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Obesity trend in the United States and economic intervention options to change it: a simulation study linking ecological epidemiology and system dynamics modeling

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Abstract

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Author contributions

HJC and YW conceived the topic. HJC and HX designed the systems models and conducted the analyses. HJC drafted the manuscript. TTKH, SL and YCW contributed to data interpretation. YW directed the study and provided administrative support. All authors made critical revisions and comments to the manuscript, and approved the final version.

Ethical statement

The authors have no conflict of interest. The study was based on secondary anonymous data in governmental open data repository systems.

Objectives: To study the country-level dynamics and influences between population weight status and socioeconomic distribution (employment status and family income) in the U.S., and to project the potential impacts of socioeconomic-based intervention options on obesity prevalence.

Study design: Ecological study and simulation

Methods: Using the longitudinal data from the 2001-2011 Medical Expenditure Panel Survey (N=88,453 adults), we built and calibrated a system dynamics model (SDM) capturing the feedback loops between body weight status and SES distribution, and simulated the effects of employment- and income-based intervention options.

Results: The SDM-based simulation projected rising overweight/obesity prevalence in the U.S. in the future. Improving people's income from lower- to middle income group would help control the rising prevalence, while only creating jobs for the unemployed did not show such effect.

Conclusions: Improving people from low to middle income levels may be effective, instead of solely improving reemployment rate, in curbing the rising obesity trend in the U.S. adult population. This study indicates the value of SDM as a virtual laboratory to evaluate complex distributive phenomena of the interplay between population health and economy.

INTRODUCTION

The relationship between the economy and obesity is complex. The prevalence of obesity in developed countries has risen in parallel with increased economic development, such as GDP [1, 2]. International comparison shows the same correlation between GDP and population body mass index [3]. In addition, worse economic conditions, such as the higher unemployment rate, is associated with lower prevalence of obesity [4]. These imply that obesity prevalence and prosperous economy are positively associated. On the other hand, nevertheless, economic downturns could also result in higher risks of obesity, as evidenced, for example, by the climbing share prices of fast food companies during the recession in 2008 [5]. A Canadian study shows that the prevalence of severely obesity increased with higher unemployment rates [6]. Furthermore, in the U.S., risk for obesity appears to be higher in the states with lower legal minimum wage [7]. It is, therefore, unclear whether and how prevalence of obesity could be effectively decreased by improving people's socioeconomic condition.

Furthermore, one of the challenges in deciphering this question lies in the potential reciprocal nature of obesity and economics at the individual level. People living with lower income, poverty, or unemployment are more likely to live in areas with higher density of food outlets selling energy-dense but nutrition-poor foods [10, 11], a constrained budget may lead to a higher sensitivity to food price [12, 13], and lower physical activity [14]. This, in turn, reinforces the effect that low socioeconomic status (SES) has on obesity [8, 9]. However, obesity may subsequently influence individual employment, financial standing, and medical costs, explained in part by the elevated chance of absenteeism, medical expenses due to obesity-related disorders, or employment discrimination [15-18]. This complex two-way interaction between weight and economic status can likely give rise to unexpected, emergent macroeconomic outcomes [15]. In order to understand the impact of macro-level economic improvement on obesity trends, there is a need to account for the potential bi-directional relationships between economics and obesity.

Evidence from previous studies is based on static data with limited information on the intertwined dynamics between obesity and SES distributions over time [1]. Even with some studies using time series across countries [1, 2], the underlying transitions across SES and weight status remained unknown. Systems science modeling has the capability of capturing the dynamic relationships between economic factors, such as income and unemployment, and obesity. In so doing, we can test potential economic intervention strategies in silico and explore their impacts on obesity [19-21]. Even though systems modeling has been applied to address different issues related to the obesity epidemics [22], there has been no study using the approach to test the potential of macro-level economic interventions on obesity prevention and control.

The present study aimed to apply the system dynamics modeling (SDM) approach to: a) understand the dynamics and interplay between obesity and SES distributions at the population-level based on empirical U.S. national data from the Medical Expenditure Panel Survey (MEPS, 2001-2011), b) explore how the future weight status distribution in the U.S. would be affected by changing the population's SES distributions through employment- or income-based strategy; and, c) provide conceptual and methodological insights in future obesity research using systems models.

