Diabetes System Model Reference Guide

Jack Homer
Andrew Jones
Don Seville
Sustainability Institute

October 2004

Introductory Note – March 2006

The Diabetes System Model Reference Guide is cited as reference #17 in the following article:

Understanding Diabetes Population Dynamics Through Simulation Modeling and Experimentation

Andrew P. Jones, MS, Jack B. Homer, PhD, Dara L. Murphy, MPH, Joyce D. K. Essien, MD, MBA, Bobby Milstein, MPH and Donald A. Seville, MS

March 2006, Vol 96, No. 3 | American Journal of Public Health 488-494
 -- DOI: 10.2105/AJPH.2005.063529

The current guide was written in October 2004 and is undergoing revision to reflect changes in the model made since that time. The AJPH paper was based on a version of the model that includes a number of changes made between October 2004 and the paper's acceptance in April 2005. For example, whereas obesity of the general population was originally modeled as a function of caloric intake and physical activity (see Sections 5.1 and 5.2), by the time the AJPH paper was written this had been changed so that obesity was now modeled simply as an exogenous time series.

As a preface to the main text of the Guide, we are including five pages of background on the philosophy and science of system dynamics modeling and its application to diabetes population modeling.

Andrew Jones and Jack Homer

Notes on System Dynamics Modeling Science and Its Application to Diabetes Population Modeling

Jack Homer and Drew Jones
With Bobby Milstein, Dara Murphy, Joyce Essien, and Don Seville

2 November 2005

Purpose

The purpose of this document is to provide background to our modeling project and more generally to the science of System Dynamics Modeling, with a particular focus on aspects that may differ from other approaches to diabetes population modeling. .

1. Project Background

The diabetes system modeling project began in September 2003 primarily as a result of two concerns: first, that existing programmatic strategies focused on reducing the immediate burden of diabetes might soon become overwhelmed or lose effectiveness in the face of rapidly increasing disease prevalence, and, second, that diabetes leaders lacked effective, quantitatively-grounded decision-support tools that could improve diabetes strategies in light of the first concern. SD was determined to be an appropriate technique for looking formally at a broad spectrum of programmatic options and considering their relative effectiveness over the short and long term. Part of the appeal of SD was its flexibility and ability to deal in an integrative and transparent way with the diverse questions and rich information sources that characterize the current state of diabetes prevention and control. Thus, an SD approach held promise as a way of answering tough questions, diminishing the sense of information overload, pointing the way toward a more effective program mix, and thereby improving the ability of DDT to engage effectively with state and local colleagues, as well as other stakeholders who would ultimately be needed as partners to champion any change in programmatic direction.

2. Modeling Approach

The way that we have been able to start accomplishing these aims over the past two years is by developing a mathematical tool that allows one to do a wide range of experiments, not unlike the artificial conditions created in a prospective clinical trial. In an SD model, however, the conditions are defined by the formal structure of a simulation model along with its baseline assumptions, and the experiments allow decision-makers to compare outcomes under carefully specified alternative scenarios. The purpose of this experimental approach is not to forecast actual future values of the system, but rather to learn about the relative impacts of alternative assumptions and interventions. One may generally draw firm conclusions about those relative impacts, even if one is not absolutely certain about the baseline (or "status quo") assumptions. Of course, the baseline assumptions should be plausible, and it is often instructive to experiment with different baseline assumptions to determine what effect they may have on the findings of relative impact.

3. Model Evolution and Role of the Reference Guide

The diabetes model is not a fixed entity but one that has evolved and continues to evolve as we learn more and engage others in an expanding dialogue about the system's structure and behavior. The model has been developed in close collaboration with a team made up of DDT staff from both the program branch and ESB, with additional input from a steering committee of experienced individuals from throughout CDC, and also with detailed input from DNPA, DACH, and other related divisions. More recently, we have been working with diabetes analysts and policymakers in the Vermont Department of Health to explore conditions in their state, and we have made further changes to the model as a result of those interactions. Face-to-face meetings have been held throughout the process, and hundreds of pages of electronic messages and memoranda document the work we have done between meetings

to improve the model's logic, gather data, derive parameter estimates, and evaluate the model's output and its implications.

The model currently contains 365 calculated variables and 134 input parameters. It is now in its 10th major version, three versions beyond where it was when the Reference Guide was written last October. This brief history of the model's iterative development underscores an important point about the Reference Guide itself: i.e., it was not written—nor should it be read—as complete and thorough documentation of a model that continues to evolve. Rather, it provides selected information that current and prospective users may find helpful as they engage with us in studying how the model functions and in improving it as necessary. The Guide was meant to be used as a backgrounder for collaborators in the project, not as the full and final explanation of the model's technical foundation. Colleagues who have used the Guide in conjunction with other forms of engagement in the project report that it is a useful and transparent resource to support their work with the model.

4. Establishing Confidence in a Model

Recognizing that the model continues to evolve, one may ask how a reader or reviewer of the model may establish confidence in it. How, for example, do referees for the field's leading journal, *System Dynamics Review*, evaluate model-based articles? Ideally, the evaluation is done as follows:

(1) If the model is not a business-proprietary one, referees will have access to the equation code themselves, which they can inspect, and which would allow them to do their own simulations.
(2) They will want to see that the article contains clear description of the model's causal structure and data sources used for parameter estimation, and that the structure and parameters described are realistic and adhere to certain basic requirements, such as laws of conservation.
(3) They will want to see that the model can convincingly reproduce in its simulated output all important aspects of the historical record.
(4) They will want to see that the model, when simulated into the future under a variety of scenarios and interventions, and even tested under extreme conditions, produces results that are plausible and non-trivial.
(5) They will want to see some discussion of the extent to which these model results may be sensitive to certain assumptions or parameters in the model, and what this may imply for a research agenda for further data collection.
(6) Finally, they will want to see a persuasive analysis of how the model's behavior under different conditions relates back to its stock-flow and feedback-loop structure; that is, an analysis of "what makes this system tick?"

These criteria for establishing confidence in an SD model differ to some degree from the tests that one might apply to other types of models. This is largely because of the inclusion of unmeasured variables, discussed below. That is why the six criteria above include both tests of model structure (reasonableness of equations and parameters) and tests of model behavior (replication of the past, persuasive and insightful portrayal of the future). These tests were first articulated in the founding book of the field, Jay Forrester's *Industrial Dynamics* (1961; Chapter 13, "Judging Model Validity", pp. 115-129); they were further elucidated in an article by Forrester and Senge (1980); and they are extensively described in Sterman's *Business Dynamics* (2000; Chapter 21, "Truth and Beauty: Validation and Model Testing", pp. 845-891. This book is the most comprehensive and up-to-date text in the field and has also become the most cited.)

5. Inclusion of Unmeasured Variables: Principles

Why does one need such a diversity of confidence-building tests in SD? Put differently, why can't we just identify solid data sources for a model and put forward a relatively small, straightforward set of equations that can properly accommodate those data sources? Why do we end up with models that are big and contain lots of variables for which no directly measured data exist? These questions highlight the differences between SD modeling and other population modeling approaches more typically used in epidemiology. The answer gets to the very purpose of SD modeling, which is to examine dynamically complex systems (characterized by significant accumulations, feedback loops, delays, multiple stakeholder goals, and nonlinearities) that are capable of producing counterintuitive behavior and possible futures that look quite different from the past—not just a straight-line extension of the past. The SD view is that in order to usefully represent such complexity, one inevitably must expand the scope of a model so that

it contains variables that might be left out of other types of models. In other words, SD models seek to formalize, and render subject to experimentation, important forces of change that may be omitted in other types of models.

In *Industrial Dynamics* (pp. 57-59, "Sources of information for constructing models"), Forrester speaks directly to the subject of including unmeasured variables in a model: "There seems to be a general misunderstanding to the effect that a mathematical model cannot be undertaken until every constant and functional relationship is known to high accuracy. This often leads to the omission of admittedly highly significant factors (most of the "intangible" influences on decisions) because these are unmeasured or unmeasurable. To omit such variables is equivalent to saying they have zero effect—probably the only value that is known to be wrong!...These comments are not to discourage the proper use of data that are available nor the making of measurements that are shown to be justified; they are to challenge the common opinion that measurement comes first and foremost."

6. Inclusion of Unmeasured Variables: An Example from the Diabetes Model

An example from the diabetes SD model illustrates how we have sought to incorporate unmeasured features that would have been wrong to omit. The model explains the incidence of diagnosed diabetes as a two-stage process in which there is first the actual, undetected onset of diabetes, and there is second the detection of the existing condition. (The model actually depicts two different pathways by which this may occur, depending upon whether or not the patient's prediabetes is detected and under regular management.) We do not have data on actual onset rates, but we do have data (e.g., from NHIS and NHANES on diagnosed prevalence and the fraction undiagnosed) that can help us to estimate actual onset through a process of simulation and curve-fitting—analogous to estimating the coefficients in a regression equation.

