Economic Long-Term Impacts of Interventions Aimed at Preventing or Reducing Obesity Among Children

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By Matthew M. Davis and Achamyeleh Gebremariam, Child Health Evaluation and Research Unit, Division of General Pediatrics, University of Michigan

Abstract

The obesity epidemic in the United States calls for action on a national level, yet the potential economic effects of such interventions are unclear. Researchers identified six randomized, controlled trials of community-based interventions to address childhood obesity at different ages that demonstrated a significant change in the prevalence of obesity in the target population. The effects obtained in those trials were applied to a new model of obesity through the life course (ages 3-65 years) in order to estimate the health and economic effects from such interventions scaled to the national level. Even the most effective intervention did not persistently affect the national prevalence of obesity more than 20 years after the intervention was completed. Furthermore, the economic impact of interventions was less than 10 percent of the total excess costs related to obesity for each birth cohort. This study underscores the challenges of addressing obesity at the national level and emphasizes how critical it will be to obtain long-term followup data on children enrolled in prior and future trials.

This study was conducted by the University of Michigan under a cooperative research contract with USDA's Economic Research Service (ERS) Food and Nutrition Assistance Research Program (FANRP): contract number 58-4000-7-0037 (ERS project representative: Elizabeth Frazao). The views expressed are those of the authors and not necessarily those of ERS or USDA.

Introduction

As a major threat to the health of the US population, obesity is a target of considerable research regarding the potential impact of interventions on groups within the population. The investigators have demonstrated previously that it is possible to use models of the dynamics of body mass index throughout the life course to understand the impact of interventions on the prevalence of obesity. By using national data that relate obesity to the costs of health care and missed work, it is then possible to understand the potential impact of interventions on the costs of obesity resulting from changes in the population prevalence of obesity.

The work at the core of this project is based on a hypothetical birth cohort in the US, followed from age 3 through age 65. This cohort was constructed in the investigators' previous research, based on longitudinal data from the national Medical Expenditure Panel Survey and benchmarked against the National Health and Nutrition Examination Survey (NHANES). This cohort model allows the investigators to:

(a) Examine the dynamics of obesity through the life course
(b) Examine the dynamics of health care and work loss costs accumulated through the life course associated with obesity, controlling for sex, race/ethnicity, income, and health insurance coverage
(c) Investigate and estimate the population-level effects on obesity prevalence and total costs for rigorously applied interventions reported in the peer-reviewed literature
(d) Investigate and estimate the population-level effects on obesity prevalence and total costs for hypothetical interventions applied at different ages and for differing durations

Investigators' prior modeling of costs associated with BMI through the life course – Methods

The Medical Expenditure Panel Survey (MEPS) is a complex national probability survey of the civilian non-institutionalized population. The survey has been conducted on annual basis since 1996 by the Agency for Healthcare Research and Quality (AHRQ). The MEPS sample design is an overlapping panel design, with data collected over a two-year period for each MEPS sample.

For the purpose of our model construction, we combined public-use data from MEPS panel data files for panels 5 through 8 (new panel years 2000 through 2003). The panel data permitted measurements of transitions in BMI group status at the individual level, and pooling data across years permitted stable annual estimates for BMI group transition probabilities. The study population was comprised of those aged 3 to 65 years at the beginning of each panel of the MEPS survey.

BMI categories were created using age- and sex-specific BMI percentiles for children 3 to 20 years (underweight=$<5^{th}$ percentile; healthy weight=5^{th} up to 85^{th}; overweight=85^{th} to less than 95^{th} and obesity $\geq 95^{th}$ percentile) and using the BMI values for those 20 and older (underweight= BMI$<$18.5; healthy weight=BMI 18.5 to 24.9; overweight= BMI 25.0-29.9 and obese= BMI $\geq$30). In this study, the underweight group was incorporated in model development, but was excluded from data reporting and cost analysis due to small sample size.

As described below, data from concurrent public-use NHANES data were used to standardize distribution of the population across BMI groups at each age.

At each age, a one-year probability of transition from each BMI group to all others was generated, based on individual data from the MEPS. For example, for all 3-year-old children who were normal weight, probabilities were generated for transitioning to underweight, overweight, and obesity, and for remaining healthy weight by age 4; for all 3-year-old children who were overweight, probabilities were generated for transitioning to underweight, healthy weight, and obesity, and for remaining overweight by age 4. From transition probabilities, prevalence estimates for the different BMI categories were calculated for normal weight, at risk for overweight and for overweight categories.

To standardize BMI category prevalence estimates from the MEPS to the gold standard from concurrent NHANES, in rare instances in which they did not match exactly the transition probabilities were iteratively modified so that the BMI group prevalences at each age matched the corresponding NHANES prevalence values.

Total health care expenditure was the primary outcome variable and was defined in the MEPS as the sum of direct payments for health care received during the year. In order to have a common reference for comparison of expenditures, expenditures were converted to 2006 USD after applying the appropriate inflation factor for each year's expenditure data from the medical care Consumer Price Index.

In order to reduce the effect of extreme expenditure values, both high and low, we excluded 0.2% of the expenditure data (0.1% on the low end and 0.1% on the high end). On the low end, among zero values we randomly excluded 0.1% of the zero-value cases from the analysis. On the high end, no standard software can give us the 99.9th percentile. So, we identified the 99.9th percentile in one-year expenditures ($105,836) and removed observations in excess of this value.

In addition to health care expenditures, measures of overall costs also included estimated work loss costs. The latter were estimated using data from the MEPS about missed days of work, and multiplying the number of days by the mean wage for earners in each year of the MEPS from the Bureau of Labor Statistics, inflated to 2006 USD.

Sample-weighted values were used in all analyses of costs. The sampling weights for the pooled data are the original sampling weights divided by four as we are pooling data across four years.

Given expected confounding by sociodemographic variables, we adjusted expenditures for age, sex, race/ethnicity, insurance status, income status, and age^2 to capture the non-linear increase in expenditure with increased age. We used two-part multiple regression models to estimate the predicted total health care expenditures and overall costs, instead of using ordinary least squares models, because of skewed data. In the first part, we modeled the probability of having an expenditure of any positive amount using logistic regression. And in the second part, we performed a multiple linear regression on the log-transformed expenditure variable for those with positive expenditure.

After each step, we obtained predicted marginals for each age and BMI category (the average predicted response if all the observations had been in a given group (i.e., for a given age and BMI category)). From the logistic regression, we calculated an average predicted probability of having expenditure and from the linear regression the average predicted total expenditure after retransformation by exponentiation. The average of the exponentiated residuals from the linear regression formed the smearing estimate, which was used as an adjustment in the retransformation. Then we combined the estimate of the probability of having expenditure, the predicted expenditure and the smearing adjustment at each age and BMI to get the overall predicted mean expenditure at each age and BMI category.

Bootstrap methods were used to obtain variance estimates and 95% percent confidence intervals for the overall predicted marginals. The prcoess required creating a predetermined number (in our case, 500) of bootstrap samples of the same size as the original data and performing the two-part models on each bootstrap sample. Then we computed the overall predicted marginals for each age and BMI category in each sample. Finally, we computed the variance as well as the 95% confidence intervals, based on the distribution of the bootstrapped overall predicted marginals.

Excess health care expenditures and excess overall costs associated with obesity were estimated by subtracting the adjusted mean value for individuals in the healthy weight group at each age from the mean value for individuals in the obese group at each age.

The national aggregate excess health care expenditures and excess overall costs were then estimated for a hypothetical birth cohort of 4 million individuals. To generate these estimates we multiplied the number of individuals in the cohort in the obese group at each age (a function of population adjusted for age-specific mortality) by the excess measure at each age, and then summed the age-specific, population-weighted estimates at each age over all the years of interest for the cohort, from age 3 through age 65.

Investigators' prior modeling of costs associated with BMI through the life course – Principal Findings
The age-specific probabilities of healthy weight, overweight, and obesity are presented in Figure A1.

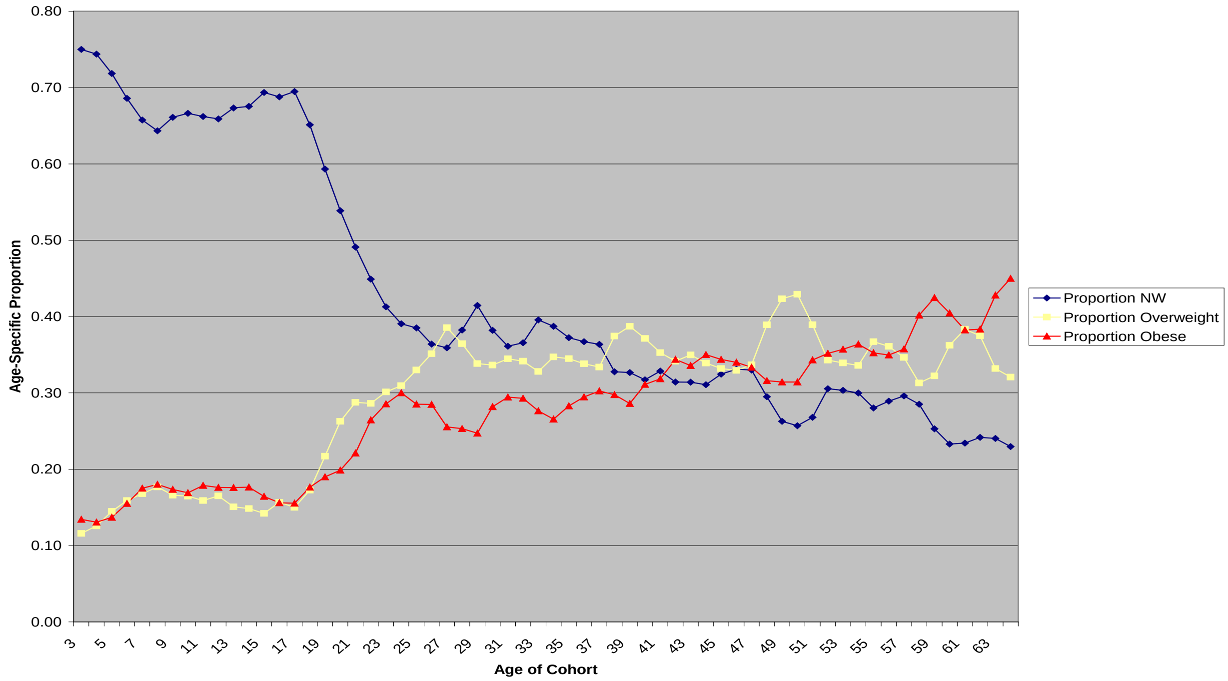

Figure A1. Age-specific prevalence proportions of normal weight, overweight, and obesity from age 3 through 65, from NHANES 1999-2002.
Prevalence proportion for underweight is not shown (<3% each year).

