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# A Complex Systems Approach to Understanding and Combating the Obesity Epidemic

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*Abstract*: The obesity epidemic represents a major and rapidly growing public health challenge, in the United States, and worldwide. The scope and scale of the obesity epidemic highlight the urgent need for well-crafted policy interventions to prevent further spread and (potentially) to reverse the tide. Yet several characteristics make obesity an especially challenging problem both to study, and to combat. I show that these challenges—the great breadth in levels of scale involved, the substantial diversity of relevant actors, and the multiplicity of mechanisms implicated—are characteristic of *complex adaptive systems*. I argue that the obesity epidemic represents such a system, and that both general lessons and techniques from the field of complexity science can help inform effective policy to combat obesity. In particular, I argue that the technique of agent-based computational modeling is especially well suited to the study of the rich and complex dynamics of obesity.

KEYWORDS: Obesity, Policy Modeling, Complex Adaptive Systems, Agent-Based Modeling, Complexity

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The obesity epidemic represents a major and rapidly growing public health challenge, in the United States, and worldwide. Between 1970 and 2000, for example, the percentage of Americans classified as obese doubled to almost 30% (Bray, Bouchard and James 2003), with fully two-thirds of American now classified as overweight (Ogden 2006). The problem of obesity is not limited to the American context—similar epidemics of obesity are underway across the globe, from Europe to South America to the Middle East and Asia (see, for example, Rennie & Jebb 2005; Cameron et al. 2003; Yumuk 2005; Mohammedpour-Ahranjania et al. 2004; Kain et al. 2002; and Albala et al. 2002). Overall, nearly half a billion worldwide were overweight or obese in 2002 (Rossner 2002).

These sharp increases in obesity rates have significant implications for public health, since obesity is linked with diabetes, high blood pressure, and high cholesterol (NHLBI 1998). In addition to higher mortality/morbidity, obesity increases health care costs dramatically (Finkelstein et al. 2005)—some estimates suggest that obesity-related medical expenses accounted for as much as 9% of total U.S. medical expenditures in 1998 (or roughly $78.5 billion), a proportion that is expected to increase (Finkelstein, Fiebelkorn, and Wang 2003).

Obesity in children, strongly linked to obesity in adulthood, is also increasing at an alarming rate (Rossner 2002; Dietz 2004). In addition to immediate obesity-related health risks in children (Dietz 2004), childhood obesity rates suggest the potential for even larger increases in adult obesity in the future unless the epidemic is contained.

In the words of one researcher, obesity is “the gravest and most poorly controlled public health threat of our time” (Katz 2005). The scope and scale of the obesity epidemic highlight the urgent need for well-crafted policy interventions to prevent further spread and (potentially) reverse the tide. Yet several characteristics make obesity an especially challenging problem to study, and to design interventions to combat. The first of these is the huge range in the levels of scale involved (Fig. 1)—from genes to social systems to environment—forming a “hierarchy” of levels (also see Glass & McAtee 2006).

[FIGURE 1 ABOUT HERE]

Another, related challenge is the diversity of actors who have impact on individual energy balance (and thus on obesity). A partial list includes: consumers, the food industry, families, schools, retailers, government agencies, policymakers, trade associations, NGOs, public health agencies, the media, and healthcare providers. Each of these actors has different goals, motivations, modes of decision-making, and forms of connection to other actors and levels above and below them in the hierarchy of levels. Policy shifts or other interventions will affect each differently, and each has a different sphere of potential influence as an agent of change. Without taking into account the diversity of these actors, policies cannot leverage potential synergies, and run the risk that successful interventions in one area may be counteracted by responses elsewhere in the system. Policies that do not take into account the full set of actors and their responses can even backfire dramatically[1].