METHODS

Study design

This is a theoretical experiment including an ecological study of distributional changes in population's weight and SES (employment status and family income level) over time, and a system dynamics simulation to explore impact of changing the population's SES on obesity trends. Figure 1 demonstrates the conceptual framework, which was designed to capture the reciprocal interactions between weight status and SES at the population level. We modeled the distributions of weight and SES ("stock", i.e. percent in each weight and SES state) and the transitions ("flow") between these states over time. There are three subsystems in the model namely, population-level transitions of weight status, employment status, and family income levels (Supplemental Figure S1).

Target population and dataset

Using the 2001-2011 Medical Expenditure Panel Survey (MEPS) longitudinal panel data (from panel 6 to panel 15), we estimated the annual transition rates and examined the relationships between the stocks and flows among the three subsystems. MEPS is an ongoing nationally representative survey of families and individuals in the U.S., based on a multistage, stratified, and clustered sampling design. A new panel starts every year, which is followed up for two years. There are five rounds of household interviews during the two years, collecting individual information such as employment status, health insurance coverage, health care utilization, and health status [23]. Participants' self-reported body weight and height are obtained at the end of each year over the two-year cycle, allowing us to estimate annual transition rates between weight status/family income/employment states. There were 159,386 subjects in all the 10 longitudinal panels, aged 0 to 85 years. Our final analysis included 21-65 years old adults (n=88,453).

SDM setup and parameterization

The model was set up in three steps: (1) Computing the population distributions of weight status/SES (i.e. states) and the annual transition probabilities (i.e. flow rates) between the states; (2) Fitting statistical model to estimate functional relationships between population-level predictors and the transition probabilities; and (3) developing the SDM based on the relationships and parameters estimated from empirical MEPS data in step (2).

Stock-and-flow diagram was built to characterize the three subsystems namely, weight status, employment status, and family income levels:

a) Weight status was defined using the WHO definition: (1) Normal/underweight, BMI<25 kg/m^2; (2) overweight, 25≤BMI<30 kg/m^2; and (3) obese, BMI≥30 kg/m^2. BMI was calculated based on self-reported height and weight.

b) Family income: (1) Higher income: family income ≥400% of federal poverty line; (2) middle income, adjusted income between 200% and 399% of federal poverty line; and (3) lower income: <200% of federal poverty line.

c) Employment status: (1) Employed, (2) not in labor force (those reporting never worked or have retired and currently have no job), and (3) unemployed (those who had worked before but is currently unemployed with no job to return to.)

Based on MEPS data, the crude flow rates across the weight status, employment status, and family income levels were calculated for each year (Supplemental Table s1), accounting for sampling weights to produce nationally representative estimates. Note that we used "flow rate" and "flow" to mean two different quantities. Flow rate is a probability of status change from one state to another, and flow is the proportion of the whole population going through that change. Meanwhile, proportion of a state at time t is the integration of the net flow to the state from the start to time t. Supplemental Table s2 presents the SES and weight status distributions in every year.

Guided by statistical techniques including stepwise selection, we modeled the flow rates as functions of a set of variables as described in Supplemental Table S3, which lists the equations and parameters used for building the SDM, and the equations with statistically significant predictors are shown as the dashed arrows in Supplemental Figure S1. Flow rates are derived from antilogit transformation of the equation. Hence, the flow rate equation without significant predictors has a steady flow rate: the antilogit of the intercept. Year and external factors such as GDP were not modeled because we aimed to build a self-sufficient model that did not rely on any exogenous input to generate the trends. The statistical analyses were performed using SAS version 9.2 (SAS Institute Inc., Cary, NC).

Simulation experiments of SES-targeted intervention options

The feedbacks and interactions between weight and SES distributions were presented in a SDM using Vensim ® PLE plus version 6.3. The initial body weight and SES distributions were configured based on the 2001 MEPS data. We performed four sets of simulation experiments:

(1) The status quo: Using the parameters estimated from MEPS, we projected the distribution and the state transitions from 2001 to 2051, assuming past trends and dynamics would continue.

(2) Experiment 1: Affecting unemployed population's annual rate to be employed ("reemployment rate") by ±20% or ±40%, starting in 2001.

(3) Experiment 2: Affecting the flow rates from lower to middle income by ±20% or ±40%, starting in 2001.

(4) Experiment 3: Combining Experiments 1 and 2, i.e., simultaneously enhancing reemployment rate and improving flow rate from lower income to middle income.