These data illustrate the dynamic prevalence of different BMI designations of a cohort of 3-year-olds as they transit through adolescence into adulthood. The most remarkable feature of Figure A1 is the rapid decline in normal weight prevalence and rapid ascent of overweight and obesity prevalence through middle adolescence into young adulthood.

Transitions from one BMI category to another underlie the patterns in Figure A1. Those transitions are presented as 3 panels in Figure A2, for individuals who are overweight or obese in the first year of measure (e.g., age 3) and subsequently transition (e.g., by age 4) (Panel A2a), versus individuals who are normal weight in the first year and transition (Panel A2b).

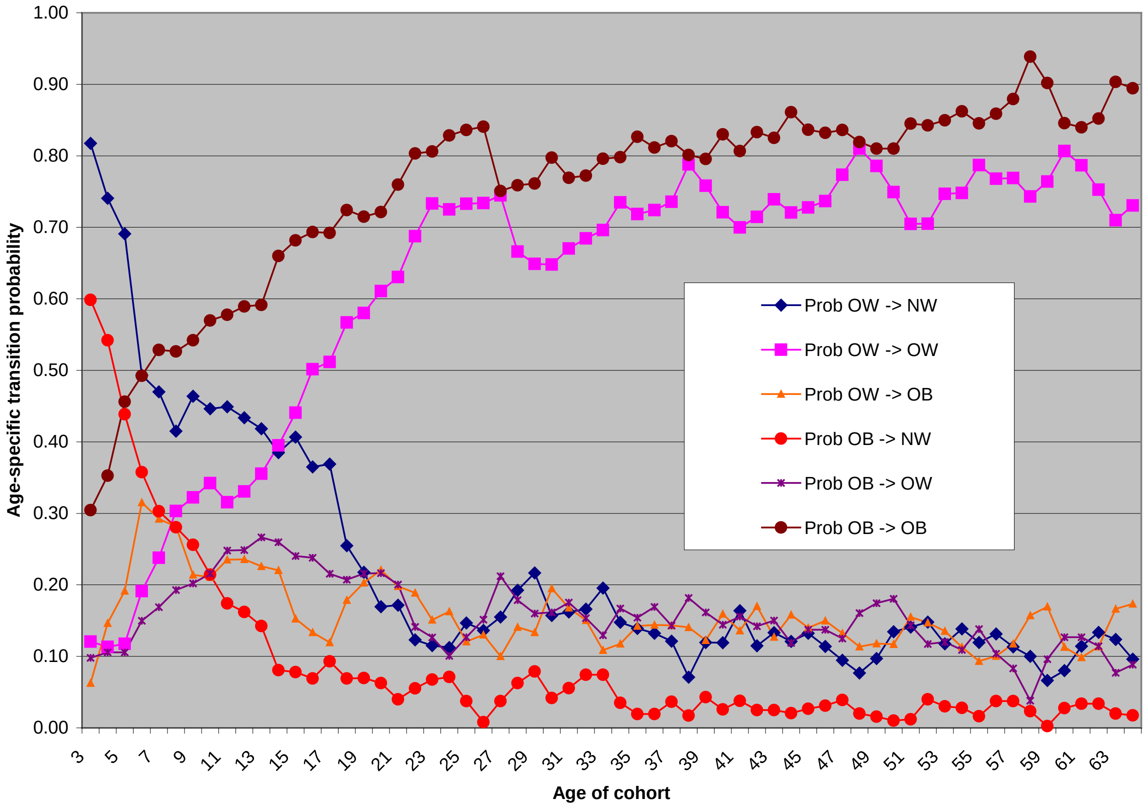

Figure A2a. Age-specific BMI transition probabilities for individuals overweight or obese at age *N* from age 3 through 65, based on longitudinal data from MEPS 2000-03.
Probabilities for individuals of healthy weight and underweight at age *N* not shown.

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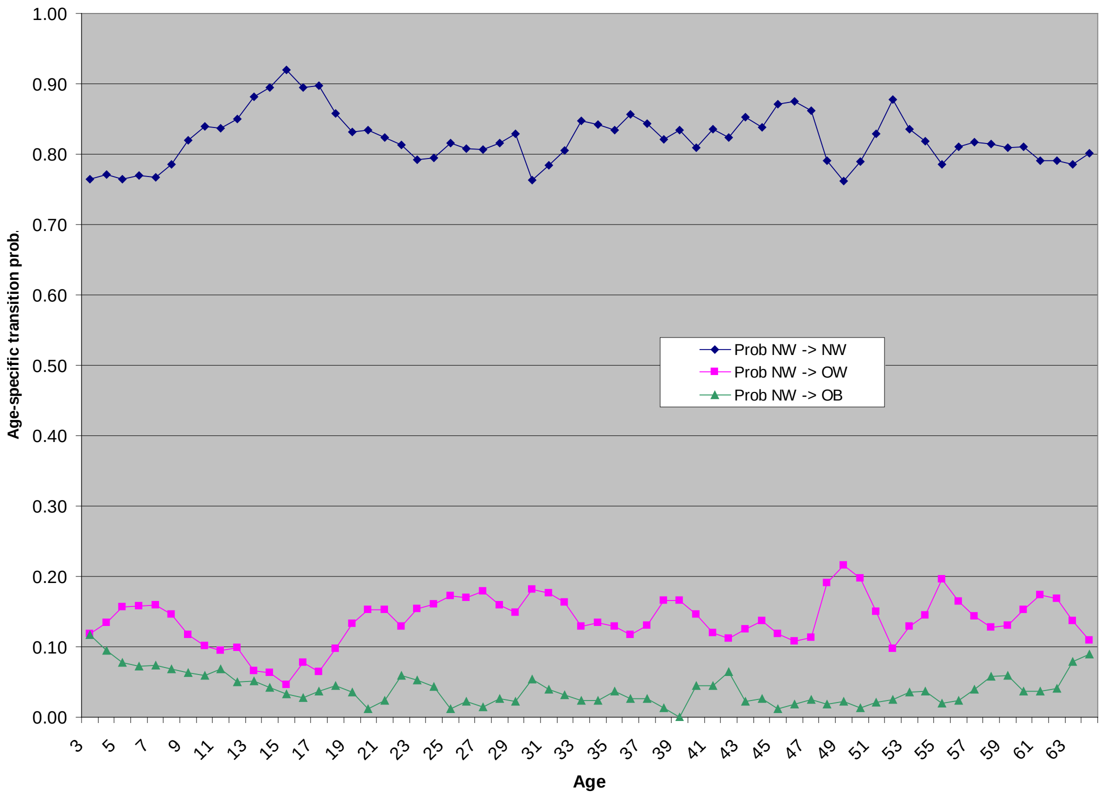

Figure A2b. Age-specific BMI transition probabilities for individuals healthy weight at age *N* from age 3 through 65, based on longitudinal data from MEPS 2000-03.

In Figure A2a, for children who are obese at age *N*, it is evident that the probability of remaining obese at age *N+1* (brown circles) increases rapidly through childhood and adolescence, while the probability of transitioning to normal weight at age *N+1* (red circles) falls rapidly through childhood and adolescence. For children obese at age *N*, the probability of transitioning to overweight at age *N+1* (purple dots) is comparatively stable.

Similarly, it is apparent for children who are overweight at age *N* that the probability of remaining overweight at age *N+1* (pink squares) increases rapidly through childhood and adolescence, whereas the probability of transitioning to normal weight at age *N+1* (blue diamonds) decreases through childhood and adolescence. For children overweight at age *N*, the probability of transitioning to obesity at age *N+1* (orange triangles) is comparatively stable.

In contrast, as shown in Figure A2b, for individuals at healthy weight at any age, the transition probabilities remain comparatively stable over the time course of the cohort.

The specific values for transition probabilities underlying the trends shown in the panels of Figure A2 are included in **Appendix A.**

Current Project - Objectives
The work completed in the course of this project centered on three central goals:

1) Estimation of long-term costs of obesity for the hypothetical cohort, with data from the Medical Expenditure Panel Survey 2000-2004 and the NHANES 1999-2004
2) Development of models of "optimal" interventions during childhood, given a fixed intervention effect but varying the population ages at which such an intervention would be applied
3) Estimation of the long-term costs of obesity in the setting of population-level application of published interventions during childhood

Based on input from the USDA staff throughout the project, we made several modifications to our work that improved its interpretation and relevance; we are grateful for these suggestions. The final work as modified and revised is presented here in this report.

Estimates of Long-term Costs of Obesity

Using the framework of the long-term model of cumulative excess costs of obesity that the investigators have developed from the Medical Expenditure Panel Survey (MEPS), the investigators estimated the cumulative long-term costs of obesity for a cohort of 4 million US children as they age from 3 years to 65 years. Direct and indirect costs (wages from lost work time associated with obesity) were estimated.

Total healthcare expenditure is the primary outcome variable and is defined as the sum of direct payments for healthcare received during the year. The distribution of total healthcare expenditure has a) a large number with no expenditures (~15% in our study data) and b) among those with some expenditure the distribution is skewed. Due to these two issues, ordinary least squares when used for modeling total expenditure will lead to imprecise estimates for the effects of the predictor variables on total expenditure.

For this reason, we use two-part multiple regression models to estimate the predicted total healthcare expenditure instead of using ordinary least squares model. In the first part, we model the probability of having an expenditure of any positive amount using logistic regression. In the second part, we perform a multiple linear regression on the log-transformed expenditure variable for those with positive expenditure. In both models, we include age, BMI category, race/ethnicity, insurance status and income level. In addition to these variables, we added age^2 to capture the non-linear increase in expenditure with increased age.