[1] A particularly good illustration of this general point can be found in the case of the Lake Victoria environmental catastrophe (Murray 1989, Fuggle 2001). In 1960, a non-native species of fish (the Nile perch) was introduced into Lake Victoria. The policy goal was to provide a new a valuable source of

A third challenge is the number of mechanisms, or moving pieces, implicated in the obesity epidemic. For example, a wealth of evidence documents the roles of: prices (Finkelstein et al 2005; Drewnowski & Darmon 2005; Cutler et al 2003), social networks (Christakis 2007), genetics (Stunkard et al. 1986; Keller et al 2003), neurobiology (Killgore et al. 2003, Broberger 2005, Tschop et al. 2000, Schwartz & Morton 2002), environment (Booth et al. 2005; Papas et al. 2007), and norms (Powell & Kahn 1999; Kemper 1994; Graham & Felton 2005; Parker et al. 1995; Lovejoy 2001; Rand & Kuldau 1990; Kumanyika 1993; Fitzgibbon et al. 2000; Patrick & Nicklas 2005). But the *linkages and feedback between these mechanisms* are not well studied or well understood. Furthermore, no single explanation seems to account for all that we know about the obesity epidemic. For example, prices provide a compelling explanation of the overall upward trend in obesity incidence (Fig. 2), but may not be able to account for the important disparities in incidence by socio-demographic groups (Fig. 3) (also see Burke & Heiland 2006), or explain why obesity appears to move through social networks (Christakis 2007). Neurobiology and genetics help explain the resilience of obesity at both the social and individual level, but have difficulty explaining the timing and speed of the epidemic, or its spatial clustering. Environmental explanations capture much of the spatial variability in obesity incidence, but cannot explain its spread across longer distances through networks or variation within spatially coherent demographic groups.

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protein, and improve the health of the communities of people surrounding the lake in Kenya, Tanzania, and Uganda. But the policy did not take into account the other actors in the system—specifically, the other organisms and ecosystems of the lake. The introduction of the perch set off a chain reaction in these ecosystems. The perch wiped out the native cichlid species of fish, which were crucial in controlling a species of snail living in the lake, and the snails flourished. Unfortunately, these snails are hosts to the larvae of Schistosomes, which cause the disease of bilharzia in humans—a disease which is always fatal if not treated promptly—and the Schistosomes also flourished. Thus, the original policy goal (improving the health of the surrounding communities of humans) backfired because the reaction of another set of actors in the system was not anticipated. Efforts to reduce obesity might face similar difficulties if systemic diversity is not factored into policy design.

[FIGURE 2 ABOUT HERE] [FIGURE 3 ABOUT HERE]

In sum, the obesity epidemic results from a system with diverse sets of actors, who are at many different levels of scale, and who have differing individual motivations and priorities. This system has many moving parts, which interact in complicated ways to produce rich variation in outcomes that cannot be reduced to a single mechanism. Taken together, these features are classic characteristics of a *complex adaptive system* (CAS). Indeed, organisms, societies, economies, and public health systems in general are complex adaptive systems, and valuable insights about how to manage them can be gained from the relatively new, interdisciplinary field of complexity science.

## Complex Adaptive Systems

A *complex adaptive system* is a system composed of many diverse pieces, interacting with each other in subtle or nonlinear ways that strongly influence the overall behavior of the system. Complex adaptive systems, sharing many general properties, occur in fields of study as diverse as economics, political science, sociology, anthropology, physics, public policy, biology, geology, computer science, and business. The general properties of such systems include:

- *Agent-based*: Complex systems often contain many levels of hierarchy, but are usually driven from the "bottom up", through decentralized, local interaction of constituent parts. Each level is made up of autonomous individual actors who adapt their behavior (based on observations of the system as a whole or of others around them), through mechanisms such as learning, imitation, or evolution.

● *Heterogeneity*: Substantial diversity among actors at each level of hierarchy may play an important role in the rich dynamics of the system. Actors have separate and possibly diverse goals, rules, adaptive repertoire, and so on.

● *Interdependence*: Complex systems usually consist of many interdependent interacting pieces, connected across different levels. There is often feedback between the different levels of the system, as well as substantial nonlinearity resulting from interconnectedness of actors at each level.

● *Rarely in equilibrium*: Complex systems are generally very dynamic, and spend little time in any long-run equilibrium. Dynamics "far from equilibrium" are important. The particular order in which events occur may strongly affect the subsequent direction of the system (a characteristic often known as "path dependence").

● *Emergence & Tipping*: Complex systems are often characterized by emergent, unexpected phenomena—patterns of collective behavior that form in the system often cannot be foreseen from separate understanding of each individual element. The sum, in other words, can be greater than the parts. Such emergent features may be "self-organized" (occurring from the bottom-up with no centralized direction). Complex systems are also often characterized by "tipping" behavior at system level.

