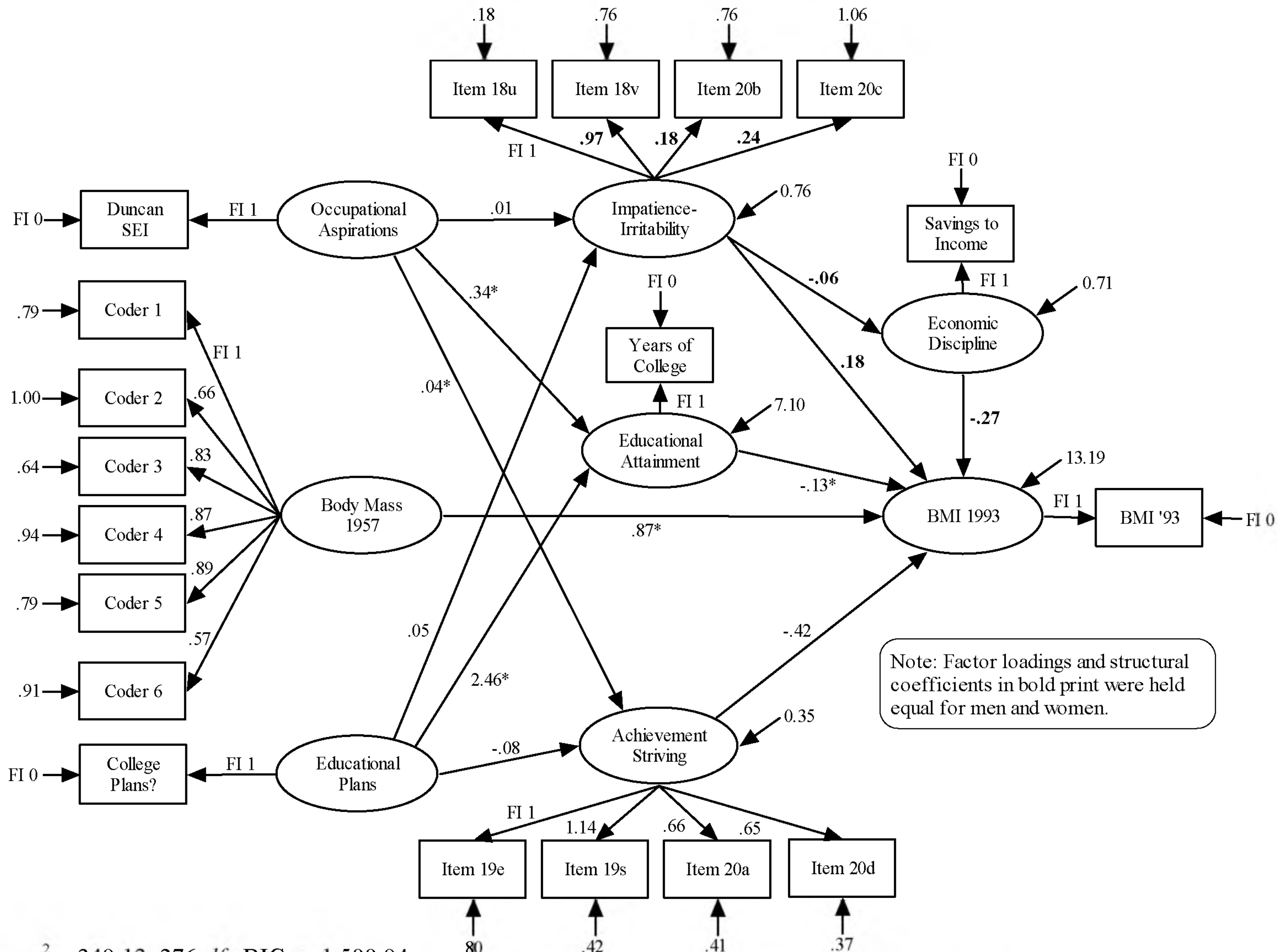
Figure 5.4. Path Diagram and Unstandardized Coefficients in the Linear Model (Model 6) Linking Impatience and Achievement Striving to BMI, Female WLS Subjects (n = 629), 1957 and 1993



χ^2 = 146.12, 134 df; BIC = -717.39

* $p \leq 0.05$ for structural coefficients ($p \leq 0.05$ for all disturbances, factor loadings and error variances)

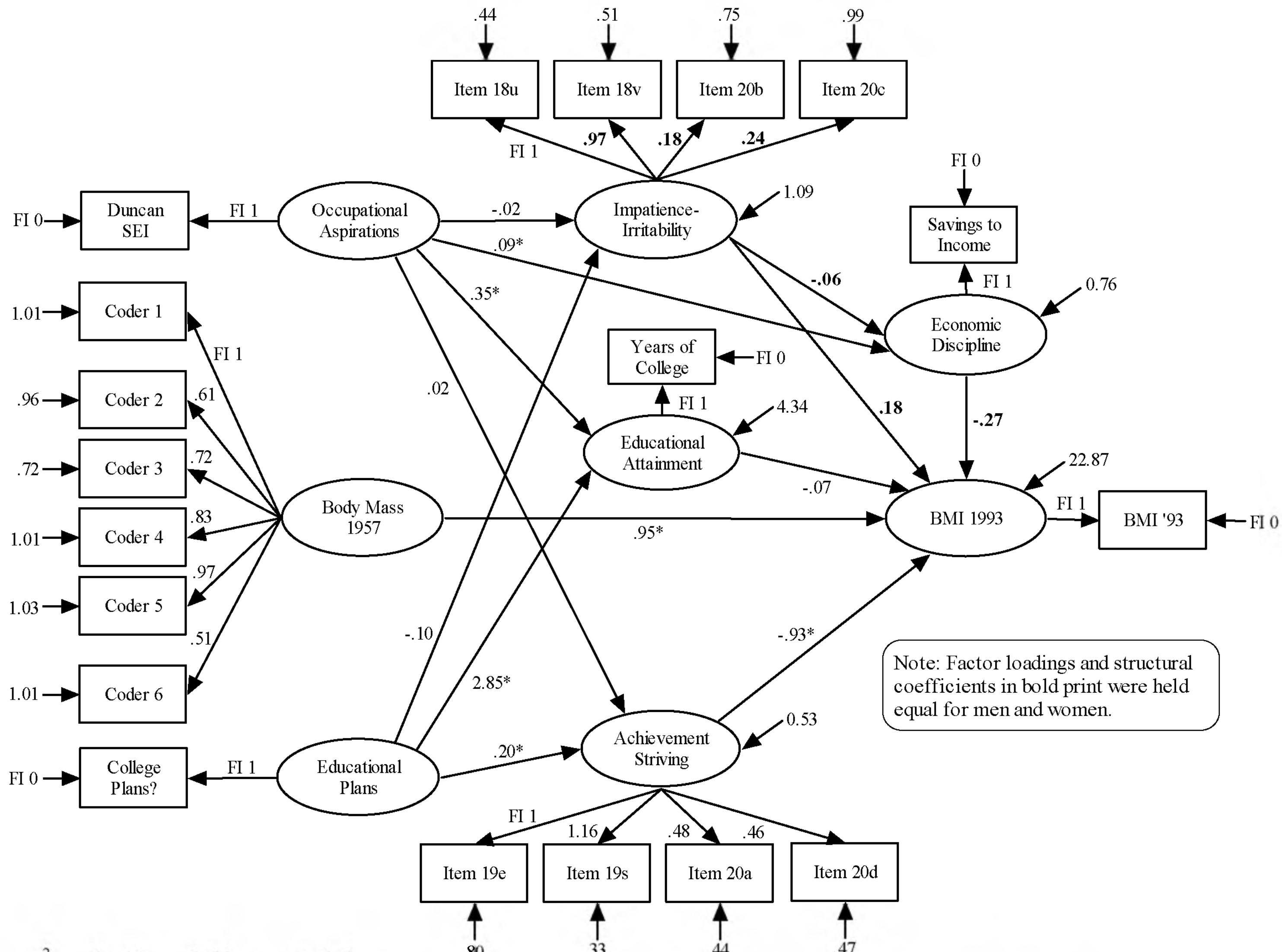
Figure 5.5. Path Diagram and Unstandardized Coefficients for Males in a Two-Group Model (Model 12) Imposing Equality Constraints across Genders (n = 1,121), 1957 and 1993