After each step, we obtain predicted marginals for each age and BMI category. Predicted marginals are defined as the average predicted response if all the observations had been in a given group (i.e., for a given age and BMI category). From the logistic regression, we calculate an average predicted probability of having expenditure and from the linear regression the average predicted total expenditure after retransformation by exponentiation. The average of the exponentiated residuals from the linear regression form the smearing estimate which is used as an adjustment in the retransformation. Then we combine the estimate of the probability of having expenditure, the predicted expenditure and the smearing adjustment at each age and BMI to get the overall predicted mean expenditure at each age and BMI category.

We compute the excess cost due to obesity at each age by subtracting the average predicted overall cost for someone in the normal weight from the predicted overall cost for someone in the obese category. The variance estimate for the average excess cost is obtained as the sum of the variances for average predicted cost for normal weight and obese/overweight. Total excess cost due to obesity at each age is obtained by multiplying the number of obese persons in the population and the excess average cost at each age. We will then cumulate across ages to get the cumulative total excess cost at each age.

The principal findings from the analysis appear below.

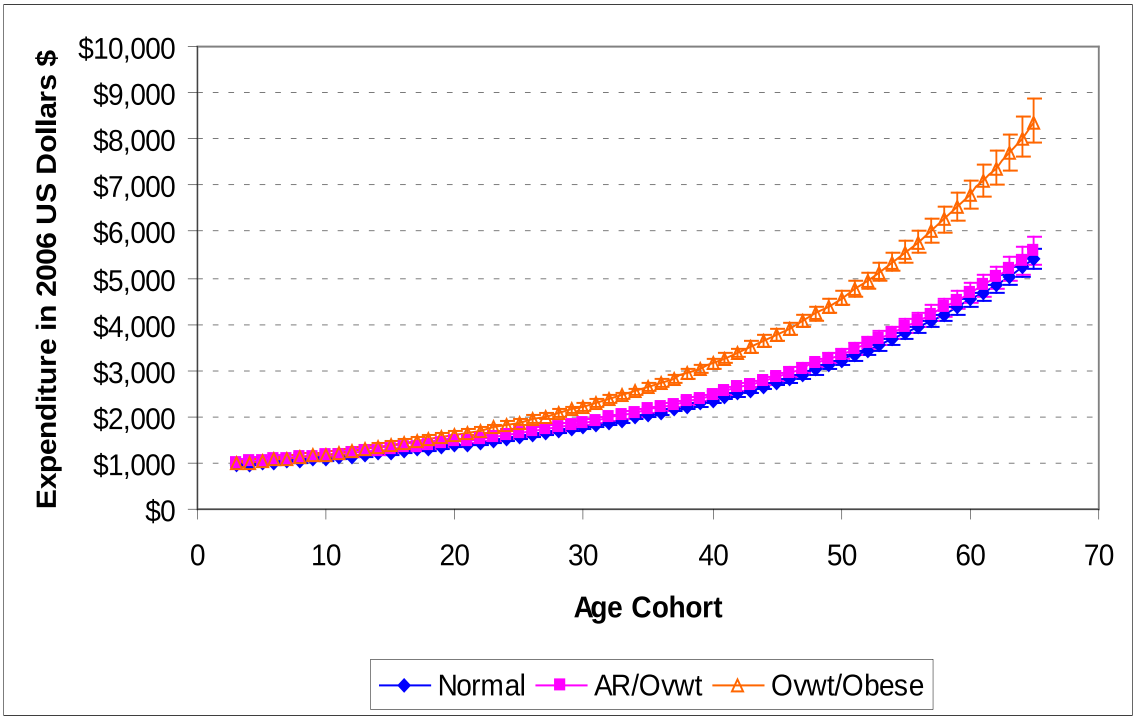

Figure 1. Mean health care expenditures associated with obesity from age 3 years-65 years, adjusted for sex, race/ethnicity, income, and health insurance status. 95% confidence intervals are shown. Normal = normal BMI. AR/Ovwt = BMI in at risk (child) or overweight (adult) range. Ovwt/Obese = BMI in overweight (child) or obese (adult) range.

As shown in Figure 1, the mean health care expenditures begin to differ for overweight/obese versus normal weight individuals beginning at about age 30, and continue to differ at progressively larger amounts at older ages. These data represent a distinct approach to costs of obesity available in the literature, because: (a) we examine the incremental health care costs of obesity from early childhood through middle to late adulthood; (b) we adjust for covariates known to be associated with the predictor (obesity) and the outcome (health care costs).

Of note, there are no differences in the health care expenditures based on BMI category during childhood, based on these measurements. This observation is critical for understanding our other findings regarding the impact of hypothetical and published interventions in childhood.

Findings regarding the cumulative excess costs of obesity through the life course appear on the next page.

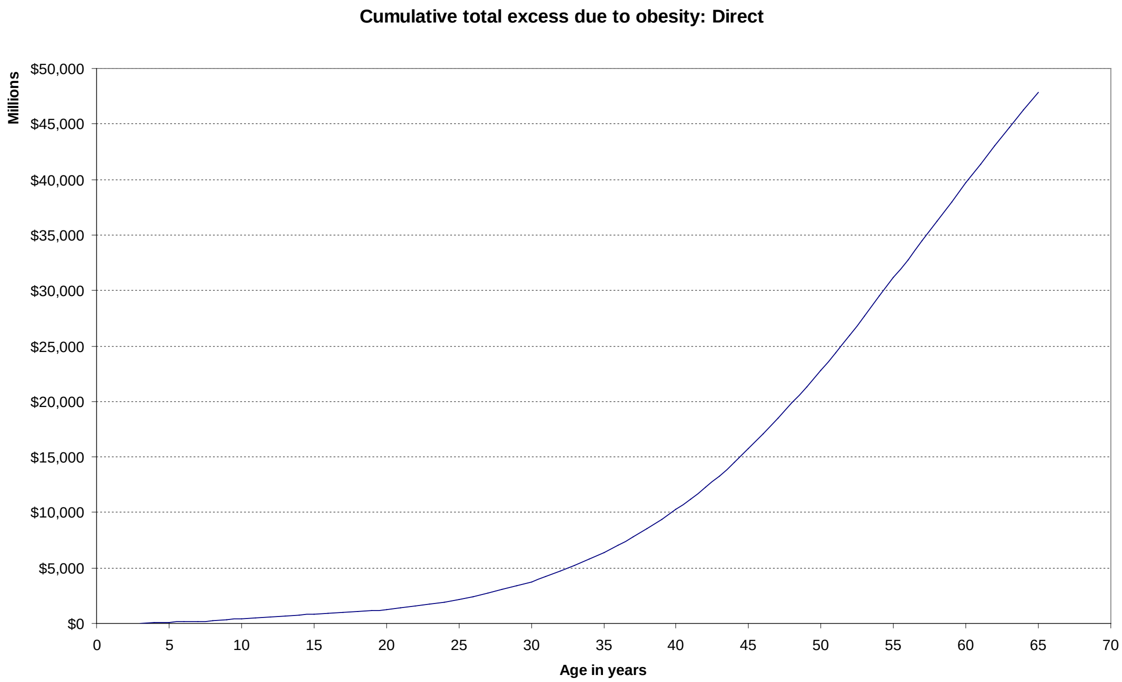

Figure 2. Cumulative excess direct costs associated with obesity for a cohort of US children from age 3 through age 65, adjusted for sex, race/ethnicity, income, and health insurance status.

As shown in Figure 2, the estimated cumulative non-discounted excess direct medical costs associated with obesity from age 3 through age 65 are $48 billion.

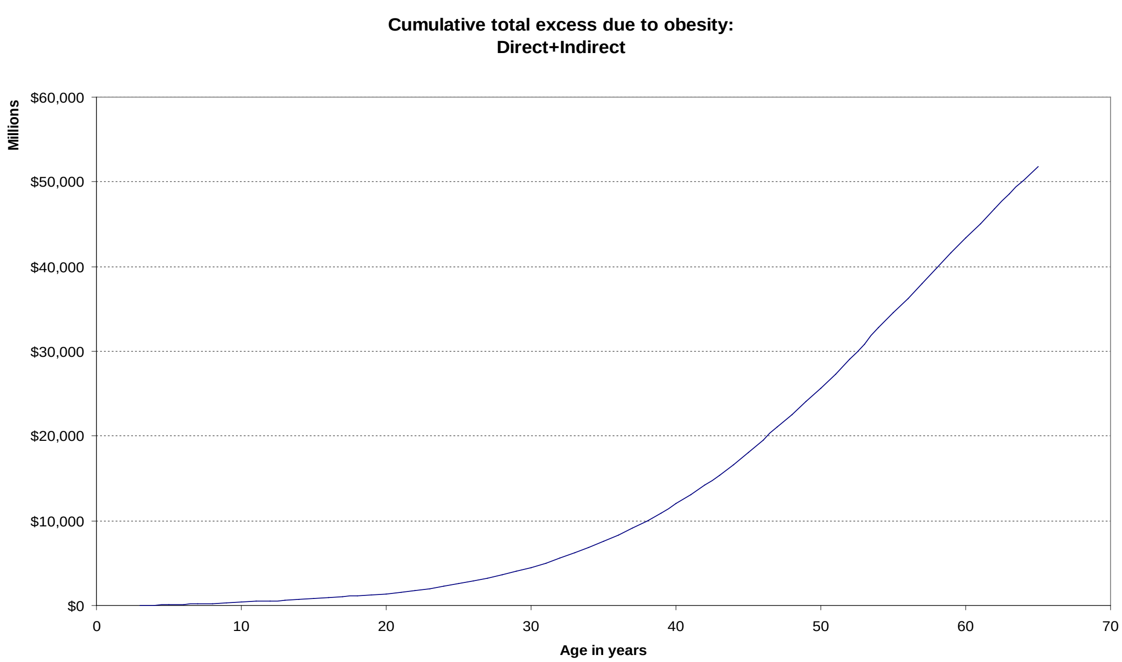

Figure 3. Cumulative total (direct + indirect) excess costs associated with obesity for a US birth cohort from age 3 through age 65, adjusted for sex, race/ethnicity, income, and health insurance status.

As shown in Figure 3, the total undiscounted cumulative excess costs (including lost wages) associated with obesity are $52 billion. In other words, consideration of lost wages adds only a modest amount to the total excess costs associated with obesity. The majority of excess costs related to obesity are attributable to medical costs.