RESULTS

The system dynamics model

Based on the MEPS data, we found the SDM to be generally comparable to our conceptual framework. The population weight status transitions were described by the population distribution of income and employment status. Supplemental Table S3 summarizes the statistical models based on MEPS data, which were integrated into a SDM as shown in Supplemental Figure S1. Faster transitions between overweight and obese statuses (both directions) were associated with the proportion of middle income adults in the previous year. A greater transition from obese to normal weight status was associated with a higher proportion of unemployed adults in the previous year. With regard to transitions between employment statuses, the more normal weight people in a population, the lower proportion of people experiencing transition from employed to unemployed status. However, contrary to the conceptual framework, income distribution was not determined by employment status.

Findings from the status quo simulation

Figure 2 shows that our SDM of the three subsystems was able to reproduce the historical trends in overweight/obesity. If the trends continued, the projected prevalence of overweight plus obesity would reach 78.5% by 2051. To calibrate the SDM, we compared the simulation-predicted prevalence of overweight and obesity to the annual prevalence of overweight and obesity from the Behavioral Risk Factors Surveillance System (BRFSS), 2001-2013. Simulated data were highly correlated with observations in the BRFSS (R^2=0.95; Supplemental Figure S3). The 95% confidence interval based on 1000 times of simulations of predicted trend of overweight/obesity prevalence was narrow (Supplemental Figure S4).

Simulation Experiments

Since employment status distribution in the model was influenced by the weight status distribution, we explored changes in the trend of overweight and obesity by changing the reemployment rate. As Figure 3A shows, increasing the reemployment rate by 20% every year, the trend in the prevalence of overweight/obesity would rise faster than the status quo simulation, and the projected prevalence reached 81.8% at 2051 (Table 1). When the reemployment rate was decreased by 20% and 40%, the prevalence of overweight/obesity in 2051 would be lowered by 4.8% and 12.5% compared to status quo simulation, although the prevalence of employment rate in 2051 was similar in the three experimental setups.

The model showed that the proportion of middle income in the population would influence the flow rates between overweight and obese statuses, and might inhibit the flow rate from overweight to normal weight. By increasing the flow rate from lower to middle income group by 20% and 40% every year, as Figure 3B shows, the prevalence of overweight/obesity in 2051 were 14.4% and 16.6% lower than the status quo simulation.

The final experiment tested whether income distribution shift would mitigate the increase in obesity-promotion from increasing employment. As Table 1 shows, when reemployment rate increased by 20%, the projected prevalence of overweight/obesity in 2051 could be attenuated by higher income improvement rates.

DISCUSSION

Based on empirical U.S. national data, we built an SDM to delineate the interactions between population SES and weight status distributions, and to explore the possible changes in weight status distribution by shifting the population SES distribution. MEPS data suggested that both distribution of employment and income status would influence weight status transition, while changes in both SES distribution did not affect each other. The model performed well in reproducing historical trends in the prevalence of overweight and obesity. The SDM-based simulations suggested that enhancing reemployment among the unemployed might contribute to higher obesity prevalence if income distribution was not improved along with the increased reemployment rate. Nevertheless, none of these interventions was able to reduce obesity rate to the level of the 1970s. This suggests that SES redistribution alone is not sufficient to offset the macro-level societal and economic forces that were built up in the past decades and have been driving the obesity epidemic.

Our model showed an "effect" of reemployment on obesity: reducing unemployment would lead to an increase in the prevalence of overweight/obesity. This is in line with findings from macroeconomic research, probably because of the decrease in non-market "leisure" time [6, 24]. Moreover, stressful working environments and constrained personal time may contribute to a more obesogenic lifestyle and obesity risk at the individual level [25-28]. Our model shows that prevalence of obesity would rise faster if the flow rate from unemployed to employed status increases. Interestingly, this "adverse effect" of the increased reemployment rate on obesity prevalence would be mitigated by increasing the population flow from low to middle income level. That is, improving employment rate solely may not effectively curb the rising prevalence of obesity in the future.