> Nonlinearity means that the impacts caused by small changes can seem hugely out of proportion. The system may spend long periods of time in a relatively stable state, yet be easily “tipped’ to another stable state by a disturbance that pushes it across a threshold

Prediction is particularly difficult in complex systems because there are multiple forces shaping the future, and their effects do not aggregate simply. Nonlinear interactions among pieces of the system mean that a coincidence of several small events can generate a large systemic effect. Yet, even in the face of substantial uncertainty about the future, insight regarding the right *questions* can prove valuable for decision-making (see Axelrod & Cohen 1999). The field of complexity can help to guide research identifying what types of situations will be most amenable to policy intervention, and where leverage may best be applied for any particular policy goal.

## Applying a Complex Systems view to Obesity

Complexity can be a source of concern for policymakers, because it creates uncertainty and can make the interconnected dynamics of societies and economies difficult to understand or uncover. It can be hard to know where to begin intervening, or how different approaches may be linked.

But complexity can also be an opportunity, because it provides possibilities for creating large-scale changes with relatively small, focused policies. Although it is often difficult to predict their behavior, complex systems do have significant structure and organization, and can be managed or directed through careful intervention. The study of complex adaptive systems in a unified framework is emerging as a relatively new, interdisciplinary scientific field. Using novel tools, the field offers important insights about how to manage complex systems.

Several general lessons from the study of complex systems are especially applicable to the study of energy balance and the design of strategies to prevent or reverse the obesity epidemic:

### *Bottom-up approaches*

As described above, the dynamics of most complex adaptive systems are driven "from the bottom up", by individual actors throughout the system. The individual is a natural initial focus in studying obesity—the core concern is, after all, individual energy balance. The scope of systems implicated in the obesity epidemic is much broader, however—markets, societies, governments, and food chains all play a role. Yet each of these is itself also a complex system, driven by decision-making of relevant *individual* actors (firms, policymakers, family members, etc.).

This focus on individually-driven dynamics leads to a first major lesson from complexity science: *decentralized* solutions to policy can sometimes be most effective, even if traditional policy tools are macro ones. "Bottom-up" dynamics may respond most readily to "bottom-up" interventions. Of course, exploring which combinations of national, regional, or local policies might provide the most effective decentralized interventions is a challenge. The link between the macro world of policy space and the micro level of individual incentives and decision-making is usually not a transparent or simple one. Fortunately, tools and techniques from complexity can help elucidate these links. In particular, *agent-based computational models* (described in detail below) mirror the bottom-up structure of complex systems, and can provide valuable "laboratories" for studying decentralized dynamics and discovering novel policy approaches.

*Diversity Matters*

Complexity research also highlights the importance of *diversity* (see especially Page, 2007). Complex systems often involve a diversity of types of actors (as in the case of obesity)—with different goals and decision-making for each type. There may also be substantial diversity *among* actors of any given type, in socio-demographics, age, gender, experience, network structure, genetics, and so on. These within-type differences can affect individuals' decision-making in important ways as well. Diversity is therefore a major challenge for policy, since no one solution or intervention necessarily fits all circumstances or affects all decision-makers similarly. Diversity *can* also be an opportunity, since it allows for rich adaptation and "tipping" (see *Tipping Points* below). But the design of policy interventions must take diversity into account, or they may be ineffective or even counterproductive. For example, a recent model of adolescent smoking and public health messages (Axtell et al. 2006) showed how the distribution of psychological "reactance" responses in networks could have a strong impact on the most effective kind of policy message—a message that worked well in some groups proved counterproductive in others.

*Tipping Points*

Nonlinearity and feedback in complex systems mean that small changes at either the micro or macro level can have large effects on the system. Marginal shifts can be enough to "tip" an entire system from one relatively stable outcome to another. This has important implications for policy-making in a complex world. It means that policies which have not taken complexity into account may have unanticipated consequences. But it also means that, if properly targeted, very small changes in policy can have a very large impact. Local changes can yield global effects. For example, my own work on the dynamics of bureaucratic corruption showed how small changes in enforcement could lead to widespread reduction of corrupt behavior, "tipping" society from high to low levels of corruption by focusing on the kinds of information used in individual decision-making and by making use of networks of social communication (Hammond 1999).