Development and Interpretation of Models of Hypothetical Interventions

To address the obesity epidemic, there is considerable policy interest in examining interventions that may be applicable at the population level. Because there have been no national interventions of this kind, the investigators wanted to model hypothetical interventions of similar magnitude and scale, to understand how the natural dynamics of BMI transitions during childhood might be affected by population-level programs.

In consideration of hypothetical periods of interventions for obesity during childhood, we considered interventions that would be applied to a cohort for a period of 10 years, beginning at differing ages:

- Ages 4 to 13 years ("preschool")
- Ages 6 to 15 years ("schoolage")
- Ages 16 to 25 years ("adolescent and young adult")

The first two interventions look very similar in their application time periods, but an important distinction is that the preschool intervention begins before the period of adiposity rebound which is thought to be so critical for childhood patterns of obesity. We chose 10 years as a uniform period of intervention in order to try to understand the comparative effects of population-level interventions of the same duration.

- Assumptions of the models include:
  - Among those in the healthy weight category, we will see 5% increase in those who stay in the healthy weight category, by reducing those who transition to the at risk category from the healthy weight category. No changes in those who transition from healthy weight to overweight. These assumptions were based on existing published interventions.
  - Among those in the at-risk weight category, 5% increase in those who transition to the healthy weight category by reducing transition probabilities to the overweight and at-risk categories by 2.5%. These assumptions were based on existing published interventions.
  - Among those in the overweight category, 5% increase in those who transition to the at-risk category by reducing the probability of staying in the overweight category. There were no changes in those who transition from overweight to healthy weight.

Those assumptions can be represented as follows:

Table of transition probability *changes* for the trial optimal intervention

Pnn	Pna	Pno	Pan	Paa	Pao	Pon	Poa	Poo
0.05	-0.05	0	0.05	-0.025	-0.025	0	0.05	-0.05

n=normal weight; a=at-risk; o=overweight

We applied these changes to the transition probabilities already established in our baseline model of obesity prevalence.

"Residual" effects: It is vitally important to consider the impact of "residual" effects of interventions – in other words, the persistent impact of interventions following their cessation. The magnitude and duration of residual effects of interventions are <u>unknown</u> in the literature, as there are no population-based cohorts that have been followed for longer than the duration of the interventions themselves. Therefore, to investigate the relative impact of intervention lengths, the investigators arbitrarily chose a 10-year durations for residual effects; in other words, a 10-year intervention + 10-year residual effect = 20 years of intervention-magnitude effects. For all residual effects, the investigators modeled a magnitude of the residual as the magnitude of the intervention itself, applied across the population.

Effect of intervention on prevalence of overweight/obesity
The prevalence of obesity in the setting of 10-year intervention + 10-year residual is demonstrated in the panels of Figure 3.

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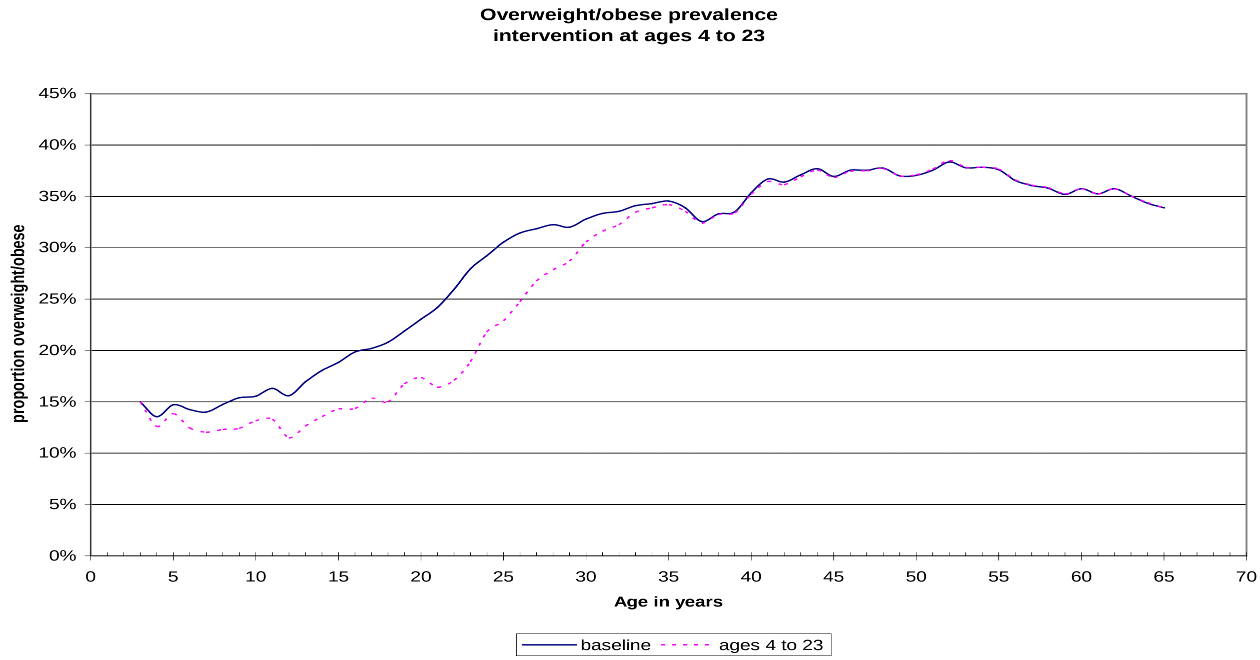

Figure 3a. Prevalence of overweight/obesity in setting of a 10-year intervention + 10-year full residual effect from age 4-23. Upper trend line is smoothed prevalence of obesity in the absence of an intervention. Lower trend line is smoothed prevalence of obesity with the intervention.

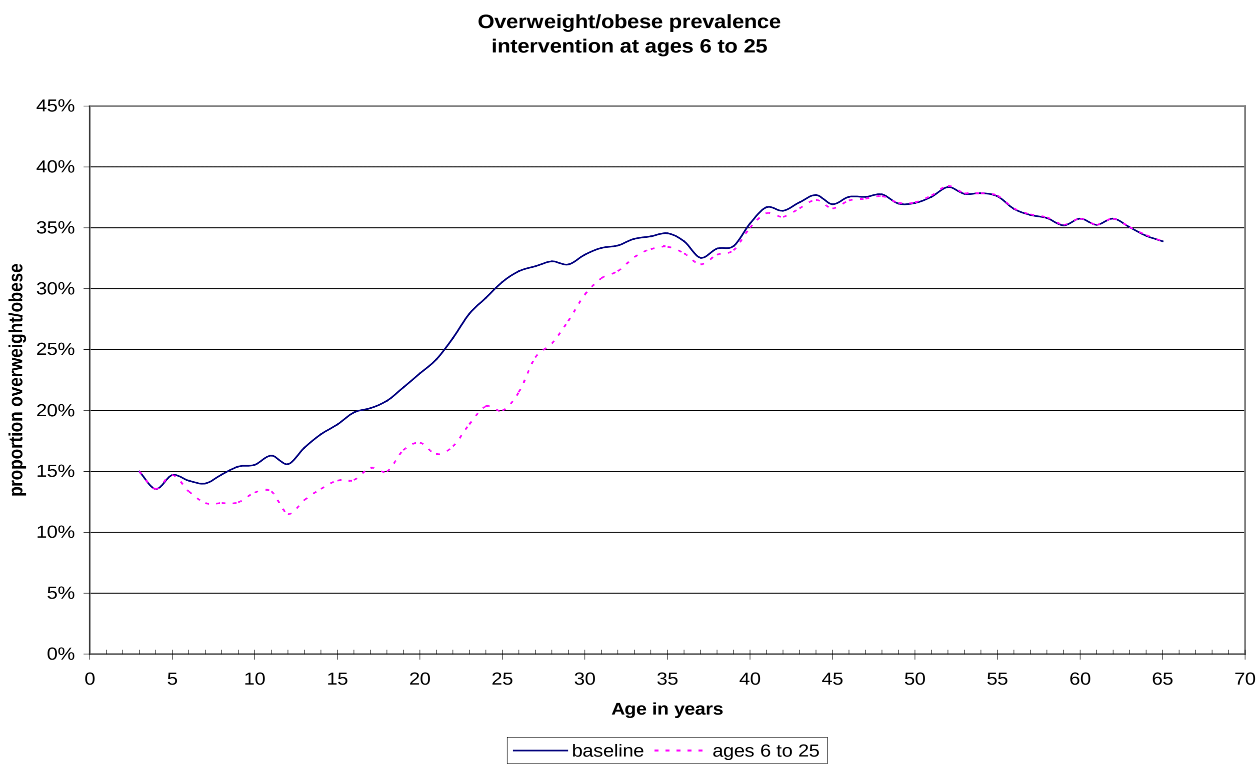

Figure 3b. Prevalence of overweight/obesity in setting of a 10-year intervention + 10-year full residual effect from age 6-25. Upper trend line is smoothed prevalence of obesity in the absence of an intervention. Lower trend line is smoothed prevalence of obesity with the intervention.