χ^2 = 349.13, 276 df; BIC = -1,588.94

* $p \leq 0.05$ for structural coefficients ($p \leq 0.05$ for all disturbances, factor loadings and error variances)

Figure 5.6. Path Diagram and Unstandardized Coefficients for Females in a Two-Group Model (Model 12) Imposing Equality Constraints across Genders (n = 1,121), 1957 and 1993



χ^2 = 349.13, 276 df; BIC = -1,588.94
* $p \leq 0.05$ for structural coefficients ($p \leq 0.05$ for all disturbances, factor loadings and error variances)

APPENDIX E

PREDICTED VERSUS OBSERVED PARAMETER ESTIMATES FOR AGE, PERIOD AND COHORT EFFECTS IN APC MODELS FROM CHAPTER 5

Appendix E provides SPSS regression output that was used to determine the optimal functional form of age, period and cohort effects in APC models of BMI. For the sake of brevity, only the best fitting models are reported here. Additionally, Appendix E provides supplementary figures that compare parameter estimates predicted by the optimal functional form to the actual parameter estimates, which permits the visual assessment of residuals.

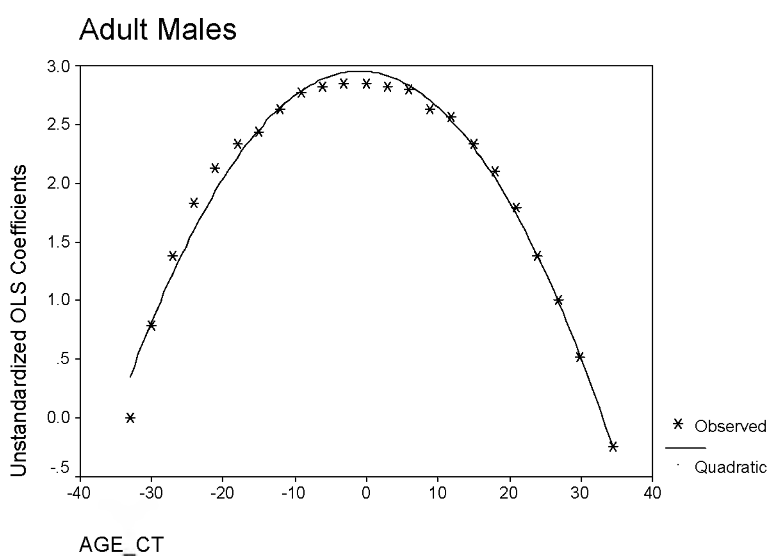
Abbreviations:

The SPSS regression output contains some abbreviations. These are defined below.

1. BMI_R2 = parameter estimates in APC models of BMI
2. AGE_CT = Age (centered)
3. AGE_CT**2 = Age (centered)^2
4. AGE_CT**3 = Age (centered)^3
5. PER_CENT = Period (centered)
6. PER_CENT**2 = Period (centered)^2
7. PER_CENT**3 = Period (centered)^3
8. COH_CENT = Cohort (centered)
9. COH_CENT**2 = Cohort (centered)^2
10. COH_CENT**3 = Cohort (centered)^3

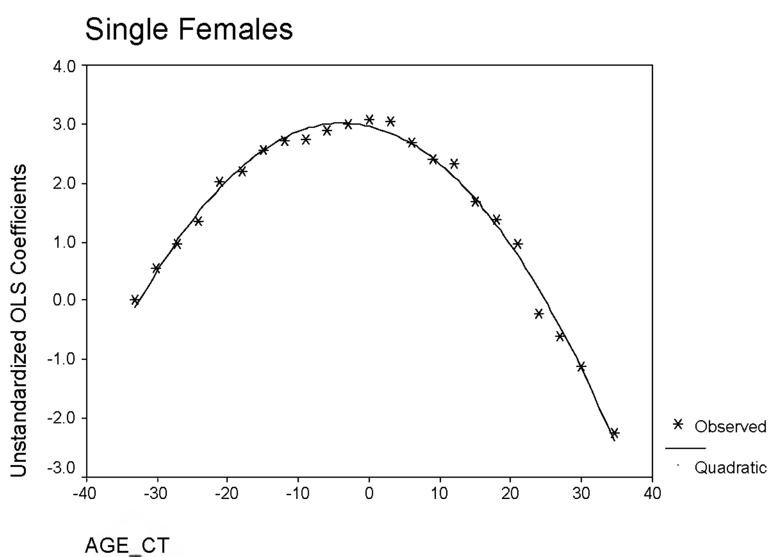
Appendix E, Part 1. The Functional Form of Age Effects in an APC Model of BMI for Adult Males, NHIS 1976-2002

```
Dependent variable.. BMI_R2              Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .99266
R Square             .98537
Adjusted R Square    .98390
Standard Error       .12102

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      2        19.724733        9.8623663
Residuals      20          .292926         .0146463

F =      673.36880       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                   B          SE B       Beta          T  Sig T

AGE_CT              -.005040      .001261   -.108151     -3.997  .0007
AGE_CT**2           -.002530   6.9529E-05   -.984415    -36.385  .0000
(Constant)          2.948078      .037593                78.422  .0000
```



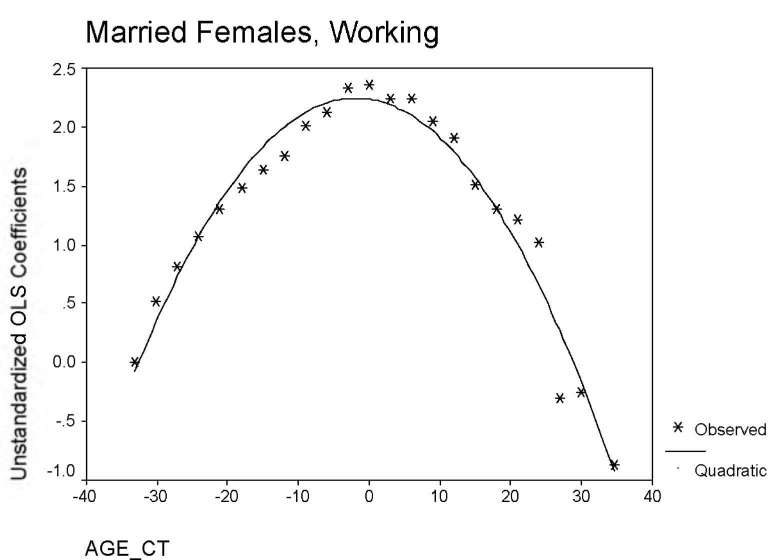
Appendix E, Part 2. The Functional Form of Age Effects in an APC Model of BMI for Single Females, NHIS 1976-2002

```
Dependent variable.. BMI_R2             Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .99506
R Square             .99015
Adjusted R Square    .98916
Standard Error       .15547

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      2        48.574132        24.287066
Residuals      20          .483440          .024172

F =    1004.76080       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                   B         SE B       Beta         T  Sig T

AGE_CT             -.027853      .001620   -.381786   -17.196  .0000
AGE_CT**2          -.003664  8.9321E-05   -.910698   -41.018  .0000
(Constant)         2.961533      .048294               61.323  .0000
```