Complexity science shows us, then, that the most effective role for policy may be a suite of small, targeted interventions that "tip" systems, rather than large ones that attempt to restructure or reshape them.

### *Designing Interventions*

A central theme in the general lessons described above is that *unless we recognize and understand the complexity of a system*, interventions may have unanticipated (and sometimes unwanted) consequences. The best policies for any particular goal may be subtle and unconventional ones. Complex systems techniques can help uncover the intricate dynamics of economic, social, and biological systems, and inform effective policy intervention. *Agent-based computational modeling* is one such technique.

## Agent-Based Computational Modeling

In order to study the rich dynamics of complex systems, the methodology of *agent-based computational modeling* (ABM) is often used. This is a powerful and relatively new approach in which complex dynamics are modeled by constructing "artificial societies" on computers. In an ABM, every individual actor (or "agent") in the system is explicitly represented in computer code. These agents are placed in a spatial context with specified starting conditions, and given a set of adaptive rules for interaction with each other and with their environment. The agents' decision processes and their interactions produce the output for agents themselves and for the systems as a whole. In this way, the computer simulation "grows" macro-level patterns and trends from the bottom up (see Epstein 2006).

While maintaining a high degree of analytical rigor, agent-based models offer several particular advantages for modeling complex systems, such as the obesity epidemic. First, they allow for substantial diversity among agents—no "representative agents", homogeneous pools, or other forms of aggregation are required because every individual is explicitly modeled. This means ABMs can easily capture and incorporate diversity in the types of actors in a system, as well as any relevant heterogeneity within types (in socio-demographics, networks, location, goals, decision-making, psychology, physiology, genetics, culture, and so on). As discussed above, taking diversity into account is often critical in designing successful interventions in complex systems.

The agent-based approach also allows for much more flexible cognitive assumptions about individual decision-making and information processing than do many standard forms of modeling—agents in simulation models are not required to be "hyper-rational" or "optimizing", but merely goal oriented in the context of limited and changing information. This kind of "bounded rationality" is often more plausible for modeling real-world decision-making (Simon 1982), and is an important source of diversity as well.

In addition, agent-based models can incorporate feedback dynamics and explicit spatial contexts that can be difficult to capture with mathematical formalism. At the individual level, for example, they can model multiple interdependent sources of influence on health outcome. At the aggregate level, they can model the interaction of actors and environments across multiple levels of analysis—agents can be implemented at multiple levels of scale simultaneously. ABMs can include explicit representations of geography, from GIS data, for example (see Axtell et al. 2002), as well as detailed social network structures. Explicit space is often hard to include in standard analytic models (see Page 1999).

A particular advantage of the ABM approach for studying complex adaptive systems is its focus on mechanisms, and ability to study non-equilibrium dynamics. Since complex systems are rarely in equilibrium (see above), and are often susceptible to dramatic "tipping", this flexibility is especially important. Because of its focus on mechanisms, ABM allows adaptation (evolution, learning, imitation) to be modeled explicitly, and "emergent" social level phenomena to be uncovered.

Finally, agent-based models are especially useful as a "computational laboratory" for policy. With an ABM, research can systematically explore the potentially complex impacts of each item on the existing menu of policy interventions, and can even uncover new ones—as discussed above, the best policies may be subtle and unconventional. Recent computing advances, in fact, allow researchers using agent-based models to search the entire space of possible combinations of interventions to find novel "policy cocktails" that best exploit potential synergies between policies[2].

Agent-based models have been used to study a wide variety of topics in social science and public health, including: cooperation, coordination, and conflict (Axelrod 1984, Epstein 2002, Cederman 2003); prejudice (Hammond & Axelrod 2006); social norms (Axelrod 1986, Macy & Willer 2002, Centola et al. 2005, Hammond & Epstein 2007); archaeology (Axtell et al. 2002); epidemiology (Longini et al 2005, Ferguson et al 2006, Epstein et al 2007); cancer research (Axelrod et al 2006); firm organization, economics, and business strategy (Axelrod & Cohen 2000, Tesfatsion & Judd 2006); and markets (Macy & Sato 2002, Kirman & Vriend 2001). ABMs have been able to provide important policy guidance in several instances. Recently, for example, work using agent-based modeling was able to help the US government understand the potential impact of travel restriction policies on the pattern of global epidemics (Epstein et al 2007), and various vaccination strategies for containing a smallpox epidemic (Longini et al 2007). Other work using this technique (Axtell & Epstein 1999) helped to explain unexpectedly slow response to changes in US retirement policy.