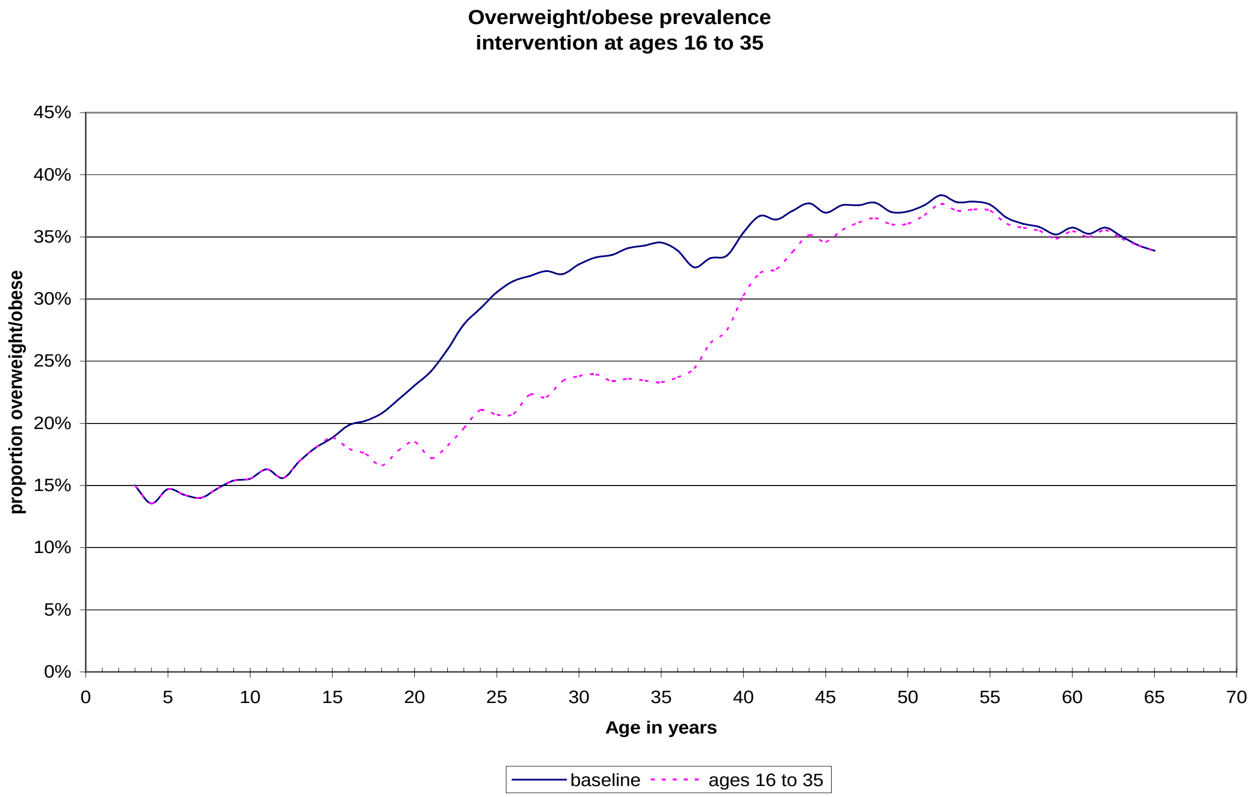

Figure 3c. Prevalence of overweight/obesity in setting of a 10-year intervention + 10-year full residual effect from age 16-35. Upper trend line is smoothed prevalence of obesity in the absence of an intervention. Lower trend line is smoothed prevalence of obesity with the intervention.

There are some key observations from the obesity prevalence patterns evident in the panels of Figure 3:

a) This modest-size intervention (in terms of changes in BMI group transition probabilities) achieves differences in obesity prevalence of greater than 10 percentage points or more at the maximum. These are comparable to differences seen with published interventions (see later sections for direct comparisons).

b) After the termination of the residual effect, the obesity prevalence then returns to the "natural" baseline prevalence over a period of 12-15 years. This return to baseline, while it seems counter-intuitive, happens to any two probability trend lines that start out at different points but have the same transition probabilities applied to them. The return to baseline happens slightly faster for the interventions applied at younger ages than the intervention applied during adolescence and young adulthood.

Effects of interventions on savings related to obesity

These differences in obesity prevalence translate into different levels of cumulative savings related to obesity, if applied to the hypothetical birth cohort, as shown in the 3 panels of Figure 4 below. The panels present findings from the 3 scenarios of interventions, first undiscounted and then discounted at 3% annually (standard in public health literature) and discounted at 7% annually (USDA and federal government standard, from the Federal Register). Discounting is applied to such analyses because of the natural human tendency to value money more today than the same amount of money in the future.

Of note, for the discounted analyses, we apply the discount rate from the first year of the intervention, in order to compare the relative savings of interventions as if they were applied at different ages of the cohort. In addition, we continue to apply the discount even after savings have stopped accruing from the intervention, because we assume that savings today are worth more than savings a year from now (ie, discounting would still apply).

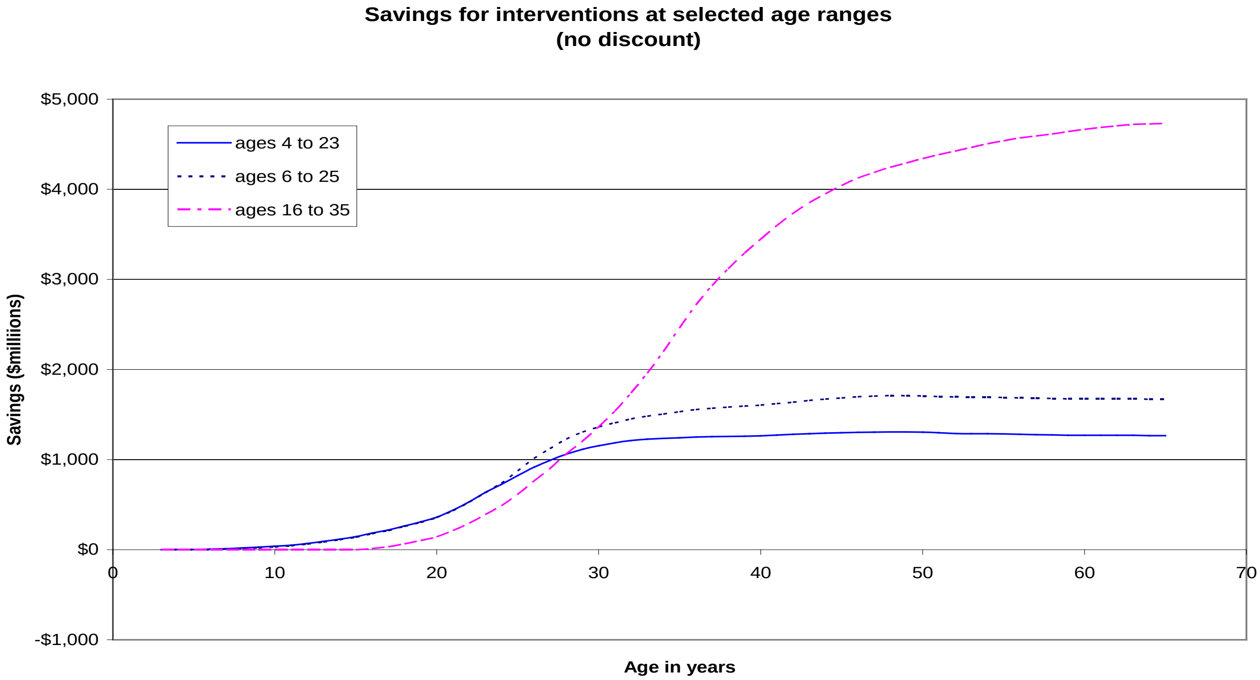

Figure 4a. Cumulative savings (undiscounted) with hypothetical interventions (10-year program + 10-year residual) applied to the population for ages 4-23 (low), 6-25 (moderate), and 16-35 (high).

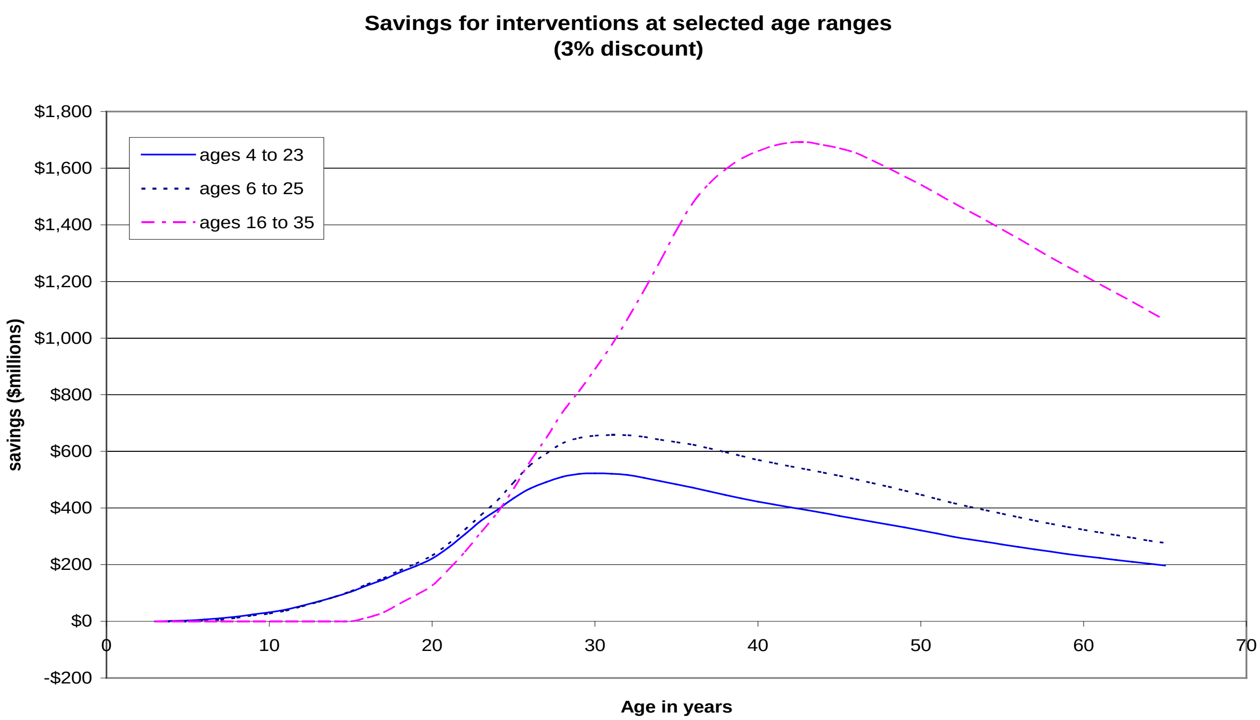

Figure 4b. Cumulative savings (3% discount) with hypothetical interventions (10-year program + 10-year intervention) applied to the population for ages 4-23 (low), 6-25 (moderate), and 16-35 (high).