Why go to such trouble to portray a two-stage process when it creates some challenges for parameter estimation? The answer to such a question always comes down to model purpose. In this case, we wanted to be able to analyze how the diagnosed incidence of diabetes *may change* in the future, both with and without interventions that could increase patient screening or address primary prevention. The only way to accomplish this purpose was to tease apart the processes of actual onset and detection. We did this teasing apart even though it would mean having to estimate parameters for which we had no direct data. We did it because otherwise we might easily have made assumptions about future changes in diagnosed incidence that are inconsistent with what we *do* know about how the system works.

In particular, we chose not to lump together the processes of actual onset and diagnosis, but rather to depict their separation in time through the portrayal of a stock of people with undiagnosed diabetes. We understood that if we did not take this step, we would not be able to explain how increases in diagnosed incidence in the late 1990s (evident in NHIS) were the result of both increases in actual onset and increases in the rate of diagnosis. Having made this separation allows one to see that although actual onset may continue to increase for some years, the diagnosed fraction (the past growth of which has been spurred largely by programmatic effort) has probably passed an inflection point and started to approach saturation. As a result, one may project that diagnosed incidence may actually decrease for a few years following a temporary peak even though actual incidence is still climbing. Our model would have been flatly in error, overestimating future diagnosed incidence rates, if we had not built it to anticipate the likelihood of such fluctuation. (We have built a small, separate simulation model that illustrates this point and indicates how much overestimation may occur due to the inflection point phenomenon.)

Thus, even though we were not sure about what values should be attached to some of the parameters that lacked direct measures, we *were* able to lay out a logical structure of the population stocks and flows that could anticipate future changes in diagnosed incidence as well as other population flows. Note that the logical stock-flow structure is more detailed than the existing data allow for, but less detailed than some of what we heard from the project team about the myriad possible pathways of diabetes progression and differences among individuals. The stock-flow structure is detailed enough so that it can address the questions for which it was designed, and do so with enough fidelity to the real world that (1) policymakers easily recognize it as "their system"; and (2) it makes formal distinctions that are necessary for anticipating likely future changes. We used that logical structure and the data that support it as our starting point for modeling rather than rely on only those variables for which we had direct measurements.

7. Aggregation of Subgroups

In SD modeling, it is always the logical stock-flow and feedback structure that, along with the key time series describing the problem, is the starting point. We have described how this approach leads immediately to an expansion of scope and an inclusion of some parameters for which no formal data exist. That expansion of scope, in turn, leads to another feature of many SD models differentiating them from standard epidemiological models: their relatively high level of aggregation in terms of subgroups. For example, although we have separated the population by stages of disease progression and diagnosis, the current diabetes model does not break the population down further by age, sex, ethnicity, income, geography, or other characteristics. Why not? Because the general consensus among the team was that such breakdowns would add little to our understanding of *future dynamics* and overall *policy impacts*. (Note again that the inclusion of detail is relative to the model's stated purpose as an interactive tool for policy experimentation. If the purpose of the model had included projecting the relative burden of diabetes by subgroup, then clearly the model would have required decomposition by subgroup.) The team agreed that to the extent that population aging or changing ethnic composition are factors that could affect the model's outputs, they could be introduced in a simpler way than by decomposing every population stock. This is something we have, in fact, done in the case of aging; see Reference Guide Figures 7, 8, 9, and 12, and accompanying text. It is an approach that has allowed us to maintain the model's transparency and utility for experimentation, without weighing the model down with hundreds or thousands of detailed data elements that would have obscured things considerably and detracted from our primary purpose of supporting greater understanding among policymakers.

8. Parameter Estimation

We come now to the question of parameter estimation, which is yet another area of difference between SD modeling and standard epidemiological modeling . Much has been written in the SD literature about what types of data may be used, how best to use them, and how the model tuning or curve-fitting process may also assist. An excellent place to start in considering this issue is with articles in the 1980 book *Elements of the System Dynamics Method* by Graham,, by Mass and Senge, and by Peterson. . Other useful references include articles by Forrester (1980) and by Homer (1983, 1996, 1997), and a chapter in Sterman (2000; Chapter 14, "Formulating nonlinear relationships" pp. 551-595).

In a nutshell, the preferred approach in estimating parameters is to use all available information, whether numerical, written, or verbal, attempting to give greater weight to those pieces of information that are most pertinent and least prone to error or bias. Other examples of parameter estimation through the combination of multiple sources are documented in the many electronic messages and memoranda that have been created throughout the project.

When it comes to model tuning, or, more generally, estimating input parameters based on time series (such as changes in diagnosed prevalence) rather than based on direct observations of the parameter or parameters closely related to it, there are two basic approaches that are accepted and in use. The first is the Kalman Filtering approach described by Peterson (1980) that applies an automated, iterative statistical algorithm to the whole-model estimation of all uncertain parameters in a model. The second is a partial-model estimation approach, as described by Homer (1983), in which the tuning of uncertain parameters is done manually but applied to the smallest possible pieces of structure and the smallest possible clusters of parameters given the configuration of available time series data. In addition to the direct use of data described in the previous paragraph, we have used the partial-model-tuning approach in the diabetes modeling for estimating parameters for which there are insufficient direct data available.

References

Forrester JW. 1961. *Industrial Dynamics*. MIT Press: Cambridge, MA.

Forrester JW. 1980. Information sources for modeling the national economy. *J Amer Stat Assoc* 75(371):555-574.

Forrester JW, Senge PM. 1980. Tests for building confidence in system dynamics models. In: *System Dynamics, TIMS Studies in the Management Sciences* 14; 209-228. North-Holland: New York.

Graham AK. 1980. Parameter estimation in system dynamics modeling. In: Randers J, *Elements of the System Dynamics Method.* MIT Press: Cambridge, MA.

Homer JB. 1983. Partial-model testing as a validation tool for system dynamics. *Proc Intl SD Conf*, Chestnut Hill, MA.

Homer JB. 1996. Why we iterate: Scientific modeling in theory and practice. *SD Review* 12(1):1-19.

Homer JB. 1997. Structure, data, and compelling conclusions: Notes from the field. *SD Review* 13(4):293-309.

Mass NJ, Senge PM. 1980. Alternative tests for selecting model variables. In: Randers J, *Elements of the System Dynamics Method.* MIT Press: Cambridge, MA.

Peterson DW. 1980. Statistical tools for system dynamics. In: Randers J, *Elements of the System Dynamics Method.* MIT Press: Cambridge, MA.

Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World* Irwin/McGraw-Hill: Boston.

Diabetes System Model Reference Guide

CONTENTS

1. Background

The diabetes system model was built according to the principles of System Dynamics (SD). SD is a simulation-based methodology for improving understanding of how problematic situations develop over time, and for analyzing the short-term and long-term effects of interventions in such evolving situations. The method was first developed by computer pioneer Jay Forrester in the late 1950s and described in his book, *Industrial Dynamics* (1961).

An SD model consists of a linked set of difference equations—differential equations in a form that can be simulated—describing a dynamic situation in terms of its key accumulations or stocks, the inflows and outflows to those stocks, and the factors, activities, and decisions determining those flows. Flows are modeled to include realistic elements of feedback, delay, constraint, and nonlinear response that can help to explain observed system behavior and that can anticipate both intended and unintended effects of interventions.

SD has been applied to nearly every realm of business, public policy, and individual and social behavior where people are interested in getting a better handle on problems that have proved resistant to simple improvement. For a complete introduction to SD and its applications, see John Sterman's *Business Dynamics* (2000).

The diabetes model was commissioned by and has been developed in partnership with the CDC's Division of Diabetes Translation. It has been used interactively in a workshop called the "Diabetes Learning Lab" that enables the participants to design and formally evaluate diabetes-related policies at a national or state level. More background to the model as well as some examples of its application are described in the paper, "The CDC's Diabetes Systems Modeling Project: Developing a New Tool for Chronic Disease Prevention and Control" (Homer, Jones, et al., 2004).

2. Model Structure Overview

Figure 1 presents an overview of the model's cause-and-effect structure. Population stocks are indicated as rectangles in yellow, and the flows into and out of these stocks are indicated as black double-thick arrows with valve symbols. Other variables shown in Figure 1, such as "Obese fraction of population", directly or indirectly affect the population flows. The causal relationships linking these variables to one another and to the population flows are indicated with blue arrows.

A special category of these other variables are those with no arrows coming into them, in pink typeface. These are time-series input to the model, each of which requires an estimate of that variable's behavior from 1980 (the model's initial year) to the present, as well as assumptions about its future behavior. Ten of these are shown in Figure 1; note that "Caloric intake" and "Physical activity" are separate inputs, as are "Self-management" and "Drug affordability". Although the model contains more time-series inputs than these ten (for example, a time series for the size of the total adult population), the ten are of particular interest because of their potential value as points of policy intervention. The direct result of any policy intervention one might want to consider would be represented in the model through manipulation of one or more of these ten time-series inputs.