[2] Efficient searching of large parameter spaces in agent-based models is made possible with additional techniques from complexity science, such as Genetic Algorithms (Holland 1992)

An agent-based modeling approach to obesity would permit modeling of multiple mechanisms simultaneously, across several levels of scale, with inclusion of important sources of diversity. For example, "agents" might be individual consumers, placed in an environment with opportunities for eating and for physical activity. Within each agent might be a representation of metabolic mechanisms or genetics, with the appropriate degree of population diversity reflected in variation between agents. These agents could be embedded in a social structure with multiple sources of influence on both eating and activity (peers, parents, media). Individual behaviors would then adapt over time through interaction with both environment and society, in ways shaped by genetics and metabolism[3]. Such an approach could offer deeper understanding of the full complexity of the obesity epidemic, and permit experimentation with different forms of policy intervention, both to slow and to reverse the epidemic.

## Conclusion

Obesity is a substantial and growing public health crisis worldwide. The obesity epidemic urgently requires well-crafted policy interventions, but also represents an especially challenging problem for study and for policy design, due to its complexity. Many of its features—breadth of scale, diversity in actors, and multiplicity of mechanisms—are hallmarks of a complex adaptive system. The lessons and tools of complexity science can help us both to understand and to combat the obesity epidemic—but only if we take complexity seriously and adopt a systems view of obesity. Agent-based computational modeling is an especially promising avenue for future research and

[3] For a more detailed outline of how such a model might take shape, see Hammond & Epstein (2007)

for policy exploration.

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**Figure 1. Levels of scale that play a role in the obesity epidemic.** For more information on each level, see: Genetic (Rossner 2002; York & Bouchard 2000; Stunkard et al. 1986; Perusse et al. 2005; Comuzzie 2002; Keller et al. 2003); Neurochemical/metabolic (Woods & Seeley 2002; Tschop et al. 2000; Schwartz & Morton 2002); Cognitive (Killgore et al. 2003; Broberger 2005); Social/Networks (Christakis 2007; Burke & Heiland 2006); Economic/Markets (Finkelstein et al. 2005, Drewnowski & Darmon 2005, Cutler et al. 2003); Environmental (Booth et al. 2005; Papas et al. 2007)

**Figure 2. Upward trend in incidence of overweight and obesity, United States**. Also of interest is the apparent acceleration in the 1980s. Data is from the National Health and Nutrition Examination Survey and National Health Examination Survey, compiled by CDC at http://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/Health_US/hus06tables/Table073.xls

**Figure 3. Disparities in incidence of overweight by race and gender, United States.** Data is from the National Health and Nutrition Examination Survey and National Health Examination Survey, compiled by CDC at http://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/Health_US/hus06tables/Table073.xls