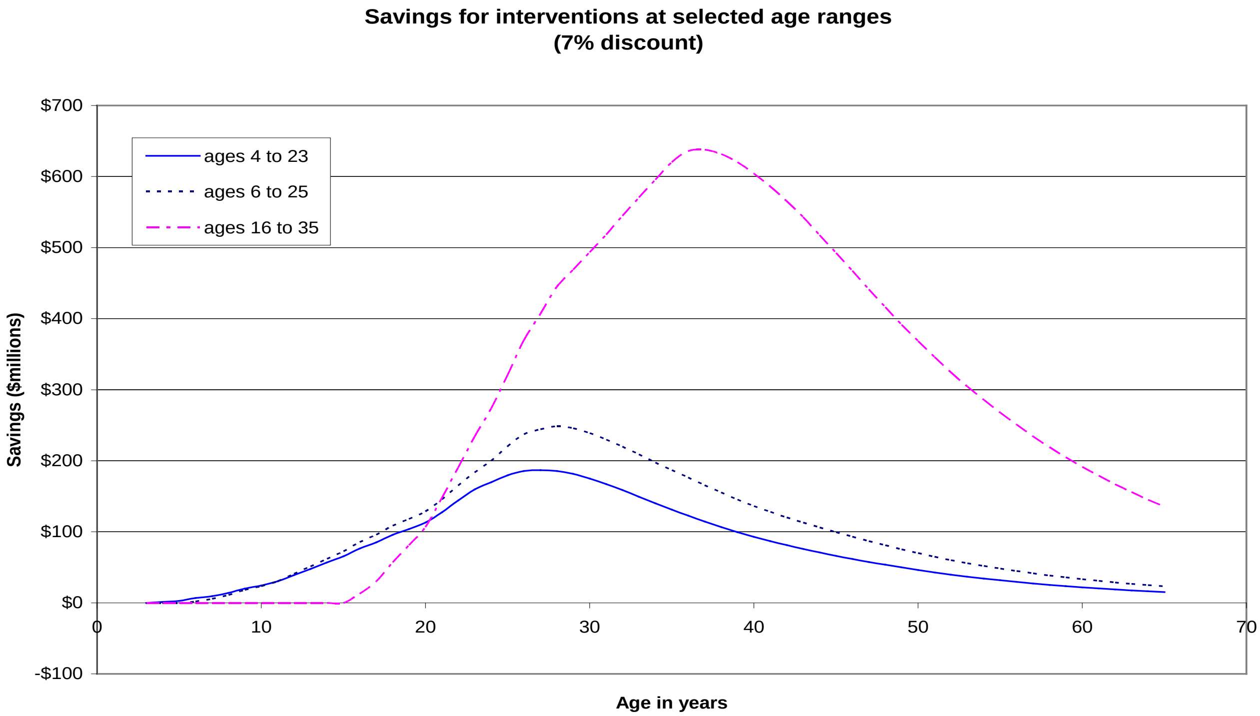

Figure 4c. Cumulative savings (7% discount) with hypothetical interventions (10-year program + 10-year residual) applied to the population for ages 4-23 (low), 6-25 (moderate), and 16-35 (high).

Key observations from these analyses of savings for the hypothetical interventions include:

a) If one assumes (as we do for these analyses, and as substantiated by the intervention literature) that it would be possible to achieve the same magnitude effect at later ages as at younger ages, then greater savings are achieved with interventions among adolescents/young adults than among schoolage and among preschool-age children. This is to be expected, given that there are no differences in mean annual health care expenditures related to obesity at younger ages (Figure 1). In other words, differences in obesity prevalence achieved with an intervention at younger ages do not translate into savings when there are no spending differences related to obesity at those ages.

   If we assume, as we have in other analyses conducted during this project period but not shown here, that interventions at later ages *cannot* achieve the same magnitude of effect as programs applied at younger ages, then the savings curves do trend more closely together. However, the programs applied at older ages are still superior when assuming up to 20% *worse* performance in terms of changes in obesity prevalence at older ages.

b) Slightly greater savings are achieved with an intervention beginning at age 6 than at age 4. In discounted analyses, however, this difference is negligible by age 65.

c) The magnitude of savings (about $4.7 billion for the 16-35 year-old intervention in undiscounted analyses) amounts to less than 10% of the overall excess expenditures. It is unknown what the costs would be for a national program to achieve the magnitude of change in obesity observed in these model analyses.

Estimation of the Long-term Costs of Obesity in the Setting of Population-level Application of Published Interventions During Childhood

The investigators performed an extensive literature review in order to identify population-based, randomized trials of obesity interventions during childhood that could be assessed with their models of obesity prevalence and related costs. During their earlier work, the investigators had identified 5 such studies. Details of these studies are presented below:

<u>Interventions:</u>

1. Reducing consumption of carbonated beverages through school-based education (James et al 2004)
    a. Ages 7-11: reduced to 0 the probability that non-obese children will become obese
2. School-based behavioral education intervention regarding TV viewing, decreased consumption of high-fat foods, increasing fruit and veg intake, and increasing moderate and vigorous physical activity (Gortmaker et al 1999)
    a. Ages 11-12 - 2-year longitudinal intervention: obesity prevalence in control increased 2.2% points, while obesity prevalence in intervention decreased 3.3% points
3. School-based behavioral education intervention to reduce TV viewing (Robinson 1999)
    a. Ages 8-9, 1-year intervention: children in intervention group had .45kg/m2 LESS increase in BMI over the year (this study does not report % obese, so this is a difficult one to apply to our models)
4. School-based behavioral education intervention regarding nutrition and physical activity (Coleman et al 2005)
    a. Age 8, 1-year intervention: By age 10 (5th grade, 1 year after intervention finished), prevalence of (overweight + obesity) was 8 points lower
5. Head Start (preschool)-based intervention regarding nutrition, physical activity, and TV watching (Fitzgibbon et al, 2005)
    a. Ages 3-4, 1-year intervention: By age 6 (2 years after end of intervention), BMI Z-score was 0.18 lower in the intervention group (this study does not present % obese, so it is challenging to apply to our models)

During this current project, the investigators identified 6 additional candidate studies with a focus on early childhood (as specified by USDA as an area of major interest); of these 6, only 1 (Hakenen M et al – *Intl Jour Obesity* 2006;30:618-26) satisfied the investigators' criteria that the study showed a significant effect of the intervention and that specified effects with respect to early childhood subjects. This paper presented an intervention from infancy through age 10; we therefore considered this intervention as if it were applied beginning at age 3 (the first year of our cohort) through age 10, and then with a 10-year residual effect.

The prevalence of overweight/obesity for the Hakanen et al intervention is presented in Figure 5 below.

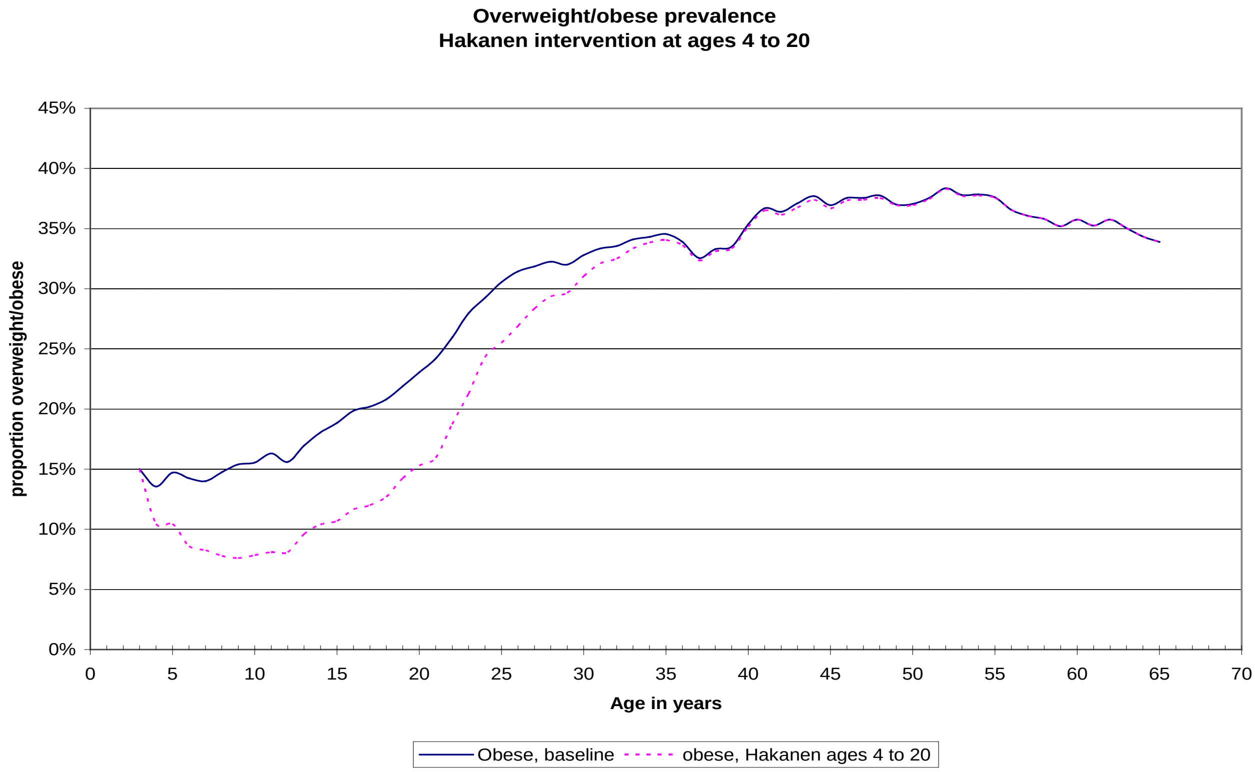

Figure 5. Prevalence of overweight/obesity in setting of a 10-year intervention (Hakanen et al) + 10-year full residual effect from age 11-20. Upper trend line is smoothed prevalence of obesity in the absence of an intervention. Lower trend line is smoothed prevalence of obesity with the intervention.

Similar to the hypothetical interventions above, note that after the termination of the residual effect by age 20, the prevalence of obesity then converges with the "natural history" of obesity by age 35.

For this report, the investigators also present the summary obesity prevalence curves for all 6 interventions considered in our analyses to date (Figure 6, p. 19). Brief descriptions of all 6 interventions are presented for comparison in Table 1 (next page).

Table 1. Descriptions of randomized, controlled trials of obesity interventions modeled in this project.