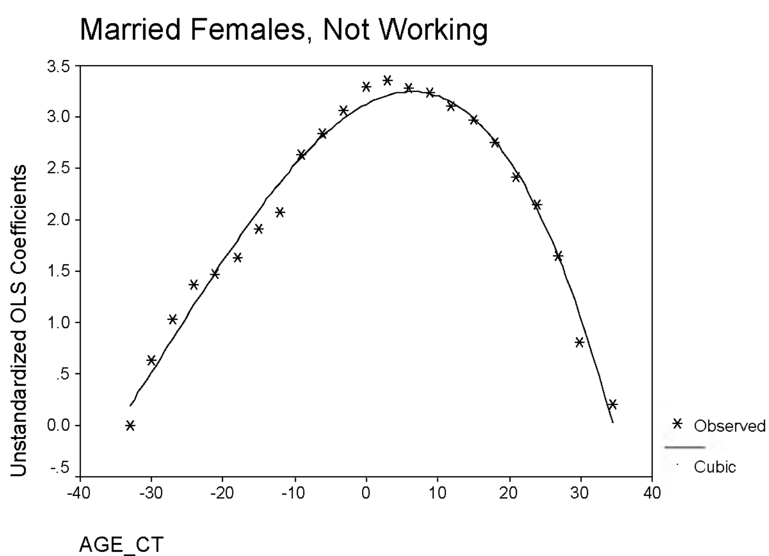
Appendix E, Part 3. The Functional Form of Age Effects in an APC Model of BMI for Married Females in the Labor Force, NHIS 1976-2002

```
Dependent variable.. BMI_R2            Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .97956
R Square             .95954
Adjusted R Square    .95550
Standard Error       .19536

            Analysis of Variance:

               DF    Sum of Squares      Mean Square

Regression      2        18.104069        9.0520343
Residuals      20          .763304         .0381652

F =     237.18020       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                    B         SE B        Beta          T  Sig T

AGE_CT               -.008929      .002035    -.197354     -4.387  .0003
AGE_CT**2            -.002383      .000112    -.955225    -21.234  .0000
(Constant)           2.236516      .060684                 36.855  .0000
```



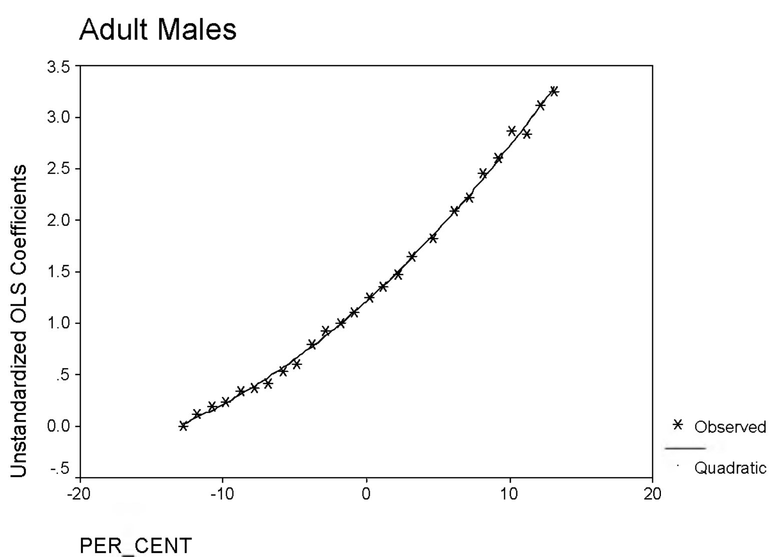
Appendix E, Part 4. The Functional Form of Age Effects in an APC Model of BMI for Married Females Not in the Labor Force, NHIS 1976-2002

```
Dependent variable.. BMI_R2           Method.. CUBIC

Listwise Deletion of Missing Data

Multiple R           .99100
R Square             .98207
Adjusted R Square    .97924
Standard Error       .15052

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      3        23.583058        7.8610193
Residuals      19          .430457         .0226557

F =     346.97827       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                      B         SE B       Beta         T  Sig T

AGE_CT                  .036625      .003839    .717559     9.541  .0000
AGE_CT**2              -.002594  8.6724E-05   -.921574   -29.910  .0000
AGE_CT**3   -3.07130347E-05  4.8061E-06   -.481137    -6.390  .0000
(Constant)             3.125602      .046793               66.797  .0000
```



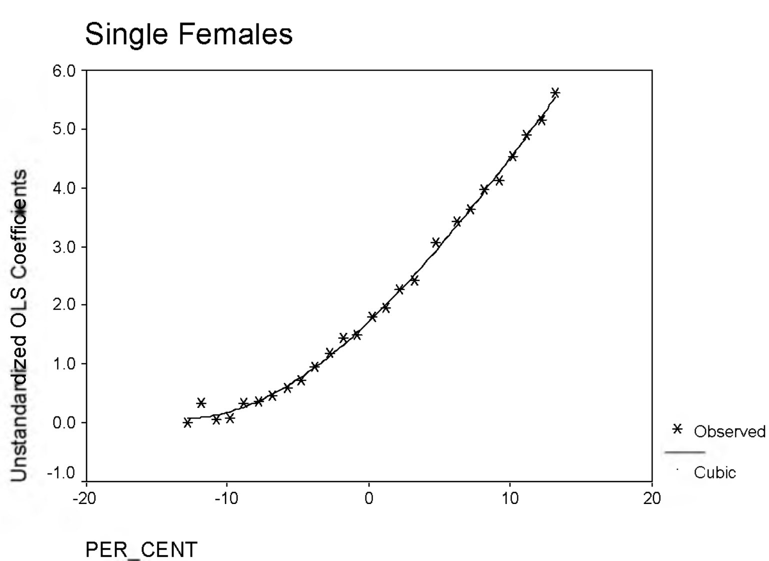
Appendix E, Part 5. The Functional Form of Period Effects in an APC Model of BMI for Adult Males, NHIS 1976-2002

```
Dependent variable.. BMI_R2              Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .99906
R Square             .99813
Adjusted R Square    .99796
Standard Error       .04633

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      2        26.294279        13.147139
Residuals      23          .049371          .002147

F =    6124.72888       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                    B          SE B       Beta         T  Sig T

PER_CENT              .125175      .001155    .980537   108.387  .0000
PER_CENT**2           .002527      .000166    .137339    15.181  .0000
(Constant)           1.212335      .013773               88.025  .0000
```



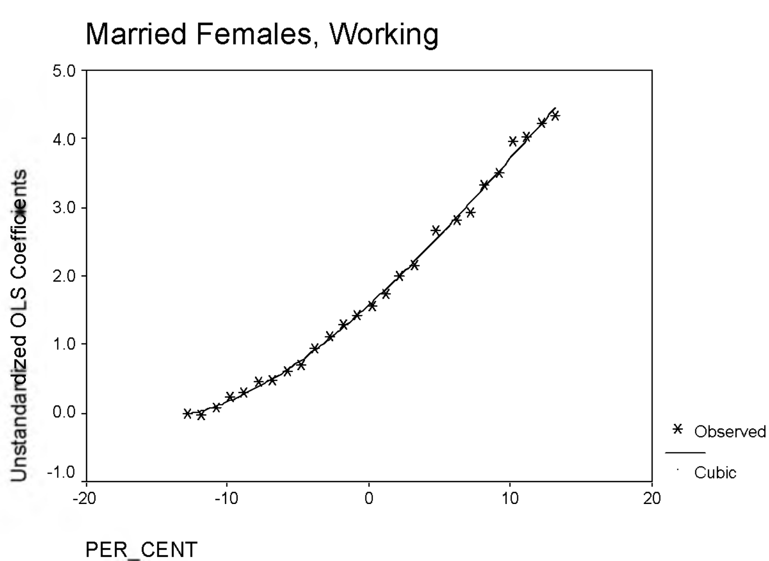
Appendix E, Part 6. The Functional Form of Period Effects in an APC Model of BMI for Single Females, NHIS 1976-2002

```
Dependent variable.. BMI_R2             Method.. CUBIC

Listwise Deletion of Missing Data

Multiple R           .99885
R Square             .99770
Adjusted R Square    .99739
Standard Error       .09148

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      3        79.845092        26.615031
Residuals      22          .184091          .008368

F =    3180.66041       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                     B         SE B       Beta         T  Sig T

PER_CENT               .230082      .005851   1.034052    39.326  .0000
PER_CENT**2            .006196      .000329    .193177    18.831  .0000
PER_CENT**3          -.000135   4.8912E-05   -.072623    -2.759  .0114
(Constant)            1.727784      .027196               63.530  .0000
```