This document describes and provides the basis and rationale for details of model structure, including assumptions for the time-series inputs.

3. Population Stocks and Flows

3.1 Overview, Population Inflow, and Deaths

Figure 2 presents the model's full population structure of 7 stocks and 18 flows. The entire adult (age 18 and over) population is represented and divided into categories of normoglycemic (one stock), prediabetes (two stocks), and diabetes (four stocks). People are assumed to enter the adult population as normoglycemic, from which they may develop prediabetes, a reversible condition of moderately elevated blood glucose. From prediabetes they may develop uncomplicated diabetes, an irreversible condition of more elevated blood glucose and insulin resistance, but not yet marked by medically significant symptoms of organ disease. From uncomplicated diabetes people may develop complicated diabetes; complications generally affect the heart, kidneys, eyes, or extremities. People who develop prediabetes or uncomplicated diabetes are initially undiagnosed but may become diagnosed through blood-test screening of the high-risk population. People may progress to complicated diabetes still undiagnosed, but their symptoms in most cases sooner or later bring them to the attention of a doctor who diagnoses the disease.

Every population stock in Figure 2 has an outflow of death. For the normoglycemic, prediabetes, and uncomplicated diabetes stocks, the deaths occur at age-normal rates, unaffected by complications. For the complicated diabetes stocks, the death flows include both age-normal deaths and complications-related deaths.

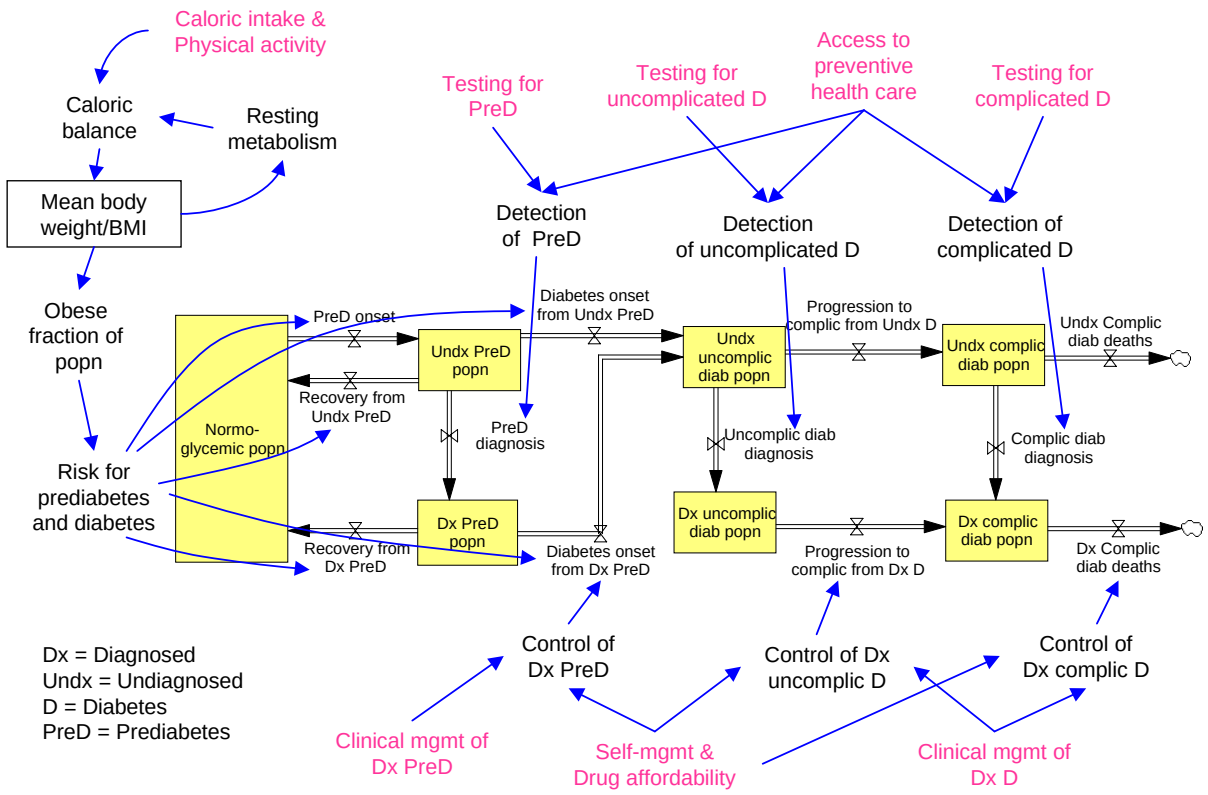

Figure 1. Overview of model structure

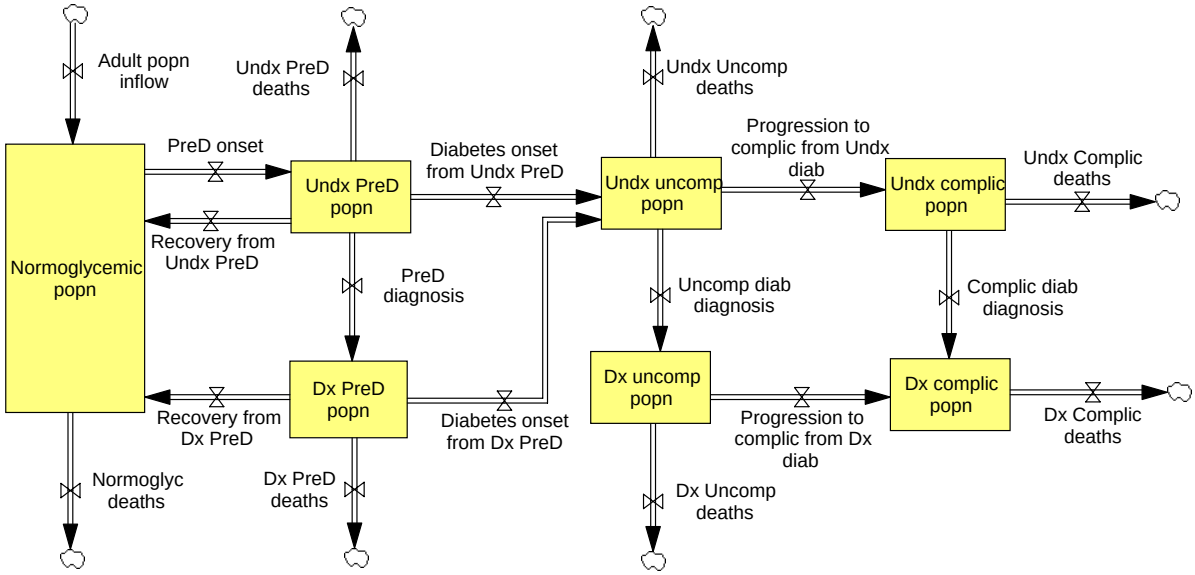

Figure 2. Population stocks and flows

Figure 3 presents the causal structure for the non-diabetes population inflow and deaths. In this and all causal diagrams to follow, a variable in black typeface is defined as a function of other variables shown in the figure; a variable in pink typeface is a time series input; a variable in *red italics* is a constant input; and a variable in <green typeface with brackets> is a variable defined elsewhere in the model.

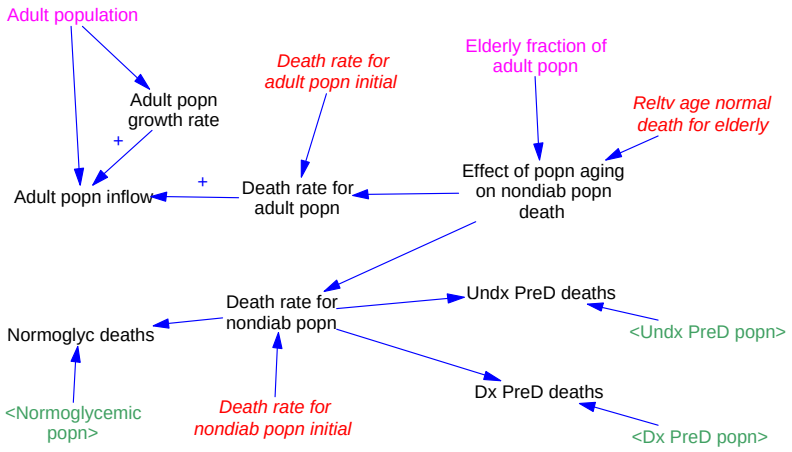

Figure 3. Non-diabetes population inflow and deaths

Like all flows in the model, the adult population inflow is expressed as people per year. Given the net rate of growth and the rate of death for the adult population, the gross inflow (the annual number of people becoming 18 years of age, ignoring flows of in- and out-migration) may be calculated as the sum of those two. In the model, the net growth rate is calculated from the time series for the adult population shown in Figure 4. This and all other estimates and projections in this section are derived from US Census reports.