Trial Description	Ages
1) Reducing consumption of carbonated beverages through school-based education	7-11
2) School-based behavioral education intervention regarding TV viewing, decreased consumption of high-fat foods, increasing fruit and veg intake, and increasing moderate and vigorous physical activity	11-12
3) School-based behavioral education intervention to reduce TV viewing	8-9
4) School-based behavioral education intervention regarding nutrition and physical activity	8-9
5) Head Start (preschool)-based intervention regarding nutrition, physical activity, and TV watching	3-5
6) Infancy and childhood-based intervention regarding nutrition and physical activity	Through age 10

The application of these RCT findings to a hypothetical population-level intervention scenario should be considered a best-case view of best evidence and practice. None of these RCTs were applied at the national level in their original forms, and no assessments of their scale-ability has been performed by the investigators or to the investigators' knowledge.

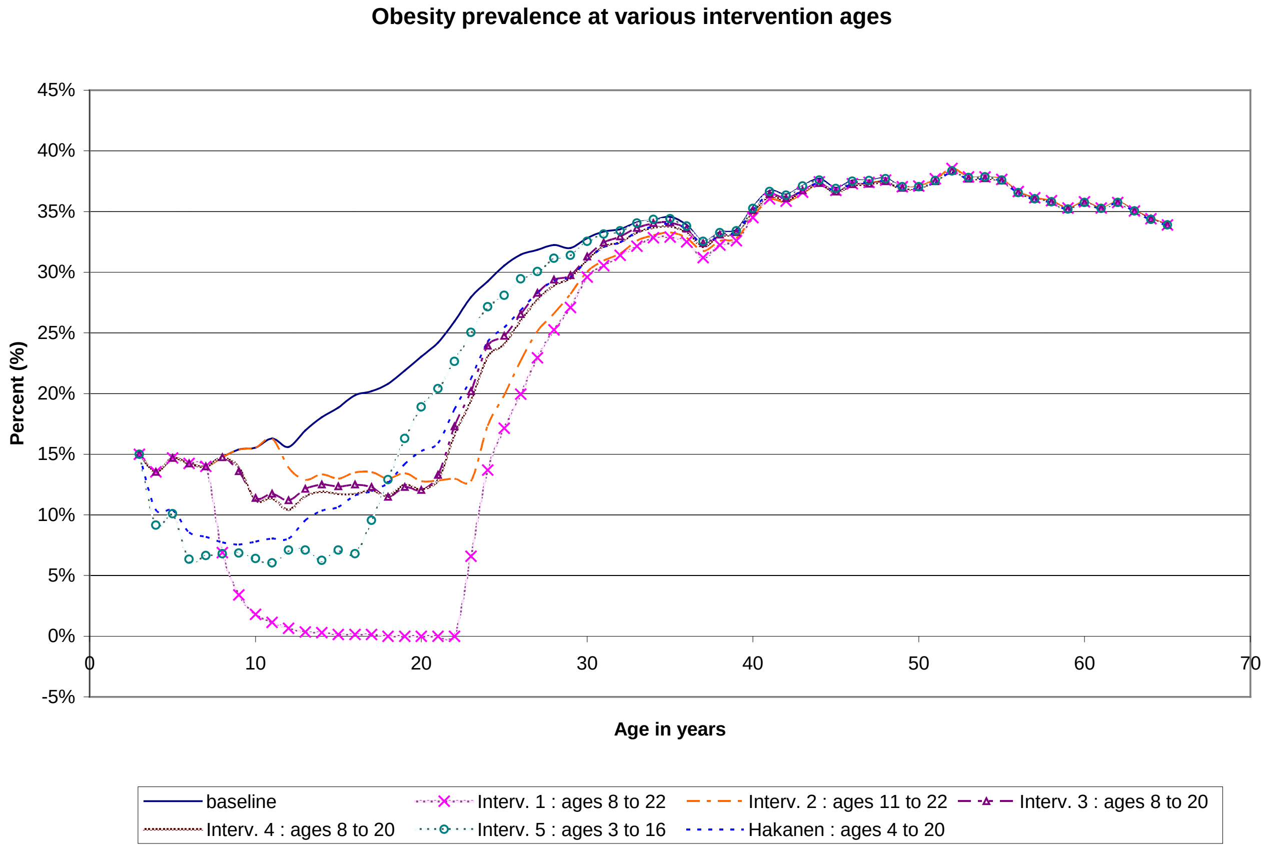

Figure 6. Obesity prevalence trends with 6 different childhood interventions + 10-year residual effects. Top trend line is population prevalence of obesity in the absence of an intervention. Other trend lines are population prevalence of obesity with the interventions.

Key observations from Figure 6 include:

a) Published interventions yield a wide variety of effects on obesity prevalence, with most about 10 percentage points lower than the prevalence without an intervention but outliers with even more substantial effects.
b) The obesity trend lines converge on the "natural history" line within 20 years of the termination of the residual effect, even in the case of the intervention with the most substantial effects.

These differences in obesity prevalence effects and timing translate into differences in expected savings with interventions (panels in Figure 7, next pages).

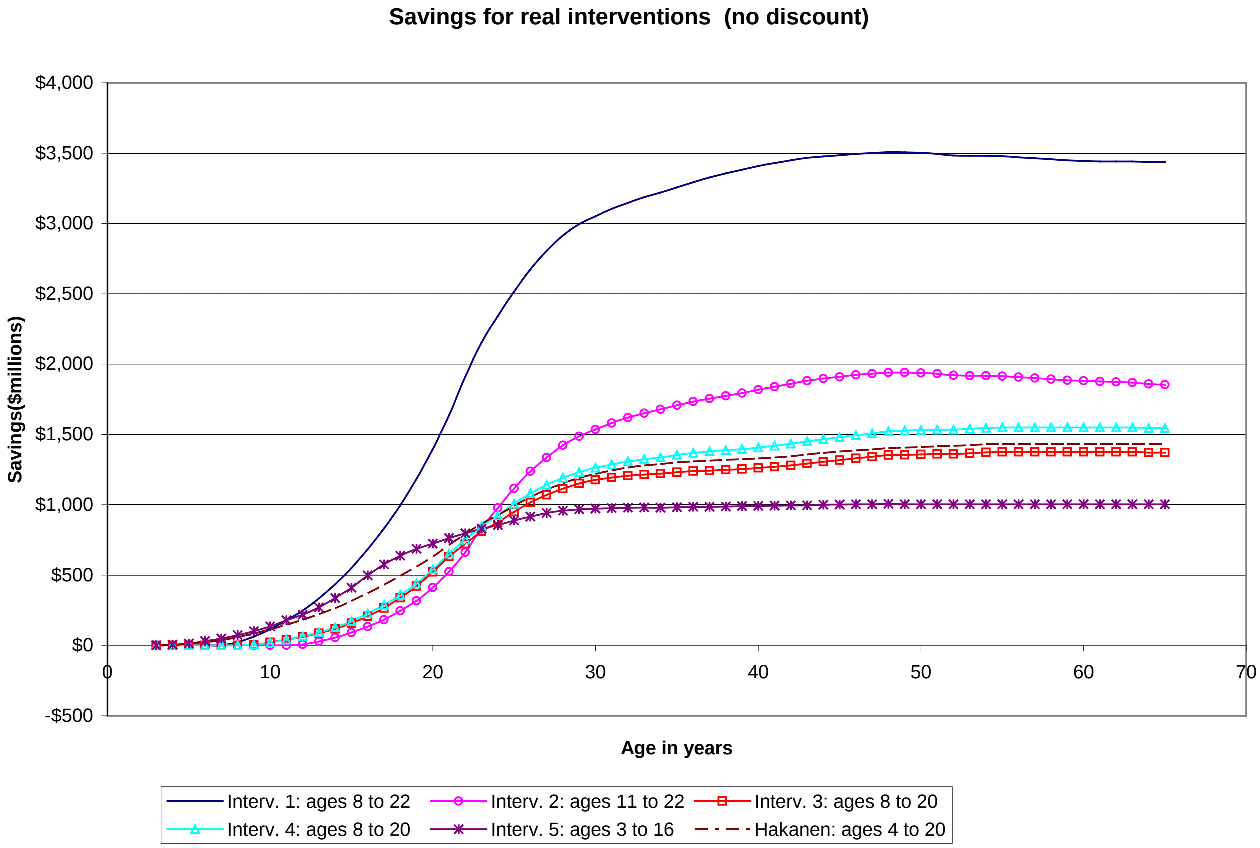

Figure 7a. Cumulative savings (undiscounted) with published interventions (program + 10-year residual) applied to the population.

In the undiscounted results (Figure 7a), it is evident that the intervention with the effect on obesity prevalence of the greatest magnitude ("Real intervention 1", smooth line without markers) would be expected to yield the greatest savings, of about $3.5 billion. Compare this with the magnitude of savings with the hypothetical intervention beginning in adolescence (Figure 4a, pg 13), and it is evident that even the strongest intervention applied at the population level may not meet the modest savings achieved under the hypothetical intervention assumptions.

The intervention with the second-largest savings magnitude was "Real intervention 2" (smooth line with square markers) beginning at age 11 and continued out (with residual effect) to age 22. One can see, looking at the obesity prevalence trend lines in Figure 6, that Real intervention 2 had the smallest magnitude effect on obesity prevalence of any of the published interventions we examined. Yet, it had the second-largest estimated savings – attributable, we believe, to its timing (beginning at the oldest age of any of the interventions we studied).

Of note, the authors conducted sensitivity analyses to evaluate how the magnitude of savings changed in the hypothetical cases for these interventions where the residual effect persisted at full magnitude until age 65. As expected, the savings did not plateau and continued to increase until age 65. Although these sensitivity analyses demonstrate the functional mechanics of the model, we do not present these data because the evidence is lacking to support such a residual effect.

Discounted savings estimates (3% and 7%) for the base case are presented on the following page.