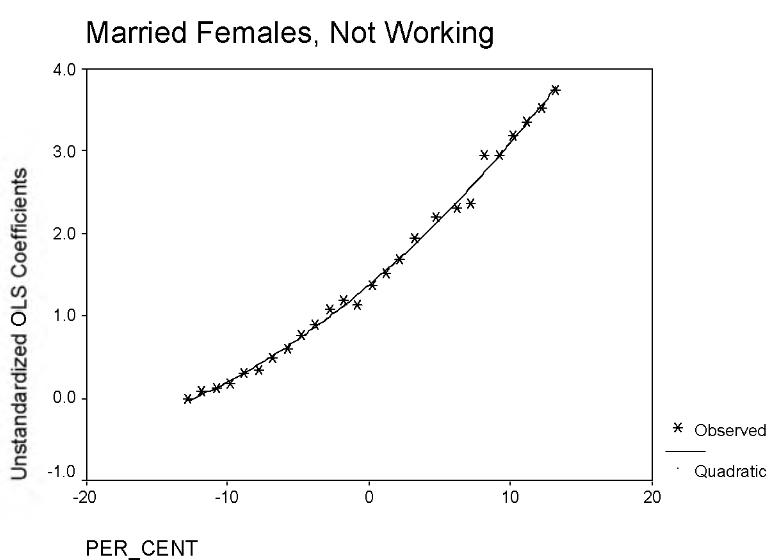
Appendix E, Part 7. The Functional Form of Period Effects in an APC Model of BMI for Married Females in the Labor Force, NHIS 1976-2002

```
Dependent variable.. BMI_R2           Method.. CUBIC

Listwise Deletion of Missing Data

Multiple R           .99875
R Square             .99751
Adjusted R Square    .99717
Standard Error       .07704

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      3        52.317344        17.439115
Residuals      22          .130576          .005935

F =    2938.20880       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                    B         SE B       Beta          T  Sig T

PER_CENT              .188111      .004927   1.044322     38.177  .0000
PER_CENT**2           .003614      .000277    .139197     13.043  .0000
PER_CENT**3          -.000106  4.1194E-05   -.070206     -2.564  .0177
(Constant)           1.579961      .022905                68.980  .0000
```



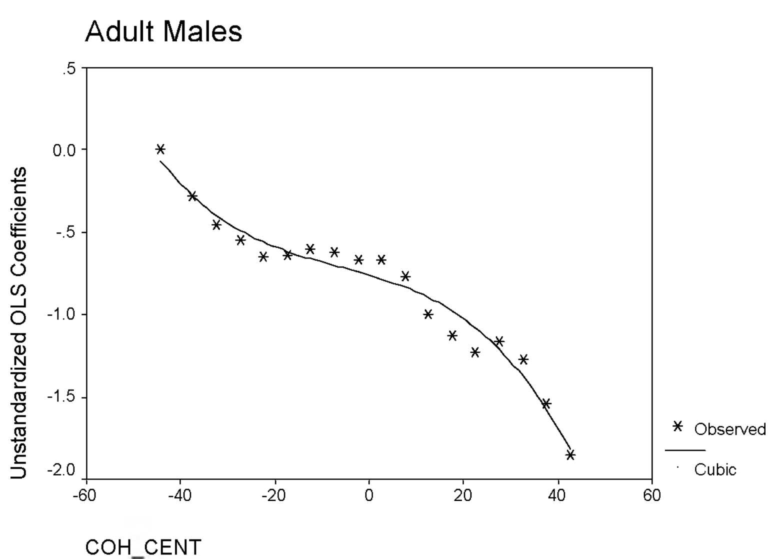
Appendix E, Part 8. The Functional Form of Period Effects in an APC Model of BMI for Married Females Not in the Labor Force, NHIS 1976-2002

```
Dependent variable.. BMI_R2           Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .99795
R Square             .99590
Adjusted R Square    .99555
Standard Error       .07948

            Analysis of Variance:

               DF    Sum of Squares      Mean Square

Regression      2        35.331366        17.665683
Residuals      23          .145277          .006316

F =     2796.79090       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                    B         SE B        Beta         T  Sig T

PER_CENT              .145335      .001981     .981031    73.361  .0000
PER_CENT**2           .002760      .000286     .129267     9.667  .0000
(Constant)           1.377417      .023625                58.302  .0000
```



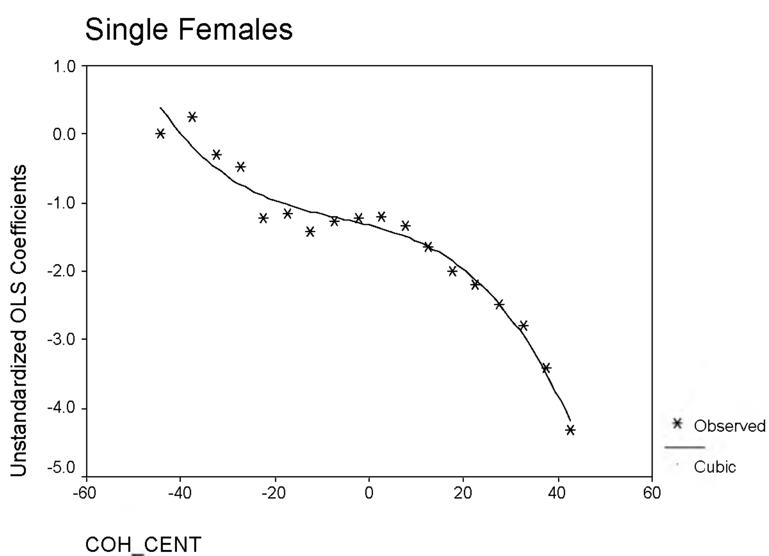
Appendix E, Part 9. The Functional Form of Cohort Effects in an APC Model of BMI for Adult Males, NHIS 1976-2002

```
Dependent variable.. BMI_R2              Method.. CUBIC

Listwise Deletion of Missing Data

Multiple R           .98307
R Square             .96643
Adjusted R Square    .95923
Standard Error       .09234

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      3        3.4360586        1.1453529
Residuals      14         .1193615         .0085258

F =     134.33930       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                    B         SE B       Beta         T  Sig T

COH_CENT            -.008362      .002052   -.491423    -4.075  .0011
COH_CENT**2         -.000117  3.5378E-05   -.163017    -3.318  .0051
COH_CENT**3 -6.34438510E-06  1.5126E-06   -.506397    -4.194  .0009
(Constant)          -.760278      .032468               -23.416  .0000
```



Appendix E, Part 10. The Functional Form of Cohort Effects in an APC Model of BMI for Single Females, NHIS 1976-2002