The SDM model suggests that improving more people from lower- to middle income groups might be followed by a lowered rise in prevalence of overweight/obesity, but identifying the right policy tool requires consideration of many other factors. Despite the inverse association between income/wage and odds of obesity in the general population [7, 8, 14, 29, 30], income interventions like direct cash transfer showed some unexpected consequences. Children of lower-income families gained more weight after the family received the governmental cash transfer, compared to children of higher-income families [31]. Receiving income assistance was also associated with adult obesity in the U.S. and other countries [32-34]. Other approaches like tax credit interventions were associated with an increased consumption of food away from home or energy-dense food [35]. These unintended obesity risks suggest the need to address other contextual and environmental factors in addition to direct and unconditional financial subsidy to needy populations [36]. Thus, caution is needed in interpreting the simulated benefit of obesity control by improving people's income level.

One interesting observation in the present study relates to the dynamic of job stability and/or security. The status quo simulation shows rising trends in inflow and outflow of the employment pool (Supplemental Figure S2; black lines), which co-occurred with the soaring prevalence of overweight and obesity. Stress and anxiety are higher under conditions of low job security or stability [37, 38], which are associated with unhealthy diets, physical inactivity, and obesity [39-42]. However, moving more people from lower to middle income can attenuate this instability in the transitions of employment status (Supplemental Figure S2; grey lines). As income distribution in the model did not directly affect any flow rate in the employment status distribution, the higher proportion of the middle-income group might lead to greater job stability via lowering prevalence of overweight and obesity, i.e., via supporting a healthier and more productive population. This is a hypothesis that arose from the systems modeling, which warrants further research to tease out the direction of relationship between a volatile job market and the prevalence of obesity.

Some limitations of this study should be noted. First, as in all forecast and simulation studies, the model relies on assumptions that the observed past dynamics and interactions would continue. Since the statistical part of the current study did not control for demographic structure and other macroeconomic factors, the estimated population transition and socioeconomic trends during 2001-2011 were implicitly absorbed in the estimated equations and parameters. Second, our model was built on a data-driven procedure, and therefore was subject to the idiosyncratic structure of the data (i.e., MEPS 2001-2011). However, the procedure allows data to speak for themselves instead of imposing more detail theory-based assumptions. Furthermore, the model assumed that the parameters would not change over the simulated years 2001-2051. Findings from our SDM simulation could be further validated using more years of future MEPS data when they become available. The MEPS is a well-conducted nationally representative survey; any data peculiarity due to sampling should be minimal. Third, body weight status was based on self-reported weight and height in the MEPS. The projected trend in obesity could be lower than those based on measured data [43, 44]. Nevertheless, compared to the BRFSS, another national survey based on self-report weight and height, our simulated prevalence of overweight and obesity was about 3% higher. In addition, BMI may not a good indicator for obesity. It has been shown that body fat percentage or waist circumference might better predict adults' wage and employment status [18]. Fourth, employment status was also based on self-reports in MEPS, and the unemployment trend based on MEPS data did not show a drastic rise during 2008-2010. However, if the proportions of unemployed and of people no longer looking for a job were counted together, the combined prevalence would show an increase during the recession years. During recession, people may lose a job or retire early. To reflect the U.S. job dynamics during recession, it would be better to look at the sum of those who were unemployed and those who were no longer searching for a job. Finally, this study was based on an ecological study design. The individual level transitions of weight status and SES were not assessed.

Despite these limitations, this study has major strengths. We used individual-level longitudinal data from a continuous U.S. national survey. Other repeated cross-sectional surveys such as the National Health and Nutrition Examination Surveys and the BRFSS only show the overall distribution shifts but cannot determine the flow directions (flows between states) and flow rates. In addition, we built a self-sufficient and parsimonious systems model without assuming any exogenous input. This model generated obesity and overweight trends that approximated the historical data based on the relationships among the three stock-and-flow subsystems of weight status and SES distributions.

In conclusion, our SDM simulation experiments suggest that solely increasing job opportunities may not be effective in reversing the obesity epidemics. Rather, moving people from low to middle income levels may be more effective in curbing the rising obesity trend in the U.S. adult population. Reemployment must be accompanied with decent income to mitigate the rising prevalence of obesity in the U.S. In addition, other obesogenic environment may need to be taken into account for effective reduction of obesity prevalence.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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HIGHLIGHTS

- Economic growths and downturns were paradoxically both associated with higher prevalence of obesity.
- We built a system dynamics model based on the observed relationships between economic indicators and dynamics of obesity incidence and remission rates.
- Improving income distribution may also curb the obesity rise in the US population.