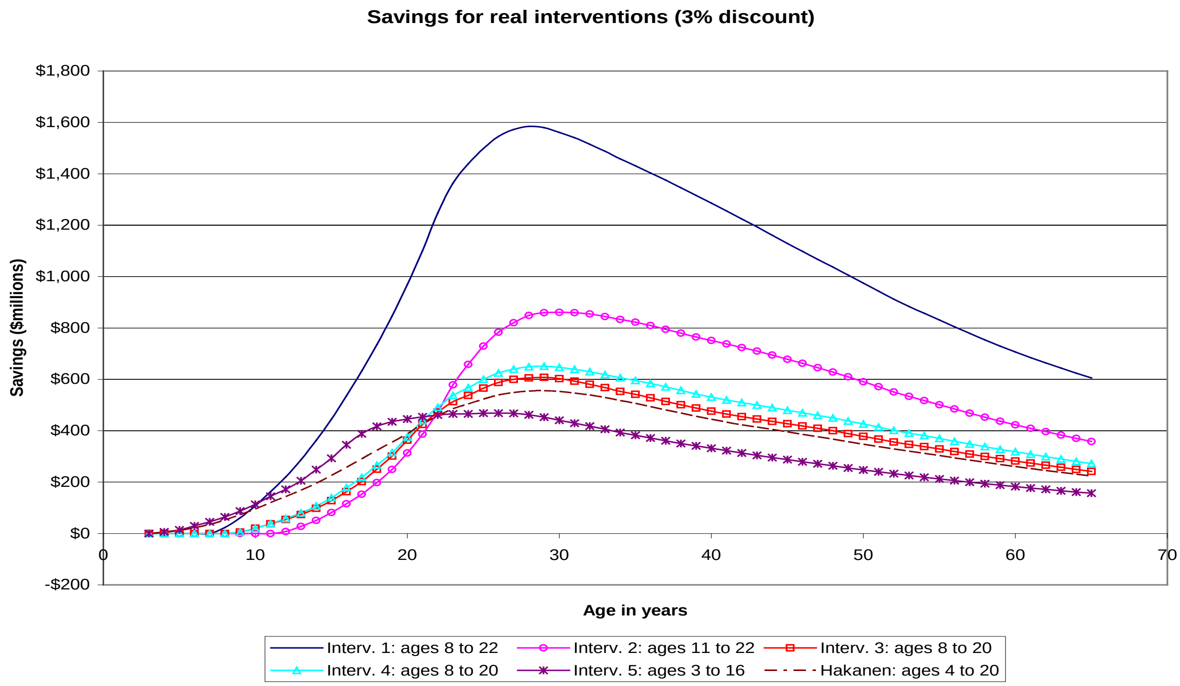

Figure 7b. Cumulative savings (3% annual discount) with published interventions (program + 10-year residual) applied to the population.

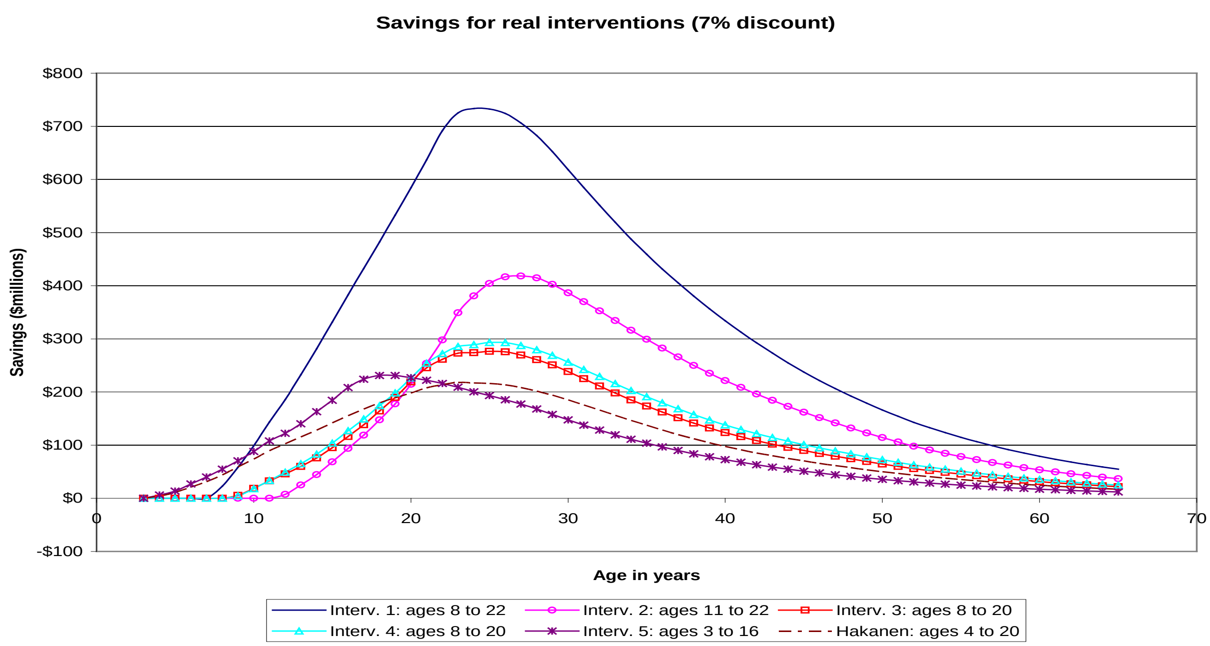

Figure 7c. Cumulative savings (7% annual discount) with published interventions (program + 10-year residual) applied to the population.

It is evident from Figures 7b and 7c that discounting diminishes the differences among the relative savings estimated to accrue with each intervention, as well as (as expected) diminishing the overall magnitude of savings with any of the interventions.

Summary Remarks

The investigators are grateful for the continued support of the USDA Economic Research Service for this work regarding the potential economic effects of obesity prevention programs at the population level.

There are 3 main domains of findings from this work:

1) **Long-term costs of obesity –** This is the only analysis of which we are aware that has attempted to estimate the long-term costs of obesity for a birth cohort of the US population. It is, therefore, difficult to compare our findings of >$50 billion in excess spending to other cross-sectional estimates of excess costs attributable to obesity. Nevertheless, because the estimates contained herein are derived from some of the same data used to derive cross-sectional estimates, the investigators believe they are comparable.

   Of note, longitudinal estimates such as these provide a basis for near- and long-term programmatic impact evaluation, unlike cross-sectional estimates. The investigators believe these estimates may be helpful for other researchers and policymakers who wish to benchmark potential interventions against a long-term standard.

2) **Models of hypothetical interventions** – Models of interventions assisted the investigators greatly in understanding the dynamics of body mass index through the life course. In addition, these models emphasize the importance of understanding:

   a) **Convergence of post-intervention obesity trends with the "natural history" of obesity** – The investigators found empirically (and substantiated theoretically, in documents shared with the USDA program officer) that applying the same transition probabilities to two sets of prevalence data will lead the two trend lines to converge within 15-25 cycles. This phenomenon, not previously recognized, has profound implications for programmatic initiatives, which *must* have sustained effects in order to avoid "returning" to the natural state. In other words, sustaining effects to adolescence, or to young adulthood, and not any longer in the life course will *not* prevent a return to the natural trend toward obesity in later years. In other words, <u>there does *not* seem to be a critical period for interventions</u>, in terms of avoiding a return to the natural state. Rather than showing an optimal period, though, what our work indicates is that all interventions seem to be similar disadvantaged: obesity is an entrenched population-wide problem with origins early in the life course that appear to intensify with time.

   b) **Residual effects of interventions –** Without residual effects, the convergence with the natural state of obesity prevalence would have occurred even earlier than in our models that assumed 10-year full-magnitude residual effects. There must be more population-level research regarding the duration and magnitude of residual effects in order to better inform future modeling work such as that carried on in this project. Without the demonstration of residual effects on BMI trends, interventions during childhood will compare unfavorably with interventions later in life, when the excess costs of obesity are higher on a per person basis.

3) **Models of published interventions –** Evaluation of "real world" interventions as if they were applied across the US at the population level assisted greatly in examining the magnitude of savings that might be achieved with such programs. Principal conclusions from these comparisons were that <u>programs with greater effects on obesity prevalence are not necessarily expected to yield greater savings</u>; rather, the timing of the interventions may be more indicative – and later (at older ages, and for longer periods) appears generally better. However, much remains to be learned about the residual effects of actual interventions, and about how they might be implemented if scaled up to the national level.

The greatest limitation of this cost analysis is its hypothetical nature. The investigators examined entirely hypothetical interventions to investigate the importance of timing and duration of residual effects. Then they used data from published trials of the highest rigor (randomized, controlled trials) to understand how population-level (countrywide) interventions might affect BMI trends on a national level. Multiple assumptions needed to be incorporated in these models in order to estimate results from these models, and empiric support for many such assumptions is simply not available at this time. Where assumptions are made, the results of models may not be accurate.

One of the most hypothetical components of this model regards how BMI transition probabilities are likely changing over time. The model presented here contains BMI transition data for a hypothetical cohort born at one point in time – although the BMI transition probabilities over the life course reflect the probabilities for individuals born at different points in time. In other words, individuals in their 50s when the MEPS data were collected were born in the 1940s and early 1950s. Those in their teens when the MEPS data were collected were born in the 1980s and early 1990s. The investigators believe that it is highly likely that those born in the 1980s will have different BMI transition probabilities when they reach their 50s than did the individuals born in the 1940s. Based on recent trajectories in population-level BMI, it appears likely that the probabilities will favor obesity even more for the 1980s birth cohort than the 1940s cohort. The data do not exist to even estimate such changes with any satisfactory precision, however. For that reason, the investigators opted not to modify the transition probabilities, but acknowledge that the economic impact of obesity may be even higher than what is measured in this study.

Another limitation of this analysis is that there are no cost estimates for the interventions themselves. Community-based interventions have not been attempted on this scale previously, but could potentially be part of obesity prevention and treamtent initiatives in the future. If there were estimates of program costs, that would permit funders (whether private or public) and program officials to anticipate what the net costs of the program(s) would be.

An additional limitation of this study is that the data source did not allow the investigators to measure other potential gains of preventing or reducing childhood obesity – namely, improvements in self-esteem and academic achievement that might result. In an applied implementation of a childhood obesity initiative, one would optimally include these metrics as outcomes as well.

In closing, by helping identify an agenda of meaningful data gathering going forward, the investigators hope that this work will help illuminate the nature of data that, if compiled in the future, will substantially advance the science and policy regarding obesity in childhood and adulthood in the United States and around the world. It is critical to emphasize that the findings in from this work do not indicate that investments in childhood obesity prevention and treatment are not worth making. Rather, the clear message from this work is that the health and economic benefits from childhood obesity initiatives will only be fully appreciated if there are concerted efforts to measure such benefits 10, 20, 30, and more years after the initial interventions were implemented.