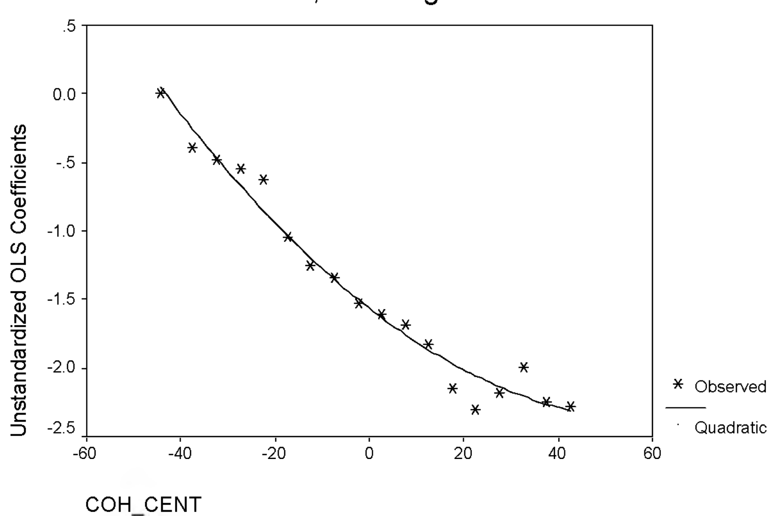
```
Dependent variable.. BMI_R2            Method.. CUBIC

Listwise Deletion of Missing Data

Multiple R           .98266
R Square             .96562
Adjusted R Square    .95826
Standard Error       .23812

            Analysis of Variance:

               DF    Sum of Squares      Mean Square

Regression      3        22.298731        7.4329103
Residuals      14          .793812         .0567009

F =     131.08984       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                     B          SE B       Beta          T  Sig T

COH_CENT             -.017574       .005292   -.405241     -3.321  .0050
COH_CENT**2          -.000357   9.1235E-05   -.194815     -3.918  .0015
COH_CENT**3 -1.87492608E-05   3.9009E-06   -.587213     -4.806  .0003
(Constant)          -1.331468       .083729                -15.902  .0000
```



Appendix E, Part 11. The Functional Form of Cohort Effects in an APC Model of BMI for Married Females in the Labor Force, NHIS 1976-2002

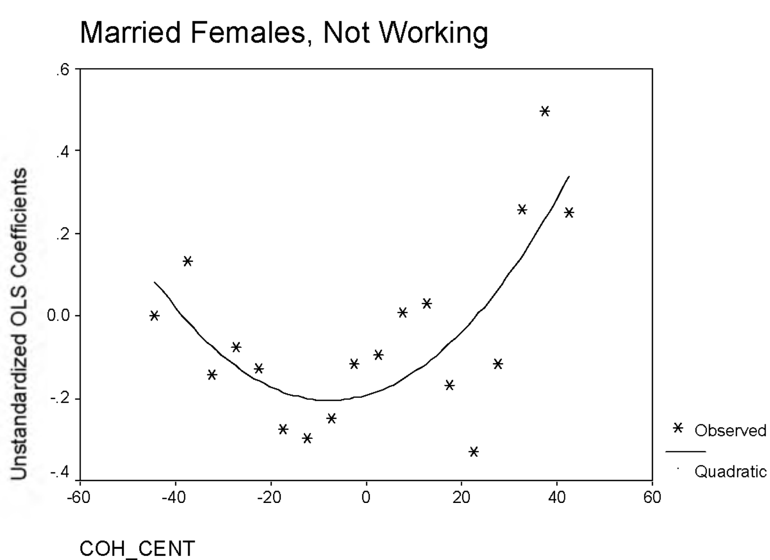
```
Dependent variable.. BMI_R2           Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .98737
R Square             .97490
Adjusted R Square    .97155
Standard Error       .12566

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      2        9.1982299        4.5991149
Residuals      15         .2368560         .0157904

F =     291.26021       Signif F =  .0000

-------------------- Variables in the Equation --------------------

Variable                  B         SE B        Beta          T  Sig T

COH_CENT          -.026760      .001134   -.965353    -23.591  .0000
COH_CENT**2        .000218  4.7995E-05    .185614      4.536  .0004
(Constant)       -1.564673      .044148               -35.441  .0000
```

Married Females, Working



Appendix E, Part 12. The Functional Form of Cohort Effects in an APC Model of BMI for Married Females Not in the Labor Force, NHIS 1976-2002

```
Dependent variable.. BMI_R2              Method.. QUADRATIC

Listwise Deletion of Missing Data

Multiple R           .74602
R Square             .55654
Adjusted R Square    .49742
Standard Error       .15373

            Analysis of Variance:

               DF   Sum of Squares      Mean Square

Regression      2        .44492076        .22246038
Residuals      15        .35451592        .02363439

F =       9.41257       Signif F =  .0022

-------------------- Variables in the Equation --------------------

Variable                    B         SE B       Beta         T  Sig T

COH_CENT              .003331      .001388    .412771     2.400  .0298
COH_CENT**2           .000216  5.8718E-05    .631331     3.671  .0023
(Constant)           -.192395      .054012               -3.562  .0028
```



APPENDIX F

CORRELATION MATRICES AND LISREL OUTPUT FOR STRUCTURAL EQUATION MODELS FROM CHAPTER 5

Appendix F provides correlation matrices, standard deviations and LISREL output for the best-fitting single-group models from Chapter 5 (i.e., Model 3 for males and Model 6 for females).

Appendix F, Part 1. Correlation Matrix and LISREL Output for the Linear Model (Model 3) Linking Impatience and Achievement Motivation to BMI, Male WLS Subjects (n = 492)

Correlation Matrix

	ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
ITEM18U	1.000					
ITEM18V	0.625	1.000				
ITEM20B	0.213	0.226	1.000			
ITEM20C	0.209	0.261	0.294	1.000		
ITEM19E	-0.107	-0.050	-0.103	-0.038	1.000	
ITEM19S	-0.153	-0.141	-0.055	-0.073	0.409	1.000
ITEM20A	-0.120	-0.123	-0.242	-0.056	0.324	0.363
ITEM20D	-0.116	-0.040	-0.127	-0.014	0.267	0.410
SAVER	-0.016	-0.023	0.070	0.106	0.066	0.043
EDUC_93	0.044	-0.019	-0.037	0.018	0.120	0.045
BMI_93	0.097	0.047	0.094	0.076	-0.058	-0.086
Coder1	0.040	0.045	0.036	0.075	-0.029	-0.052
Coder2	-0.017	0.008	-0.042	0.011	-0.027	0.002
Coder3	-0.002	-0.012	-0.058	0.015	-0.023	-0.024
Coder4	0.041	0.058	-0.012	0.036	0.043	-0.034
Coder5	0.019	0.026	-0.022	0.057	-0.045	-0.076
Coder6	0.054	0.025	0.008	-0.004	-0.043	-0.063
Duncan	0.040	0.024	-0.010	0.020	0.119	0.066
Educplan	0.048	0.000	-0.014	0.097	0.058	0.032

	ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93	Coder1
ITEM20A	1.000					
ITEM20D	0.439	1.000				
SAVER	0.027	-0.023	1.000			
EDUC_93	0.053	0.120	0.066	1.000		
BMI_93	-0.051	-0.006	-0.028	-0.099	1.000	
Coder1	-0.007	0.019	-0.004	0.085	0.307	1.000
Coder2	0.029	0.007	-0.022	-0.023	0.276	0.615
Coder3	0.056	0.040	-0.012	0.061	0.257	0.772
Coder4	0.033	0.047	-0.004	0.100	0.312	0.720
Coder5	0.014	0.017	0.007	0.009	0.360	0.757
Coder6	-0.055	-0.006	-0.034	0.005	0.236	0.527
Duncan	0.102	0.089	0.073	0.512	-0.113	0.020
Educplan	-0.006	0.016	0.084	0.544	-0.015	0.027