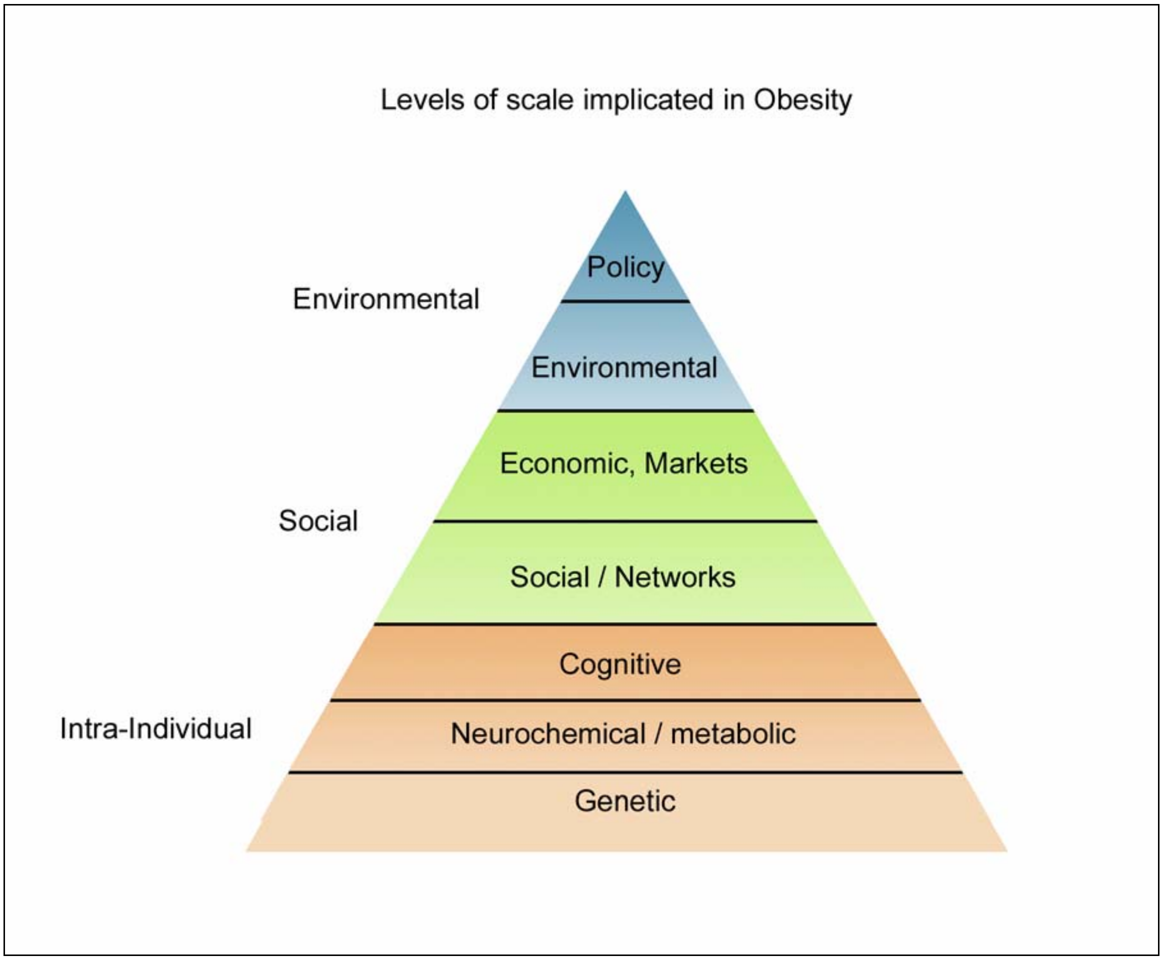
Levels of scale implicated in Obesity
Environmental
Policy
Environmental
Economic, Markets
Social
Social / Networks
Cognitive
Intra-Individual
Neurochemical / metabolic
Genetic

Fig. 1

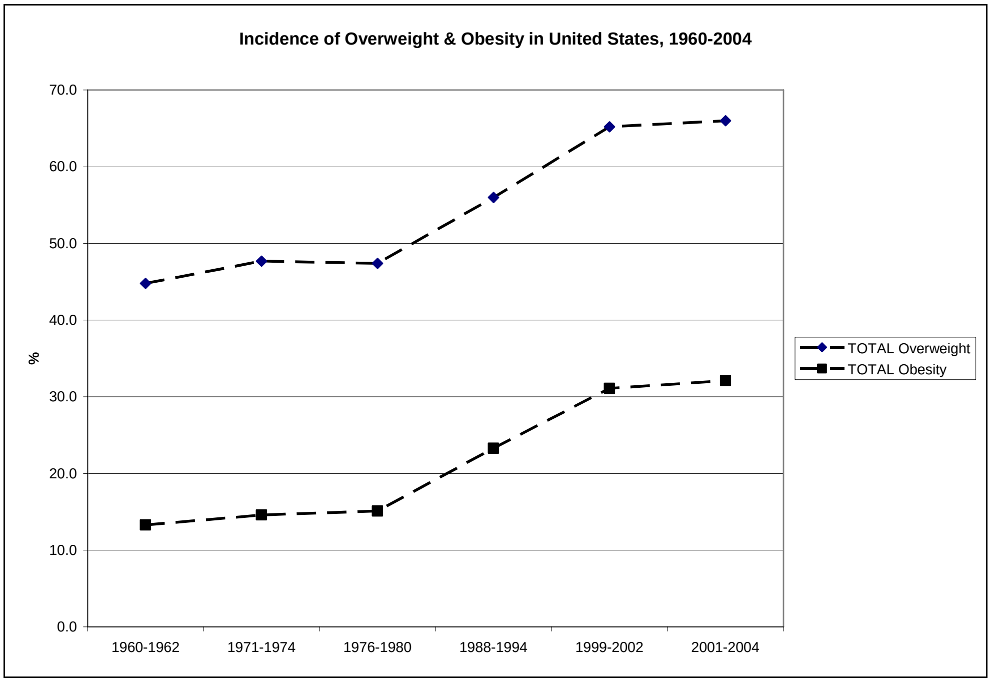
Incidence of Overweight & Obesity in United States, 1960-2004
%
70.0
60.0
50.0
40.0
30.0
20.0
10.0
0.0
1960-1962
1971-1974
1976-1980
1988-1994
1999-2002
2001-2004
TOTAL Overweight
TOTAL Obesity