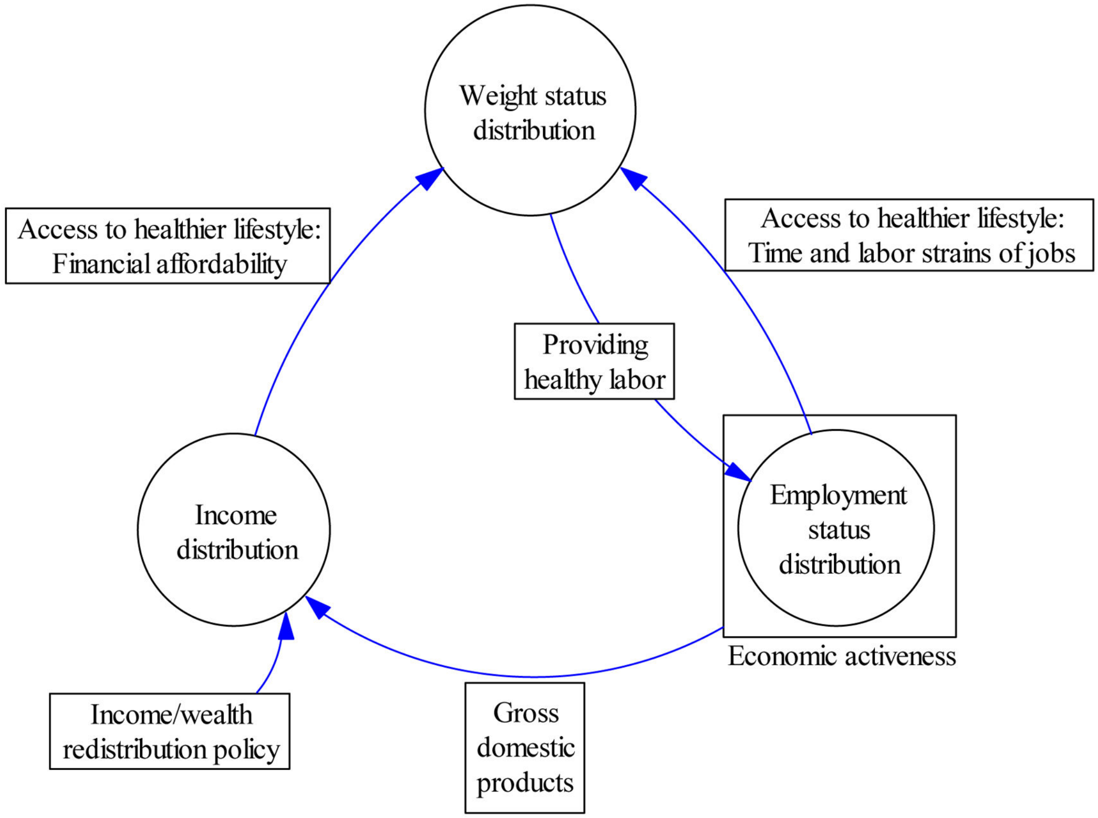


Figure 1.
Conceptual framework of the interplays between weight status, employment status, and income distribution at the population level