The death rate for the adult population is the product of two factors: the adult population death rate initially (that is, in 1980; estimated at **1.2%** per year), and an effect of population aging after 1980. The adult population death rate for the entire 1980-2050 period is seen as the blue line in Figure 5. The effect of population aging here is calculated based on the elderly (age 65-plus) fraction of the adult population (time series presented in Figure 6), and an estimate of **8.0** for the death rate of the elderly compared with non-elderly adults. Note that the elderly fraction of the population does not change much from 1980 to 2010, but then nearly doubles from 2010 to 2030, after which it becomes flat again.

The non-diabetes (normoglycemic and prediabetes) population death rate for the 1980-2050 period is seen as the red line in Figure 5. This rate is calculated as the product of an initial rate (estimated at **1.0%** per year, based on the somewhat younger-than-average age of the non-diabetes population) and the effect of population aging described in the previous paragraph.

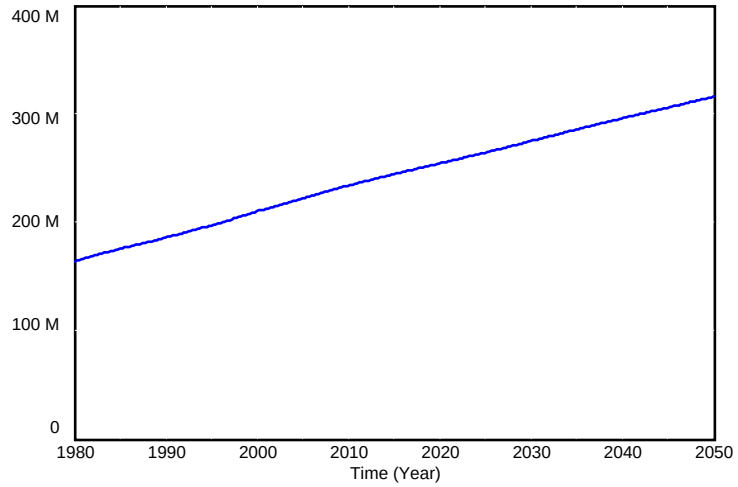

Figure 4. Adult population (age 18 and over), 1980-2050 (US Census)

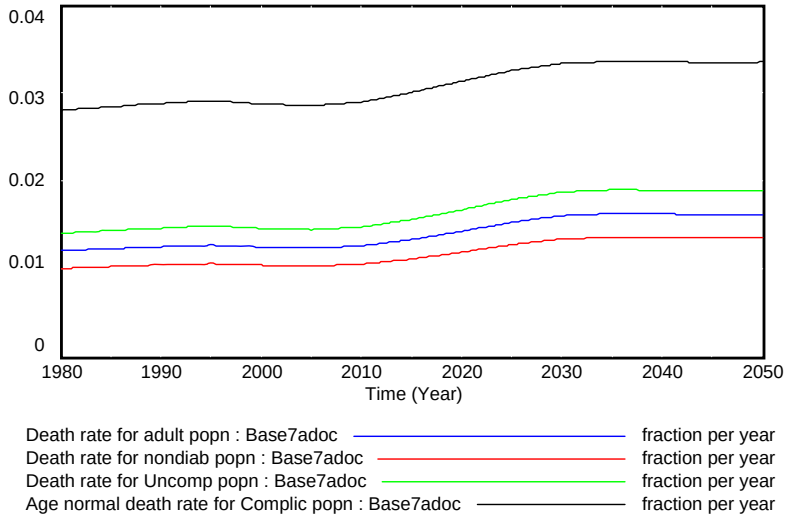

Figure 5. Age-normal death rates, as calculated in the model, 1980-2050

Figure 7 presents the causal structure for uncomplicated diabetes population deaths. The uncomplicated diabetes population death rate for the 1980-2050 period is seen as the green line in Figure 5. This age-normal rate is calculated as the product of an initial rate (estimated at **1.4%** per year, based on the somewhat older-than-average age of the uncomplicated diabetes population) and an effect of population aging. The elderly fraction of the uncomplicated diabetes population is calculated based on the elderly fraction of the general non-diabetes population (as seen in Figure 6) and the relative risk of uncomplicated diabetes for the elderly versus the non-elderly. This relative risk, set at **1.9**, is calculated based on a year 2000 estimate of 28% elderly within the uncomplicated diabetes population and 17% elderly in the general population. (The calculation is: Relative risk = (.28)(1 - .17) / [(.17)(1 - .28)] = 1.9.)

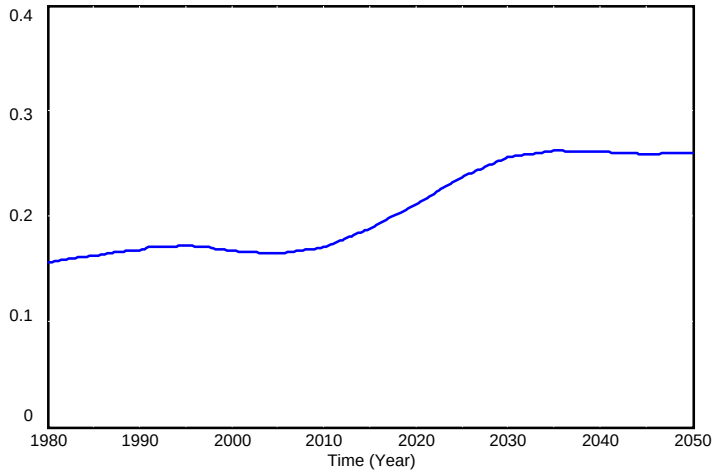

Figure 6. Elderly (age 65 and over) fraction of adult population, 1980-2050 (US Census)

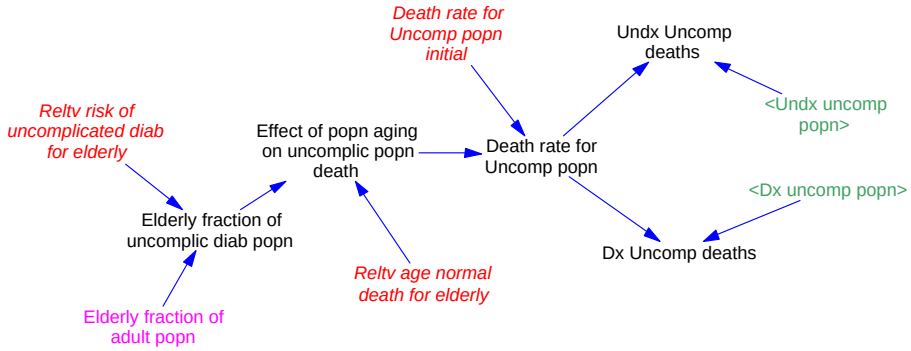

Figure 7. Uncomplicated diabetes population deaths

Figure 8 presents the causal structure for complicated diabetes population deaths. The death rate is the sum of an age-normal rate and a rate due to complications; the latter is different for the diagnosed than it is for the undiagnosed. The age-normal death rate for the 1980-2050 period is seen as the black line in Figure 5. This age-normal rate is calculated as the product of an initial rate (estimated at **2.8%** per year, based on the older-than-average age of the complicated diabetes population) and an effect of population aging. The elderly fraction of the uncomplicated diabetes population is calculated based on the elderly fraction of the general non-diabetes population (as seen in Figure 6) and the relative risk of complicated diabetes for the elderly versus the non-elderly. This relative risk, set at **7.6**, is calculated based on a year 2000 estimate of 61% elderly within the uncomplicated diabetes population and 17% elderly in the general population. (The calculation is: Relative risk = (.61)(1 - .17) / [(.17)(1 - .61)] = 7.6.)