	Coder2	Coder3	Coder4	Coder5	Coder6	Duncan
Coder2	1.000					
Coder3	0.663	1.000				
Coder4	0.616	0.702	1.000			
Coder5	0.609	0.724	0.715	1.000		
Coder6	0.551	0.593	0.582	0.522	1.000	
Duncan	0.029	0.070	0.051	0.023	0.051	1.000
Educplan	0.002	0.056	0.036	-0.019	0.056	0.596

	Educplan
Educplan	1.000

Standard Deviations (in order of variables)

ITEM18U ITEM18V ITEM20B ITEM20C ITEM19E ITEM19S ITEM20A ITEM20D SAVER EDUC_92 BMI_92 Coder1 Coder2 Coder3 Coder4 Coder5 Coder6 Duncan Educplan

0.962949739 1.215159055 0.897516706 1.061804053 1.076486049 0.942036701 0.758863532 0.722834828 0.843458284 3.305683804 3.942388922 1.864877064 1.470128215 1.572750495 1.72202694 1.705518466 1.342310777 2.805324874 0.498681885

Number of Iterations = 37

LISREL Estimates (Maximum Likelihood)

LAMBDA-Y

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
ITEM18U	1.000	- -	- -	- -	- -
ITEM18V	1.264 (0.154) 8.220	- -	- -	- -	- -
ITEM20B	0.324 (0.062) 5.260	- -	- -	- -	- -
ITEM20C	0.418 (0.075) 5.603	- -	- -	- -	- -
ITEM19E	- -	1.000	- -	- -	- -
ITEM19S	- -	1.146 (0.139) 8.266	- -	- -	- -
ITEM20A	- -	0.666 (0.087) 7.643	- -	- -	- -
ITEM20D	- -	0.650 (0.085) 7.656	- -	- -	- -
SAVER	- -	- -	1.000	- -	- -
EDUC_93	- -	- -	- -	1.000	- -
BMI_93	- -	- -	- -	- -	1.000

LAMBDA-X

	RBM_57	OCC_ASP	ED_ASP
Coder1	1.000	- -	- -
Coder2	0.659 (0.033) 19.707	- -	- -
Coder3	0.826 (0.032) 25.830	- -	- -
Coder4	0.868 (0.036) 23.978	- -	- -
Coder5	0.888 (0.035) 25.277	- -	- -
Coder6	0.574 (0.035) 16.365	- -	- -
Duncan	- -	1.000	- -
Educplan	- -	- -	1.000

BETA

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	- -	- -	- -	- -	- -
ACH_STR	- -	- -	- -	- -	- -
SAVER	-0.013 (0.057) -0.223	- -	- -	- -	- -
EDUC	- -	- -	- -	- -	- -
BMI_93	0.372 (0.259) 1.439	-0.359 (0.348) -1.033	-0.065 (0.195) -0.334	-0.136 (0.050) -2.716	- -

GAMMA

	RBM_57	OCC_ASP	ED_ASP
IRR_IMP	- -	0.007 (0.017) 0.418	0.030 (0.097) 0.306
ACH_STR	- -	0.039 (0.015) 2.649	-0.079 (0.081) -0.982
SAVER	- -	- -	- -
EDUC	- -	0.342 (0.053) 6.412	2.459 (0.300) 8.187
BMI_93	0.870 (0.106) 8.235	- -	- -

PHI

	RBM_57	OCC_ASP	ED_ASP
RBM_57	2.688 (0.222) 12.128		
OCC_ASP	0.209 (0.214) 0.973	7.870 (0.502) 15.668	
ED_ASP	0.026 (0.038) 0.696	0.834 (0.074) 11.351	0.249 (0.016) 15.668

PSI

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	0.577 (0.086) 6.728				
ACH_STR	-0.111 (0.030) -3.655	0.349 (0.065) 5.349			
SAVER	- -	- -	0.711 (0.045) 15.668		
EDUC	- -	- -	- -	7.097 (0.453) 15.668	

BMI_93	- -	- -	- -	- -	13.153 (0.850) 15.466

Squared Multiple Correlations for Structural Equations

IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
0.002	0.023	0.000	0.351	0.152

Squared Multiple Correlations for Reduced Form

IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
0.002	0.023	0.000	0.351	0.134

THETA-EPS

	ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
ITEM18U	0.349 (0.070) 5.009					
ITEM18V	- -	0.553 (0.111) 4.963				
ITEM20B	- -	- -	0.741 (0.048) 15.329			
ITEM20C	- -	- -	0.197 (0.041) 4.823	1.027 (0.067) 15.219		
ITEM19E	- -	- -	- -	- -	0.801 (0.065) 12.340	
ITEM19S	- -	- -	- -	- -	- -	0.418 (0.057) 7.307
ITEM20A	- -	- -	-0.108 (0.025) -4.273	- -	- -	- -
ITEM20D	- -	- -	- -	- -	- -	- -
SAVER	- -	- -	- -	- -	- -	- -
EDUC_93	- -	- -	- -	- -	- -	- -
BMI_93	- -	- -	- -	- -	- -	- -

THETA-EPS

	ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93
ITEM20A	0.409 (0.033) 12.298				
ITEM20D	0.076 (0.024) 3.131	0.372 (0.031) 12.102			
SAVER	- -	- -	- -		
EDUC_93	- -	- -	- -	- -	
BMI_93	- -	- -	- -	- -	- -

Squared Multiple Correlations for Y - Variables

ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
0.623	0.626	0.076	0.090	0.309	0.529

Squared Multiple Correlations for Y - Variables

ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93
0.280	0.289	1.000	1.000	1.000

THETA-DELTA

	Coder1	Coder2	Coder3	Coder4	Coder5	Coder6
Coder1	0.789 (0.070) 11.229					
Coder2	- -	0.995 (0.069) 14.475				
Coder3	- -	- -	0.640 (0.051) 12.527			
Coder4	- -	- -	- -	0.940 (0.070) 13.380		
Coder5	- -	- -	- -	- -	0.787 (0.065) 12.160	
Coder6	-0.220 (0.052) -4.228	- -	- -	- -	-0.172 (0.050) -3.439	0.912 (0.067) 13.526

Duncan	- -	- -	- -	- -	- -	- -
Educplan	- -	- -	- -	- -	- -	- -

THETA-DELTA

	Duncan	Educplan
Duncan	- -	
Educplan	- -	- -

Squared Multiple Correlations for X - Variables

Coder1	Coder2	Coder3	Coder4	Coder5	Coder6
0.773	0.539	0.741	0.683	0.730	0.493

Squared Multiple Correlations for X - Variables

Duncan	Educplan
1.000	1.000

Completely Standardized Solution

LAMBDA-Y

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
ITEM18U	0.789	- -	- -	- -	- -
ITEM18V	0.791	- -	- -	- -	- -
ITEM20B	0.275	- -	- -	- -	- -
ITEM20C	0.299	- -	- -	- -	- -
ITEM19E	- -	0.555	- -	- -	- -
ITEM19S	- -	0.728	- -	- -	- -
ITEM20A	- -	0.529	- -	- -	- -
ITEM20D	- -	0.537	- -	- -	- -
SAVER	- -	- -	1.000	- -	- -
EDUC_93	- -	- -	- -	1.000	- -
BMI_93	- -	- -	- -	- -	1.000

LAMBDA-X

	RBM_57	OCC_ASP	ED_ASP
Coder1	0.879	- -	- -
Coder2	0.734	- -	- -
Coder3	0.861	- -	- -
Coder4	0.827	- -	- -
Coder5	0.854	- -	- -
Coder6	0.702	- -	- -
Duncan	- -	1.000	- -
Educplan	- -	- -	1.000