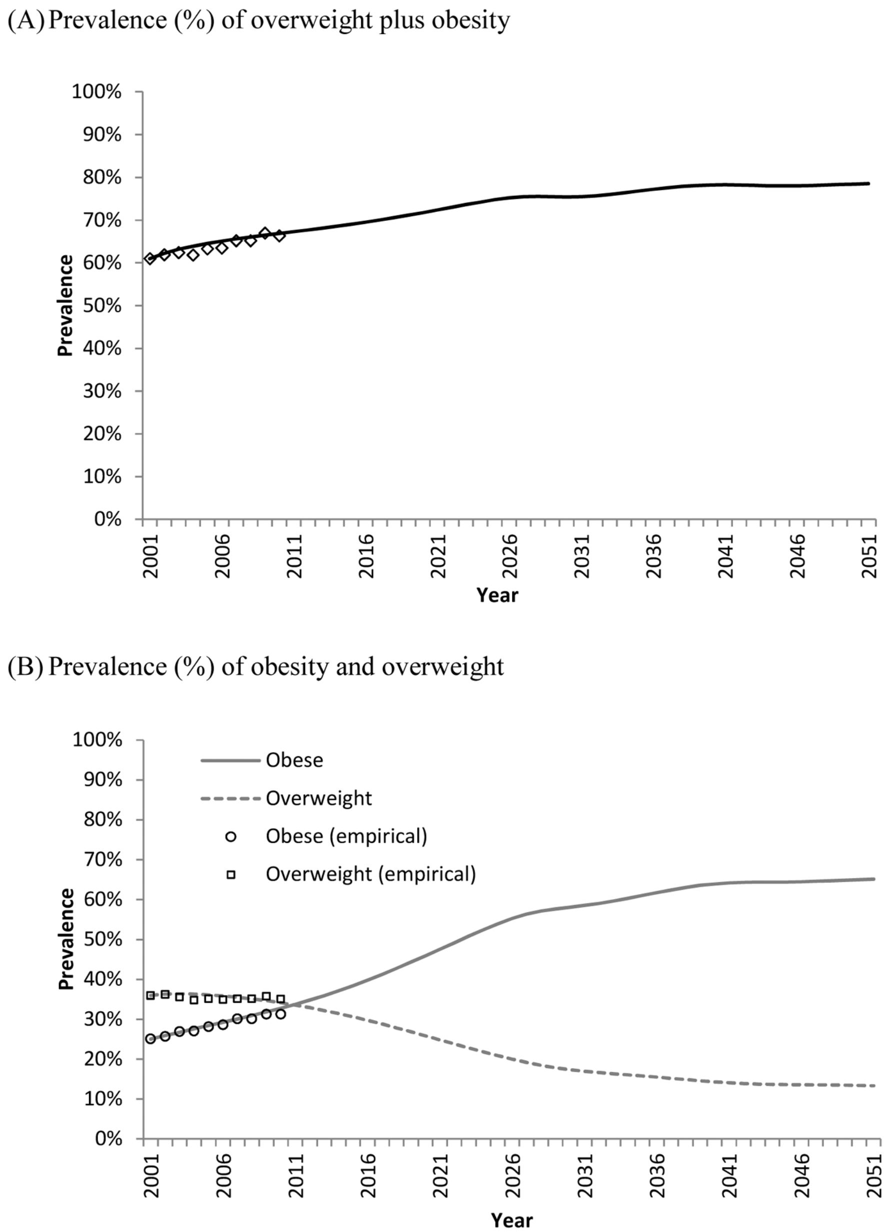
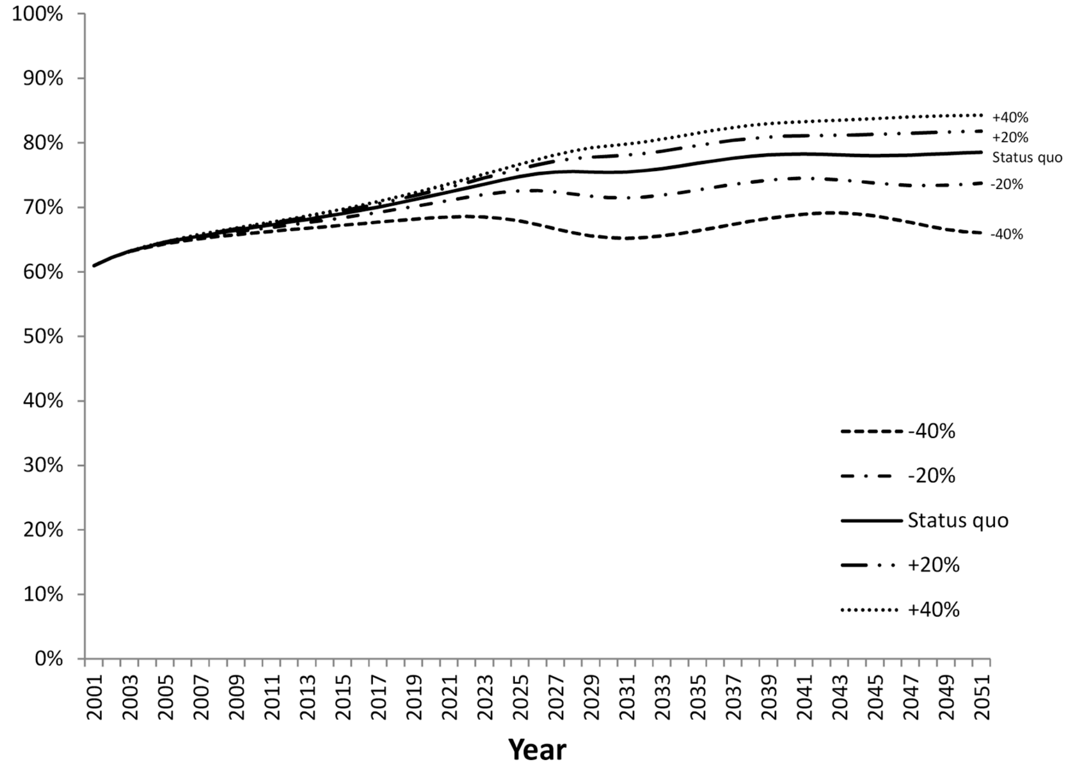