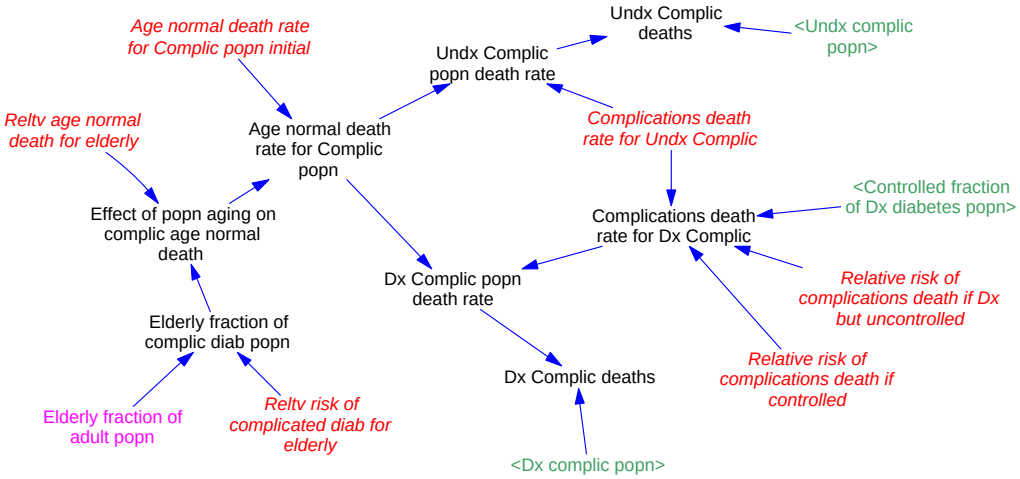

Figure 8. Complicated diabetes population deaths

The complications death rate for the undiagnosed complicated population is estimated at **12%** per year. The complications death rate for the diagnosed is less than that of the undiagnosed (1) by virtue of the basic level of medical management implied by diagnosis, and (2) even more so if the disease is brought under control in terms of measured glucose, blood pressure, and lipids. We assume that HbA1c (glycosolated hemoglobin) levels for the complicated are brought from an average of 10.5 for the undiagnosed down to an average of 9 for the diagnosed-but-uncontrolled, and down to an average of 7 for the diagnosed-and-controlled. We further assume, in line with clinical findings, that the complications death rate is reduced by 40% for each point of HbA1c reduction (DHHS/AHRQ, 2003). These assumptions translate into a relative risk of complications death (compared to the undiagnosed) of **46.5%** for the diagnosed-but-uncontrolled, and **16.7%** for the diagnosed-and-controlled.

Taken together (and with assumptions, discussed further below, determining the controlled fraction of diagnosed diabetes), the assumptions described above result in a year 2000 simulated value of 530,000 deaths of people with diagnosed diabetes, of which 261,000 are from complications of the disease. These simulated results may be compared with separate estimates of 500,000 total deaths (Honeycutt, Boyle, et al., 2003) and 200,000 from complications (ADA, 2003).

3.2 Prediabetes Onset and Recovery

Figure 9 presents the causal structure for prediabetes onset, formulated as a fraction per year of the normoglycemic population. This onset rate may change over time, as affected by the obese fraction of the normoglycemic population (discussed further below) and by population aging. Obesity is the leading modifiable risk factor for prediabetes. The initial (1980) prediabetes onset rate for the non-obese is set to **4.3%** per year, and the relative risk for the obese is **2.6**. (An unpublished analysis of NHANES III and 1999-2000 data suggests a relative risk of 1.7, but that analysis is static and underestimates the true relative risk to the extent that prediabetes was still growing at the time the surveys were done. Thanks to Edward Gregg of the CDC for his assistance with the NHANES queries.)

The relative risk of prediabetes onset for the elderly (relative to the non-elderly) is estimated at **1.15**. (This figure was estimated together with the relative risk of diabetes onset for the elderly, described in the next section below. These estimates were based on data from Honeycutt, Boyle et al. 2003; and the analysis of NHANES III data in Harris, Flegal, et al., 1998).

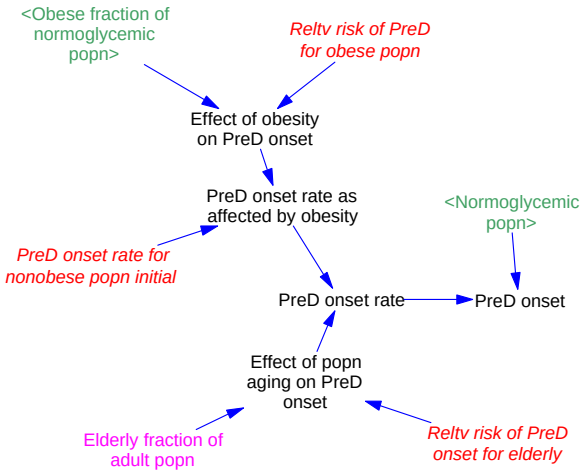

Figure 9. Prediabetes onset

Figure 10 presents the causal structure for recovery from prediabetes, formulated as a fraction per year of the prediabetes population (both undiagnosed and diagnosed). This recovery rate may change over time, as affected by changes in the obese fraction of the prediabetes population (discussed further below). If the obese fraction has been flat or increasing, the recovery rate is set to a normal value of **10%** per year. If the obese fraction has been decreasing, then it is assumed that, in addition to this normal rate of recovery, **50%** of the reduction in obesity will translate into recovery from prediabetes. That is, half of the people who had been obese with prediabetes will return to normoglycemia when they lose weight and become no longer obese.

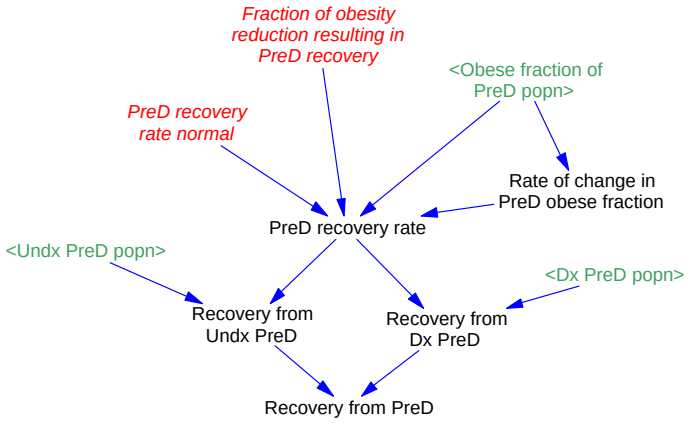

Figure 10. Prediabetes recovery

Figure 11 shows the model's simulated behavior of prediabetes onset (blue line) and recovery (red line) for the period 1980-2004, given all of the assumptions discussed above. A legacy of gradual growth in obesity (dating back at least to the 1960s) causes prediabetes onset to exceed recovery even in 1980. The gap between onset and recovery becomes noticeably greater during the 1990s due to further increases in population obesity driving the onset rate upward.

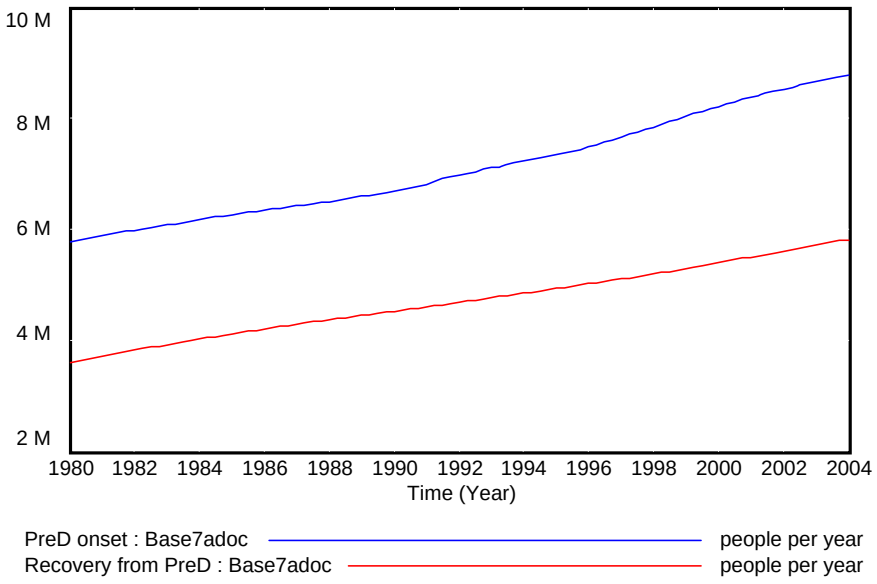

Figure 11. Simulated prediabetes onset and recovery, 1980-2004

3.3 Diabetes Onset and Progression

Figure 12 presents the causal structure for diabetes onset from prediabetes. We assume that by the logic of gradual over-time blood-glucose elevation, prediabetes is a necessary precursor to diabetes. Two fractional diabetes onset rates are calculated, one for the undiagnosed prediabetes population and the other for the diagnosed. Both of these rates may change over time, as affected by the obese fraction of the prediabetes population and by population aging. For people with prediabetes, obesity is the leading modifiable risk factor for diabetes. In other words, an obese prediabetic has a greater risk for developing diabetes than a non-obese prediabetic. The initial (1980) diabetes onset rate for non-obese people with prediabetes is set to **1.35%** per year, and the relative risk for the obese is **2.6**. (The unpublished analysis of NHANES III and 1999-2000 data described in the previous section suggests a relative risk in the range of 1.6 to 2.5, but again the static nature of that analysis means that it underestimates the true relative risk to the extent that diabetes was growing at the time the surveys were done.)

The relative risk of diabetes onset for elderly prediabetics (relative to non-elderly ones) is estimated at **1.52**. (As described in the previous section, this figure was estimated together with the relative risk of prediabetes onset for the elderly, based on data presented in Honeycutt, Boyle et al. 2003 and Harris, Flegal et al. 1998.)