BETA

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	- -	- -	- -	- -	- -
ACH_STR	- -	- -	- -	- -	- -
SAVER	-0.011	- -	- -	- -	- -
EDUC	- -	- -	- -	- -	- -
BMI_93	0.072	-0.055	-0.014	-0.114	- -

GAMMA

	RBM_57	OCC_ASP	ED_ASP
IRR_IMP	- -	0.027	0.020
ACH_STR	- -	0.182	-0.066
SAVER	- -	- -	- -
EDUC	- -	0.291	0.371
BMI_93	0.362	- -	- -

PSI

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	0.998				
ACH_STR	-0.245	0.977			
SAVER	- -	- -	1.000		
EDUC	- -	- -	- -	0.649	
BMI_93	- -	- -	- -	- -	0.848

THETA-EPS

	ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
ITEM18U	0.377					
ITEM18V	- -	0.374				
ITEM20B	- -	- -	0.924			
ITEM20C	- -	- -	0.207	0.910		
ITEM19E	- -	- -	- -	- -	0.691	
ITEM19S	- -	- -	- -	- -	- -	0.471
ITEM20A	- -	- -	-0.161	- -	- -	- -
ITEM20D	- -	- -	- -	- -	- -	- -
SAVER	- -	- -	- -	- -	- -	- -
EDUC_93	- -	- -	- -	- -	- -	- -
BMI_93	- -	- -	- -	- -	- -	- -

THETA-EPS

	ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93
ITEM20A	0.720				
ITEM20D	0.140	0.711			
SAVER	- -	- -	- -		
EDUC_93	- -	- -	- -	- -	
BMI_93	- -	- -	- -	- -	- -

THETA-DELTA

	Coder1	Coder2	Coder3	Coder4	Coder5	Coder6
Coder1	0.227					
Coder2	- -	0.461				
Coder3	- -	- -	0.259			
Coder4	- -	- -	- -	0.317		
Coder5	- -	- -	- -	- -	0.270	
Coder6	-0.088	- -	- -	- -	-0.075	0.507
Duncan	- -	- -	- -	- -	- -	- -
Educplan	- -	- -	- -	- -	- -	- -

THETA-DELTA

	Duncan	Educplan
Duncan	- -	
Educplan	- -	- -

Appendix F, Part 2. Correlation Matrix and LISREL Output for the Linear Model (Model 6) Linking Impatience and Achievement Motivation to BMI, Female WLS Subjects (n = 629)

Correlation Matrix

	ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
ITEM18U	1.000					
ITEM18V	0.694	1.000				
ITEM20B	0.153	0.108	1.000			
ITEM20C	0.185	0.143	0.332	1.000		
ITEM19E	-0.166	-0.138	-0.030	-0.076	1.000	
ITEM19S	-0.188	-0.170	-0.062	-0.097	0.525	1.000
ITEM20A	-0.088	-0.083	-0.173	-0.080	0.311	0.382
ITEM20D	-0.066	-0.063	-0.110	-0.036	0.265	0.378
SAVER	-0.072	-0.105	0.032	-0.019	0.051	0.053
EDUC_93	0.044	-0.031	0.066	0.080	0.002	0.126
BMI_93	0.014	0.049	0.053	-0.006	-0.077	-0.153
Coder1	0.009	-0.010	-0.047	-0.005	0.078	-0.041
Coder2	-0.018	-0.023	-0.050	0.024	0.027	-0.034
Coder3	0.022	0.002	-0.062	0.027	0.044	-0.046
Coder4	-0.007	-0.031	-0.042	0.033	0.014	-0.056
Coder5	-0.004	-0.005	-0.024	0.004	0.009	-0.079
Coder6	-0.053	-0.088	-0.029	0.051	0.035	-0.006
Duncan	-0.015	-0.074	-0.001	0.045	0.063	0.097
Educplan	-0.028	-0.072	0.021	-0.016	0.077	0.129

	ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93	Coder1
ITEM20A	1.000					
ITEM20D	0.399	1.000				
SAVER	0.026	-0.023	1.000			
EDUC_93	0.055	0.159	0.036	1.000		
BMI_93	-0.069	-0.077	-0.108	-0.108	1.000	
Coder1	0.015	-0.051	-0.030	-0.155	0.261	1.000
Coder2	-0.031	-0.080	0.025	-0.108	0.234	0.615
Coder3	0.010	-0.085	-0.021	-0.165	0.278	0.711
Coder4	-0.017	-0.064	-0.010	-0.127	0.252	0.703
Coder5	-0.021	-0.051	-0.010	-0.178	0.288	0.740
Coder6	0.066	-0.049	0.012	-0.129	0.240	0.531
Duncan	0.050	0.079	0.142	0.474	-0.074	-0.111
Educplan	0.059	0.110	0.049	0.603	-0.067	-0.125

	Coder2	Coder3	Coder4	Coder5	Coder6	Duncan
Coder2	1.000					
Coder3	0.653	1.000				
Coder4	0.603	0.670	1.000			
Coder5	0.617	0.682	0.689	1.000		
Coder6	0.564	0.564	0.523	0.566	1.000	
Duncan	-0.078	-0.109	-0.075	-0.128	-0.102	1.000
Educplan	-0.065	-0.095	-0.101	-0.137	-0.114	0.580

	Educplan
Educplan	1.000

```
Standard Deviations (in order of variables)

ITEM18U ITEM18V ITEM20B ITEM20C ITEM19E ITEM19S ITEM20A ITEM20D SAVER EDUC_92 BMI_92
Coder1 Coder2 Coder3 Coder4 Coder5 Coder6 Duncan Educplan

1.246034082 1.23264434 0.880305903 1.016033006 1.158169555 1.031311365 0.755340737
0.764932327 0.884322081 2.660888324 5.139337259 1.964108138 1.426220633 1.485294606
1.725201353 1.923370991 1.328149786 1.402232174 0.457432264


Number of Iterations = 10

 LISREL Estimates (Maximum Likelihood)

         LAMBDA-Y

             IRR_IMP    ACH_STR      SAVER       EDUC     BMI_93
            --------   --------   --------   --------   --------
  ITEM18U      1.000       - -        - -        - -        - -

  ITEM18V      0.858       - -        - -        - -        - -
             (0.101)
               8.525

  ITEM20B      0.130       - -        - -        - -        - -
             (0.035)
               3.689

  ITEM20C      0.185       - -        - -        - -        - -

             (0.042)
               4.438

  ITEM19E       - -       1.000       - -        - -        - -

  ITEM19S       - -       1.159       - -        - -        - -
                        (0.107)
                         10.815

  ITEM20A       - -       0.477       - -        - -        - -
                        (0.051)
                          9.424

  ITEM20D       - -       0.460       - -        - -        - -
                        (0.051)
                          9.014

    SAVER       - -        - -       1.000       - -        - -

  EDUC_93       - -        - -        - -       1.000       - -

   BMI_93       - -        - -        - -        - -       1.000
```

LAMBDA-X

	RBM_57	OCC_ASP	ED_ASP
Coder1	1.000	- -	- -
Coder2	0.614 (0.029) 20.813	- -	- -
Coder3	0.723 (0.029) 25.315	- -	- -
Coder4	0.831 (0.033) 25.033	- -	- -
Coder5	0.968 (0.036) 26.855	- -	- -
Coder6	0.513 (0.028) 18.092	- -	- -
Duncan	- -	1.000	- -
Educplan	- -	- -	1.000

BETA

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	- -	- -	- -	- -	- -
ACH_STR	- -	- -	- -	- -	- -
SAVER	-0.072 (0.034) -2.078	- -	- -	- -	- -
EDUC	- -	- -	- -	- -	- -
BMI_93	-0.065 (0.198) -0.330	-1.021 (0.319) -3.203	-0.554 (0.219) -2.536	-0.065 (0.073) -0.886	- -