Figure 2.

Status quo: Projections of future trends for body weight status and SES distribution among U.S. adults,2001-2051^

^Solid lines: simulated trends based on the SDM; symbol data points: observations in the Medical Expenditure Panel Survey (MEPS) 2001-2009 data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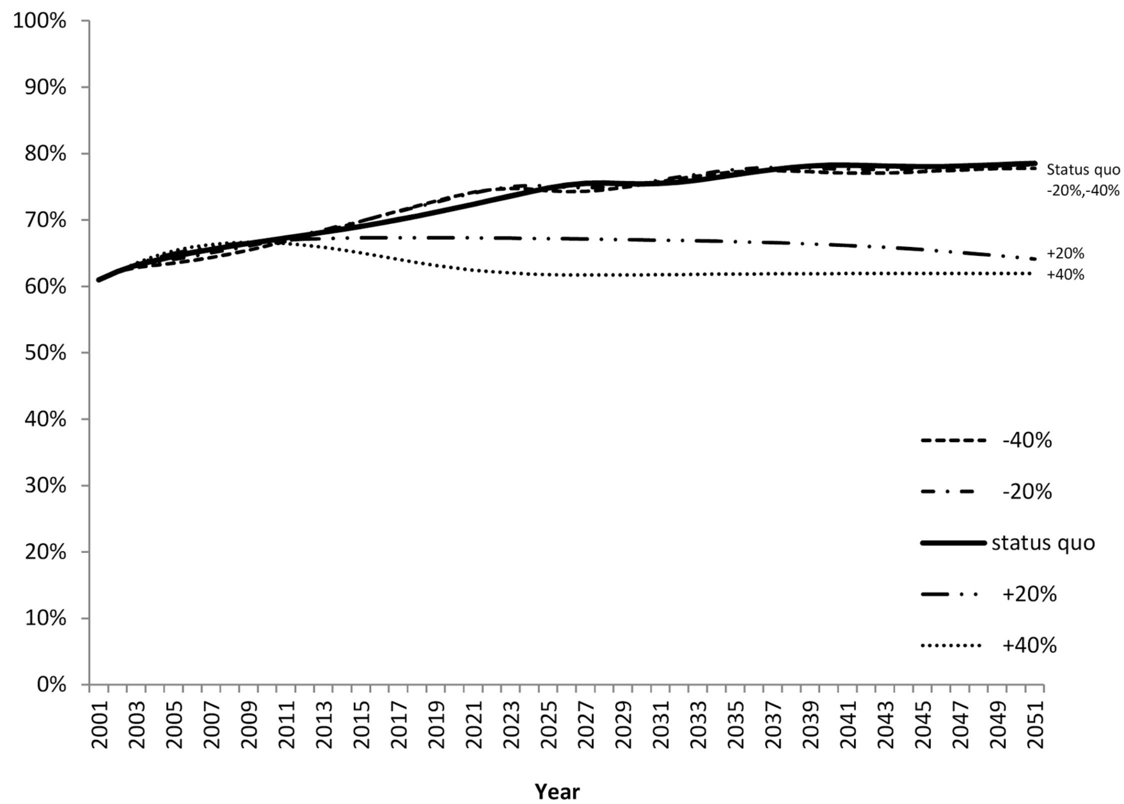
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-40%
-20%
status quo
+20%
+40%

Figure 3.

Simulation of perturbations to the socioeconomic distribution and the projected prevalence (%) of overweight and obesity in U.S. adults

(A) by affecting flow rate from unemployed to employed

(B) by affecting flow rate from lower income to middle income

Table 1.