Fig. 2

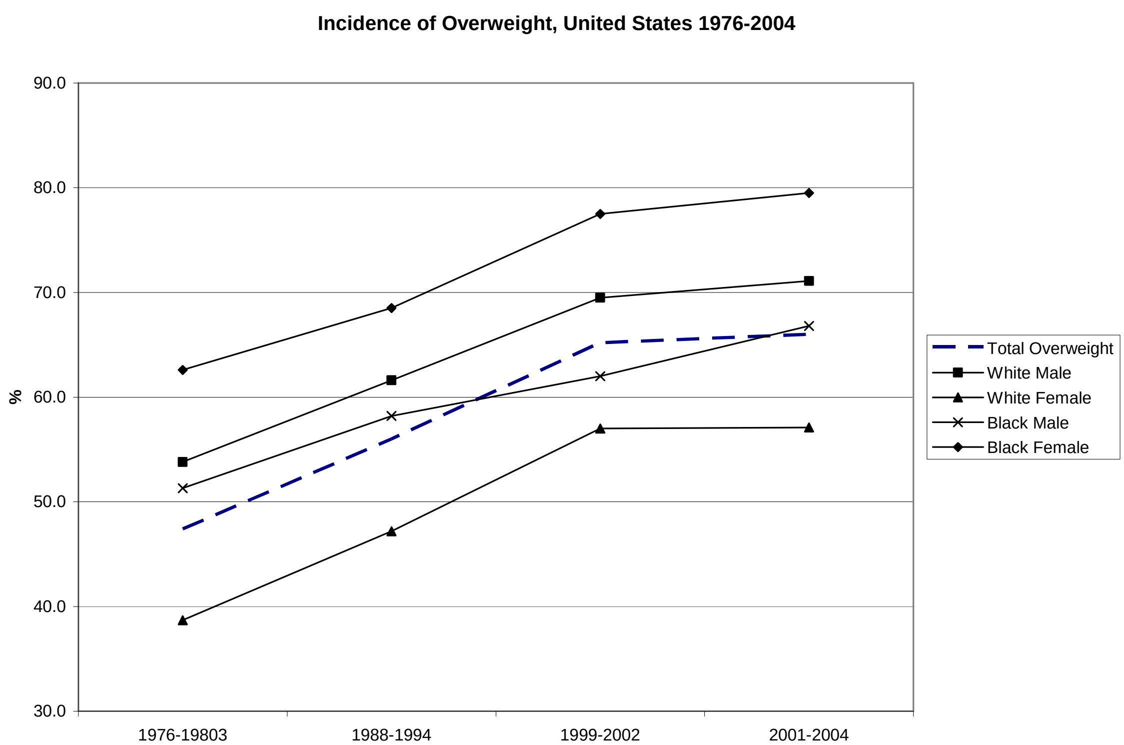
Incidence of Overweight, United States 1976-2004
%
90.0
80.0
70.0
60.0
50.0
40.0
30.0
1976-19803
1988-1994
1999-2002
2001-2004
Total Overweight
White Male
White Female
Black Male
Black Female

Fig. 3