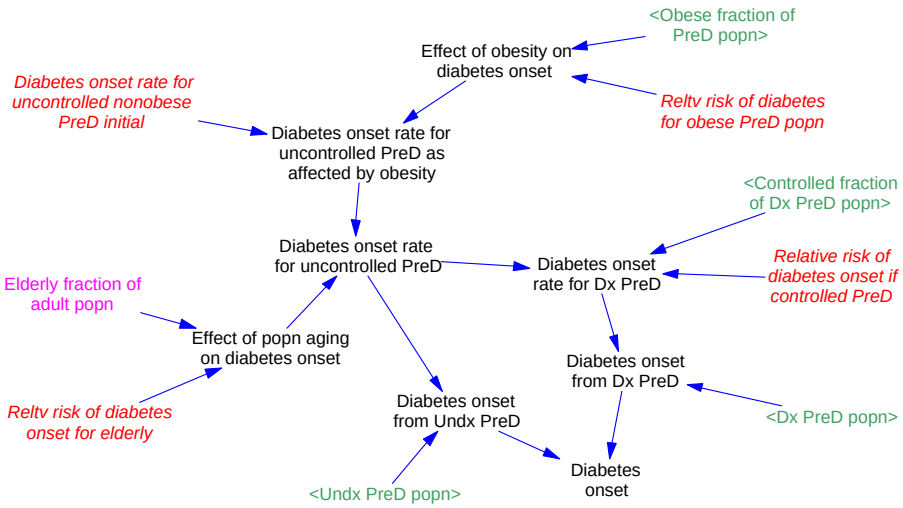

Figure 12. Diabetes onset

The diabetes onset rate for people with diagnosed prediabetes who have their measured glucose, blood pressure, and lipids brought under control within normal ranges is less than that of the undiagnosed and uncontrolled. (We assume that diagnosis and basic medical management without risk-factor control do not lead to any reduction in diabetes onset. Calculation of the controlled fraction of diagnosed prediabetes is discussed further below.) We assume that the risk of diabetes onset for patients under control is **58%** relative to those not under control. (See: Knowler, Barrett-Connor et al., 2002.)

Figure 13 presents the causal structure for progression to complicated diabetes from uncomplicated. Two fractional progression rates are calculated, one for the undiagnosed uncomplicated diabetes population and the other for the diagnosed. The progression rate for the undiagnosed is estimated at **7.9%** per year. We assume that HbA1c levels for the uncomplicated average 9 for both the undiagnosed and the uncontrolled, and are reduced to an average of 7 for the controlled. We also assume that the risk of progression is reduced by 40% for each point of HbA1c reduction. These assumptions translate into a relative risk of complications death (compared to the undiagnosed) of **100%** for the diagnosed-but-uncontrolled, and **36%** for the diagnosed-and-controlled.

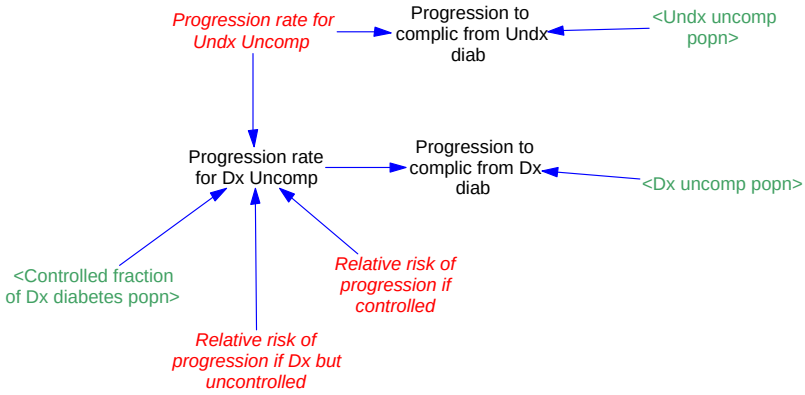

Figure 13. Progression to complicated diabetes

3.4 Diagnosis of Complicated Diabetes

Figure 14 presents the causal structure for the diagnosis of complicated diabetes. The equations for this diagnosis flow and for the diagnosis flows for uncomplicated diabetes and prediabetes are among the most complex in the model, and have been tested to ensure their proper behavior. We will present these equations in full so that they may be inspected and better understood.

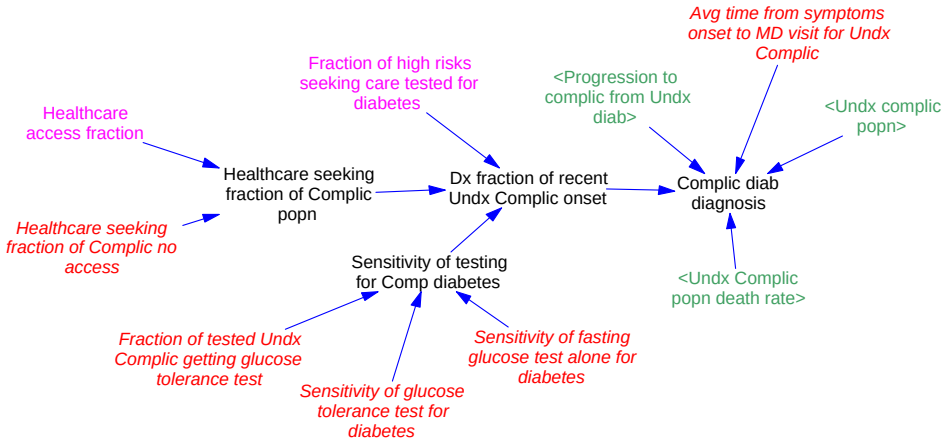

Figure 14. Diagnosis of complicated diabetes

Complic diab diagnosis =

DELAY1(Progression to complic from Undx diab, Avg time from symptoms onset to MD visit for Undx Complic) *

(1-Undx Complic popn death rate*Avg time from symptoms onset to MD visit for Undx Complic) * Dx fraction of recent Undx Complic onset

+

(Undx complic popn/Avg time from symptoms onset to MD visit for Undx Complic) *

(Dx fraction of recent Undx Complic onset - DELAY1(Dx fraction of recent Undx Complic onset, Avg time from symptoms onset to MD visit for Undx Complic)) /

(1 - DELAY1(Dx fraction of recent Undx Complic onset, Avg time from symptoms onset to MD visit for Undx Complic))

The equation describes the detection of complicated diabetes in people whose diabetes was not previously diagnosed when their disease was uncomplicated. This equation is in two parts, separated by a plus (+) sign, each part representing a particular “route” to diagnosis.

The first part of the equation represents the diagnosis of people with diabetes who have recently progressed to complicated disease. The calculation of such diagnosis involves a first-order delay of the progression flow, with a delay time describing the average time from the onset of symptoms to when the patient has a physician visit for those symptoms; this delay time has been set to **1.0** year. The calculation next subtracts out those who, during that one year delay time,

have died. Finally, it applies the current prevailing diagnosis fraction for recent-onset complicated diabetes (*Dx fraction of recent Undx Complic onset*), the calculation of which is described below.

The second part of the equation represents the diagnosis of people whose complicated diabetes was not diagnosed soon after onset, but who are now diagnosed because the prevailing diagnosis fraction for recent-onset complicated diabetes has recently increased. Such "playing catch-up" diagnosis represents some fraction of the stock of the undiagnosed complicated diabetes population, who we assume come in for a physician visit every year or so (using the same delay time described above) due to their continuing symptoms. The "playing catch-up" fraction is constructed as a ratio and calculated in the last four lines of the equation: In the denominator is the fraction of people who did not, as of a year ago, get diagnosed, according to the *Dx fraction of recent Undx Complic onset*. In the numerator is the difference between what the *Dx fraction of recent Undx Complic onset* is currently and what it was a year ago.

The *Dx fraction of recent Undx Complic onset* is the product of three fractions: (1) the fraction of the undiagnosed complicated population who seek care from a physician, (2) the fraction of those who are tested for diabetes, and (3) the average sensitivity of the tests used.

The care-seeking fraction for complicated diabetes is formulated as the sum of (1) the fraction who have ready access to healthcare, and (2) for those who have do not have such access the fraction who have symptoms of diabetes severe enough to cause them to seek medical attention, perhaps via a hospital emergency room; we have estimated the latter at **33%**. In regard to access, Census data on the fraction of the population with current health insurance coverage (commercial or government-funded) are available annually for 1987-2002. The input time series in Figure 15 was constructed from these data, and assumes a fixed value of 87.5% for 1980-1986, and 85% for 2003 and beyond.