GAMMA

	RBM_57	OCC_ASP	ED_ASP
IRR_IMP	- -	-0.010 (0.042) -0.238	-0.099 (0.130) -0.762
ACH_STR	- -	0.022 (0.029) 0.762	0.204 (0.090) 2.263
SAVER	- -	0.088 (0.025) 3.532	- -
EDUC	- -	0.353 (0.072) 4.888	2.854 (0.222) 12.877
BMI_93	0.946 (0.121) 7.803	- -	- -

PHI

	RBM_57	OCC_ASP	ED_ASP
RBM_57	2.852 (0.217) 13.155		
OCC_ASP	-0.303 (0.100) -3.039	1.966 (0.111) 17.720	
ED_ASP	-0.106 (0.033) -3.242	0.372 (0.030) 12.574	0.209 (0.012) 17.720

PSI

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	1.238 (0.163) 7.586				
ACH_STR	-0.207 (0.044) -4.717	0.530 (0.073) 7.213			
SAVER	- -	- -	0.760 (0.043) 17.693		
EDUC	- -	- -	- -	4.340 (0.245) 17.720	

BMI_93	- -	- -	- -	- -	22.769 (1.308) 17.405

Squared Multiple Correlations for Structural Equations

IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
0.002	0.024	0.028	0.384	0.135

Squared Multiple Correlations for Reduced Form

IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
0.002	0.024	0.020	0.384	0.105

THETA-EPS

	ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
ITEM18U	0.312 (0.140) 2.224					
ITEM18V	- -	0.606 (0.108) 5.610				
ITEM20B	- -	- -	0.752 (0.043) 17.654			
ITEM20C	- -	- -	0.263 (0.036) 7.300	0.990 (0.056) 17.571		
ITEM19E	- -	- -	- -	- -	0.799 (0.063) 12.635	
ITEM19S	- -	- -	- -	- -	- -	0.334 (0.061) 5.465
ITEM20A	- -	- -	-0.073 (0.022) -3.298	- -	- -	- -
ITEM20D	- -	- -	- -	- -	- -	- -
SAVER	- -	- -	- -	- -	- -	- -
EDUC_93	- -	- -	- -	- -	- -	- -
BMI_93	- -	- -	- -	- -	- -	- -

THETA-EPS

	ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93
ITEM20A	0.443				
	(0.028)				
	15.933				
ITEM20D	0.103	0.469			
	(0.021)	(0.029)			
	4.927	16.151			
SAVER	- -	- -	- -		
EDUC_93	- -	0.164	- -	- -	
		(0.057)			
		2.883			
BMI_93	- -	- -	- -	- -	- -

Squared Multiple Correlations for Y - Variables

ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
0.799	0.601	0.027	0.041	0.404	0.686

Squared Multiple Correlations for Y - Variables

ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93
0.218	0.197	1.000	1.000	1.000

THETA-DELTA

	Coder1	Coder2	Coder3	Coder4	Coder5	Coder6
Coder1	1.006					
	(0.078)					
	12.930					
Coder2	- -	0.956				
		(0.062)				
		15.448				
Coder3	- -	0.109	0.716			
		(0.040)	(0.051)			
		2.722	14.042			
Coder4	- -	- -	- -	1.005		
				(0.070)		
				14.440		
Coder5	- -	- -	- -	- -	1.026	
					(0.077)	
					13.323	
Coder6	- -	0.162	- -	- -	- -	1.012
		(0.044)				(0.062)

		3.719				16.436
Duncan	- -	- -	- -	- -	- -	- -
Educplan	- -	- -	- -	- -	- -	- -

THETA-DELTA

	Duncan	Educplan
Duncan	- -	
Educplan	- -	- -

Squared Multiple Correlations for X - Variables

Coder1	Coder2	Coder3	Coder4	Coder5	Coder6
0.739	0.529	0.675	0.662	0.723	0.426

Squared Multiple Correlations for X - Variables

Duncan	Educplan
1.000	1.000

Completely Standardized Solution

LAMBDA-Y

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
ITEM18U	0.894	- -	- -	- -	- -
ITEM18V	0.775	- -	- -	- -	- -
ITEM20B	0.165	- -	- -	- -	- -
ITEM20C	0.203	- -	- -	- -	- -
ITEM19E	- -	0.636	- -	- -	- -
ITEM19S	- -	0.828	- -	- -	- -
ITEM20A	- -	0.466	- -	- -	- -
ITEM20D	- -	0.443	- -	- -	- -
SAVER	- -	- -	1.000	- -	- -
EDUC_93	- -	- -	- -	1.000	- -
BMI_93	- -	- -	- -	- -	1.000

LAMBDA-X

	RBM_57	OCC_ASP	ED_ASP
Coder1	0.860	- -	- -
Coder2	0.727	- -	- -
Coder3	0.822	- -	- -
Coder4	0.814	- -	- -
Coder5	0.850	- -	- -
Coder6	0.653	- -	- -

Duncan	- -	1.000	- -
Educplan	- -	- -	1.000

BETA

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	- -	- -	- -	- -	- -
ACH_STR	- -	- -	- -	- -	- -
SAVER	-0.090	- -	- -	- -	- -
EDUC	- -	- -	- -	- -	- -
BMI_93	-0.014	-0.147	-0.096	-0.033	- -

GAMMA

	RBM_57	OCC_ASP	ED_ASP
IRR_IMP	- -	-0.013	-0.041
ACH_STR	- -	0.042	0.127
SAVER	- -	0.139	- -
EDUC	- -	0.187	0.492
BMI_93	0.312	- -	- -

PSI

	IRR_IMP	ACH_STR	SAVER	EDUC	BMI_93
IRR_IMP	0.998				
ACH_STR	-0.252	0.976			
SAVER	- -	- -	0.972		
EDUC	- -	- -	- -	0.616	
BMI_93	- -	- -	- -	- -	0.865

THETA-EPS

	ITEM18U	ITEM18V	ITEM20B	ITEM20C	ITEM19E	ITEM19S
ITEM18U	0.201					
ITEM18V	- -	0.399				
ITEM20B	- -	- -	0.973			
ITEM20C	- -	- -	0.294	0.959		
ITEM19E	- -	- -	- -	- -	0.596	
ITEM19S	- -	- -	- -	- -	- -	0.314
ITEM20A	- -	- -	-0.110	- -	- -	- -
ITEM20D	- -	- -	- -	- -	- -	- -
SAVER	- -	- -	- -	- -	- -	- -
EDUC_93	- -	- -	- -	- -	- -	- -
BMI_93	- -	- -	- -	- -	- -	- -

THETA-EPS

	ITEM20A	ITEM20D	SAVER	EDUC_93	BMI_93
ITEM20A	0.782				
ITEM20D	0.180	0.803			
SAVER	- -	- -	- -		
EDUC_93	- -	0.081	- -	- -	

```
  BMI_93       - -          - -          - -          - -          - -


       THETA-DELTA

               Coder1       Coder2       Coder3       Coder4       Coder5       Coder6
              --------     --------     --------     --------     --------     --------
   Coder1      0.261
   Coder2       - -         0.471
   Coder3       - -         0.052        0.325
   Coder4       - -          - -          - -         0.338
   Coder5       - -          - -          - -          - -         0.277
   Coder6       - -         0.086         - -          - -          - -         0.574
   Duncan       - -          - -          - -          - -          - -          - -
 Educplan       - -          - -          - -          - -          - -          - -

       THETA-DELTA

               Duncan     Educplan
              --------     --------
   Duncan       - -
 Educplan       - -          - -
```