Projected prevalence of overweight/obesity, employment status, and people in middle income household by years.

	Overweight/obesity (%)						Employed population (%)						Middle income (%)					
Simulation experiment setups	**2001**	**2011**	**2021**	**2031**	**2041**	**2051**	**2001**	**2011**	**2021**	**2031**	**2041**	**2051**	**2001**	**2011**	**2021**	**2031**	**2041**	**2051**
Status quo	61.0%	67.3%	72.4%	75.5%	78.3%	78.5%	82.1%	83.7%	79.7%	78.4%	77.6%	77.9%	31.5%	29.5%	29.5%	29.5%	29.5%	29.5%
Reemployment rate +20%	61.0%	67.5%	73.1%	78.1%	81.1%	81.8%	82.1%	84.6%	80.5%	78.3%	77.6%	77.7%	31.5%	29.5%	29.5%	29.5%	29.5%	29.5%
Reemployment rate +40%	61.0%	67.7%	73.6%	79.8%	83.3%	84.3%	82.1%	85.3%	81.1%	78.2%	77.7%	77.6%	31.5%	29.5%	29.5%	29.5%	29.5%	29.5%
Reemployment rate −20%	61.0%	66.9%	71.1%	71.5%	74.5%	73.7%	82.1%	82.7%	79.0%	78.6%	77.8%	78.4%	31.5%	29.5%	29.5%	29.5%	29.5%	29.5%
Reemployment rate −40%	61.0%	66.3%	68.5%	65.2%	68.9%	66.1%	82.1%	81.5%	78.3%	79.1%	78.3%	78.9%	31.5%	29.5%	29.5%	29.5%	29.5%	29.5%
Low to middle income improvement rate +20%	61.0%	67.0%	67.3%	67.0%	66.2%	64.1%	82.1%	84.9%	84.8%	84.9%	85.5%	86.5%	31.5%	30.9%	30.9%	30.9%	30.9%	30.9%
Low to middle income improvement rate +40%	61.0%	66.5%	62.5%	61.8%	61.9%	61.9%	82.1%	86.1%	87.0%	87.9%	88.1%	88.1%	31.5%	32.1%	32.0%	32.0%	32.0%	32.0%
Low to middle income improvement rate −20%	61.0%	67.2%	74.0%	76.0%	77.6%	78.3%	82.1%	83.0%	78.1%	78.8%	77.9%	77.9%	31.5%	27.8%	27.8%	27.8%	27.8%	27.8%
Low to middle income improvement rate −40%	61.0%	66.8%	74.2%	75.8%	77.1%	77.8%	82.1%	82.7%	77.7%	78.8%	78.1%	78.0%	31.5%	25.6%	25.6%	25.6%	25.6%	25.6%
Reemployment rate +20%, low to middle income improvement rate −10%	61.0%	67.6%	74.3%	78.5%	81.0%	81.7%	82.1%	84.2%	79.4%	78.6%	77.8%	77.7%	31.5%	28.7%	28.7%	28.7%	28.7%	28.7%
Reemployment rate +20%, low to middle income improvement rate +10%	61.0%	67.4%	71.1%	77.4%	80.5%	81.7%	82.1%	85.1%	82.3%	77.6%	77.9%	77.8%	31.5%	30.3%	30.3%	30.3%	30.3%	30.3%
Reemployment rate +20%, low to middle income	61.0%	67.2%	67.8%	68.1%	69.2%	72.7%	82.1%	85.8%	85.6%	85.3%	84.3%	81.4%	31.5%	30.9%	30.9%	30.9%	30.9%	30.9%

	Overweight/obesity (%)						Employed population (%)						Middle income (%)					
Simulation experiment setups	**2001**	**2011**	**2021**	**2031**	**2041**	**2051**	**2001**	**2011**	**2021**	**2031**	**2041**	**2051**	**2001**	**2011**	**2021**	**2031**	**2041**	**2051**
improvement rate +20%																		
Reemployment rate +40%, low to middle income improvement rate +20%	61.0%	67.4%	68.2%	69.0%	71.7%	78.1%	82.1%	86.5%	86.3%	85.6%	83.3%	78.4%	31.5%	30.9%	30.9%	30.9%	30.9%	30.9%

*2001 is the base setup year of the model so the values are the same for all experiment setups.