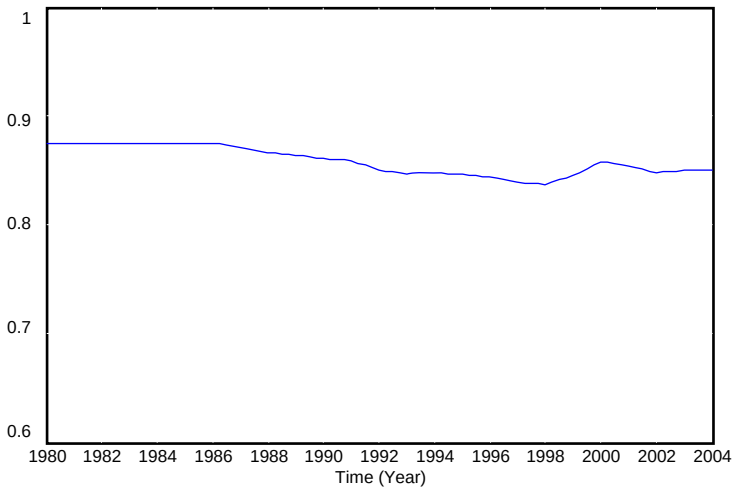

Figure 15. Healthcare access fraction, 1980-2004
(for 1987-2002, annual data from Census on fraction of the total population with health insurance)

Figure 16 presents the model's input time series for the tested fraction of high-risk healthcare users, which would include all people with significant risk factors for diabetes as well as those who present with symptoms that may be complications of diabetes. There are no survey data available on this variable, although experts agree that it has risen over time. We have estimated this time series through a process of fine-tuning to get a close fit of the model to historical data on the diagnosed fraction of diabetes; those data and model results are presented further below.

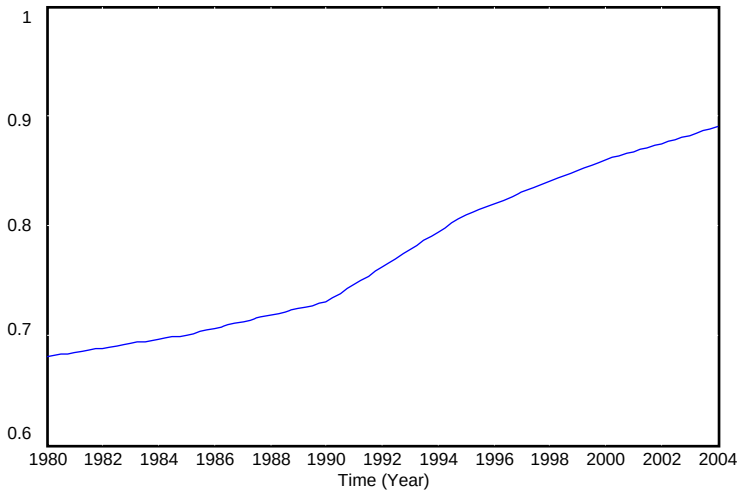

Figure 16. Tested fraction of high-risk healthcare users, 1980-2004
(estimated through model simulation and adjustment)

The sensitivity of testing for complicated diabetes is determined by whether only a fasting-plasma glucose test (FPGT) is done, or whether a more conclusive two-hour oral glucose tolerance test (OGTT) is done (sometimes as a follow-up to an inconclusive FPGT). A good review of information on diabetes testing is presented in (Harris, 1995), which includes a table indicating that the sensitivity of the OGTT for diabetes is **97%**, whereas the sensitivity of the FPGT for diabetes is only 31%. But the FPGT has a much higher sensitivity for overall hyperglycemia (including both diabetes and prediabetes), and it is likely that many patients found positive for hyperglycemia by a first FPGT receive a follow-up FPGT to investigate further whether they might be diabetic. (In the model, we use a value of **84%** for the sensitivity of the FPGT for diabetes.) It is unclear what fraction of patients get the OGTT as opposed to the FPGT. For the complicated diabetes population, the great majority of detection probably occurs in response to symptoms (rather than due to risk factors alone), in which case we suspect a physician is much more likely to take the time to do the more sensitive OGTT rather than just the FPGT; we assume that **90%** of the undiagnosed complicated diabetes population being tested get an OGTT.

3.5 Diagnosis of Uncomplicated Diabetes

Figure 17 presents the causal structure for the diagnosis of uncomplicated diabetes, and the equation for this flow is shown below.

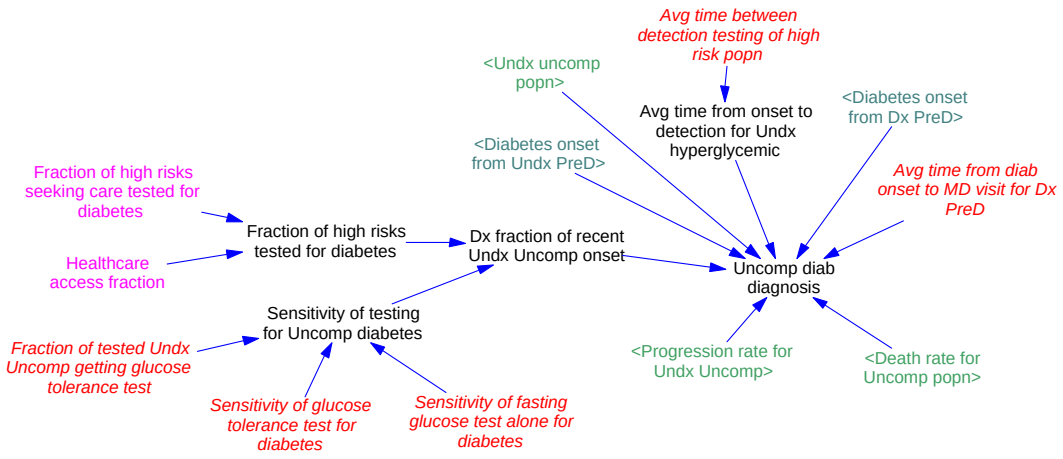

Figure 17. Diagnosis of uncomplicated diabetes

Uncomp diab diagnosis =

DELAY1(Diabetes onset from Dx PreD, Avg time from diab onset to MD visit for Dx PreD)

+

DELAY1(Diabetes onset from Undx PreD,Avg time from onset to detection for Undx hyperglycemic)*(1-(Death rate for Uncomp popn +Progression rate for Undx Uncomp) *

Avg time from onset to detection for Undx hyperglycemic) * Dx fraction of recent Undx Uncomp onset

+

(Undx uncomp popn/Avg time from onset to detection for Undx hyperglycemic) *

(Dx fraction of recent Undx Uncomp onset - DELAY1(Dx fraction of recent Undx Uncomp onset, Avg time from onset to detection for Undx hyperglycemic)) /

(1 - DELAY1(Dx fraction of recent Undx Uncomp onset, Avg time from onset to detection for Undx hyperglycemic))

The equation is in three parts, separated by plus (+) signs, each part representing a particular "route" to diagnosis of uncomplicated diabetes.

The first line of the equation represents the diagnosis of people who were previously diagnosed with prediabetes and who have recently progressed to diabetes. It is assumed all people previously diagnosed with prediabetes are under the regular care and monitoring of a physician, so that all cases of diabetes onset in these people are detected at the time of their next office visit; the *Avg time from diab onset to MD visit for Dx PreD* is set to **0.5** years.

The second part of the equation represents the diagnosis of people with previously undiagnosed prediabetes who have recently progressed to diabetes. The diagnosis occurs as the result of screening of the population with significant risk factors for diabetes. The calculation involves a first-order delay of the onset flow, with an average delay time equal to half of the average time between detection testing; the *Avg time between detection testing of high risk popn* is assumed per guidelines to be **3** years, half of which is 1.5 years average time from onset to detection. The calculation also subtracts out those who, during that 1.5 year delay time, have died. Finally, it applies the current prevailing diagnosis fraction for recent-onset uncomplicated diabetes not previously diagnosed with prediabetes (*Dx fraction of recent Undx Uncomp onset*), the calculation of which is described below.

The third part of the equation represents the diagnosis of people whose uncomplicated diabetes was <u>not</u> diagnosed soon after onset, but who are now diagnosed because the diagnosis fraction for recent-onset uncomplicated diabetes has recently increased. The calculation of such "playing catch-up" diagnosis of uncomplicated diabetes has the same form as that described above for complicated diabetes, but the operative parameters are a bit different. For one thing, the delay time is longer, equal to the 1.5 year average time from onset to detection noted above. Also, the determinants of *Dx fraction of recent Undx Uncomp onset* are somewhat different than they are for complicated diabetes.

The recent-onset diagnosis fraction for uncomplicated diabetes is the product of two factors: (1) the fraction of high-risks screened for diabetes, and (2) the average sensitivity of the screening tests used for uncomplicated diabetes.

The screening fraction is itself the product of two things seen previously: (1) the fraction of high risks seeing their physician regularly, as reflected by the healthcare access fraction shown in Figure 15, and (2) the fraction of these high-risk care-seekers who get tested, shown in Figure 16. (Note that, since uncomplicated diabetes is asymptomatic, there is <u>no</u> additional fraction of the uncomplicated diabetes population who despite lack of health insurance are getting tested due to an emergency room visit for urgent symptoms, as can occur for complicated diabetes.)

The average sensitivity of the screening test for uncomplicated diabetes is calculated in the same way as it is for complicated diabetes, involving estimates of sensitivity for the FPGT (84%) and the OGTT (97%), and the fraction getting the OGTT. The fraction getting the more sensitive OGTT is likely to be lower in the case of screening for asymptomatic uncomplicated diabetes than it is in the case of symptomatic complicated diabetes, because it is harder to justify doing the more time-consuming OGTT with a patient lacking symptoms. In line with numbers presented in Table 2.6 of (Harris, 1995), we assume that **60%** of the undiagnosed uncomplicated diabetes population being tested get an OGTT, often as a follow-up to an initial FPGT result that indicates the possibility of diabetes.

3.6 Diagnosis of Prediabetes

Figure 18 presents the causal structure for the diagnosis of prediabetes, and the equation for this flow is shown below.

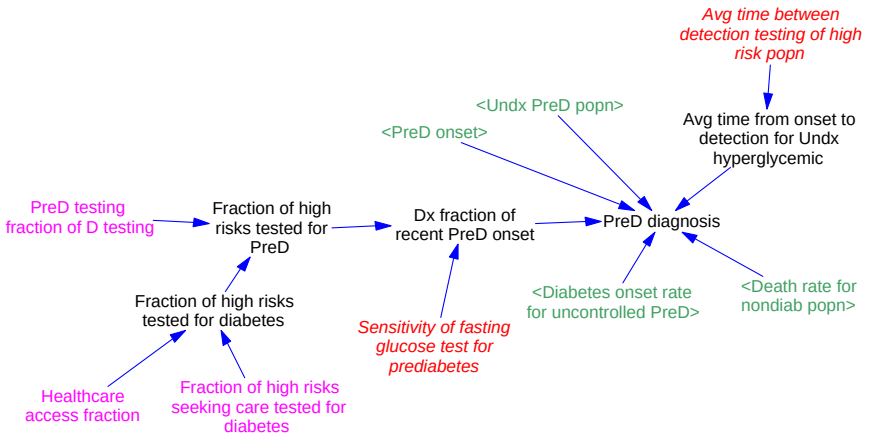

Figure 18. Diagnosis of prediabetes

PreD diagnosis =

DELAY1(PreD onset,Avg time from onset to detection for Undx hyperglycemic) * (1-(Death rate for nondiab popn+Diabetes onset rate for uncontrolled PreD)*Avg time from onset to detection for Undx hyperglycemic) * Dx fraction of recent PreD onset

+

(Undx PreD popn/Avg time from onset to detection for Undx hyperglycemic) *

(Dx fraction of recent PreD onset - DELAY1(Dx fraction of recent PreD onset, Avg time from onset to detection for Undx hyperglycemic)) /

(1 - DELAY1(Dx fraction of recent PreD onset, Avg time from onset to detection for Undx hyperglycemic))

The equation is in two parts, separated by a plus (+) sign, each part representing a particular "route" to diagnosis of prediabetes.

The first part of the equation represents the diagnosis of people with recent-onset prediabetes. The calculation involves a first-order delay of the onset flow, using a 1.5 year delay time that equals half of the 3 year average time between screenings of a person in the high-risk population (as described above in connection with uncomplicated diabetes testing.) The calculation next subtracts out those who have died during that 1.5 year delay time. Finally, it applies the current prevailing diagnosis fraction for recent-onset prediabetes (*Dx fraction of recent PreD onset*), the calculation of which is described below.

The second part of the equation represents the diagnosis of people whose prediabetes was not diagnosed soon after onset, but who are now diagnosed because the diagnosis fraction for recent-onset prediabetes has recently increased. The calculation of such "playing catch-up" diagnosis prediabetes has the same form as that described above for complicated and uncomplicated diabetes, using the 1.5 year average time from onset to detection noted above, and the *Dx fraction of recent PreD onset*.

The recent-onset diagnosis fraction for prediabetes is the product of two factors: (1) the fraction of high-risks screened for prediabetes, and (2) the average sensitivity of the screening test used for prediabetes.

Guidelines for the detection and treatment of prediabetes were defined and promulgated only relatively recently, starting in the mid-to-late 1990s, and in fact are still in a state of evolution. (See Harris, 1995; ADA/NIDDK, 2002; and Kahn, Genuth et al., 2003.) In the model, the fraction of high-risks screened for prediabetes is expressed relative to the fraction screened for uncomplicated diabetes (as described above). Figure 19 presents our educated guess as to how prediabetes screening as a fraction of diabetes screening has grown, starting at zero in 1995 and reaching 30% by 2004.

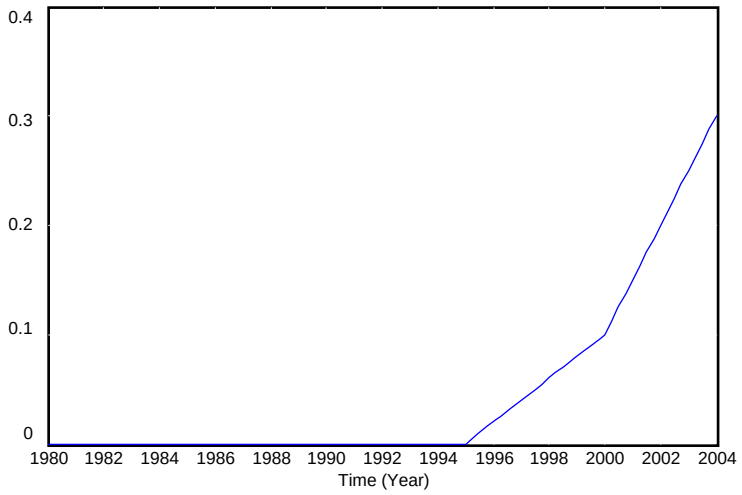

Figure 19. Prediabetes testing as a fraction of diabetes testing, 1980-2004

The average sensitivity of the screening test for prediabetes is estimated at **84%**. We assume that the FPGT is used for the identification of prediabetes, as it is easier to administer and actually more sensitive for prediabetes than is the OGTT (based on current cut points). Prediabetes is currently defined as having an FPGT measure of 100-124 mg/dl or an OGTT measure of 140-199 mg/dl. In a recent analysis of NHANES III data (see Kahn, Genuth et al. 2003), 84% of the 40% of people age 40-74 with prediabetes were found prediabetic by the FPGT criterion.

3.7 Simulation of Historical Diabetes and Prediabetes Prevalence

In concluding this section on population stocks and flows we present model output on diabetes and prediabetes prevalence for the period 1980-2004, and compare these simulated results with the historical record where possible. The variables presented below are fractions calculated from population variables described earlier in this section (Section 3) of the document. Note that the simulated results shown here depend not only on factors already discussed but also, in part, on factors discussed in the next two sections, dealing with diabetes and prediabetes control, and with obesity, respectively.

Figure 20 presents simulated results for diabetes prevalence expressed as a fraction of the adult population; both total (blue) and diagnosed (red) prevalence are shown. Total and diagnosed prevalence grow throughout the 24-year time period, accelerating somewhat in the 1990s. The acceleration is more pronounced in diagnosed prevalence, due to the fact that the diagnosed fraction of diabetes grows rapidly during the 1990s (see Figure 22 below). Simulated diagnosed prevalence demonstrates a good fit to prevalence data from NHIS (green line, through 2003).

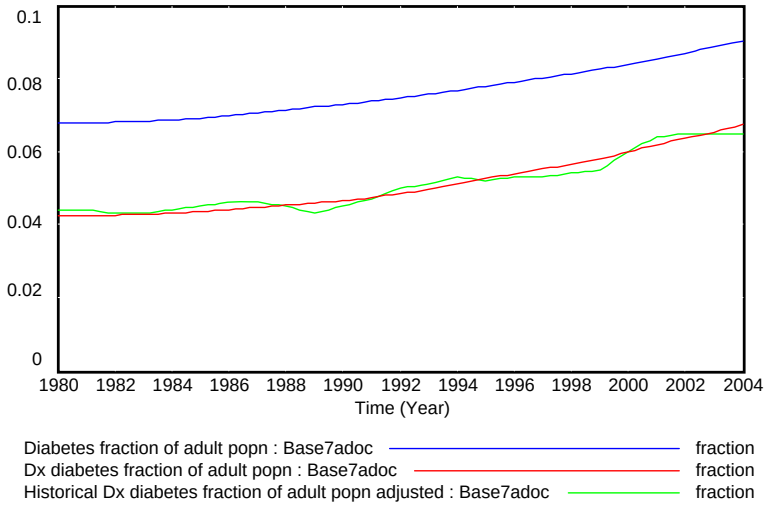

Figure 20. Simulated total and diagnosed diabetes prevalence 1980-2004, and comparison with NHIS data on diagnosed diabetes prevalence through 2003 (flat line indicates no data for 2004)

Figure 21 presents simulated results for prediabetes prevalence expressed as a fraction of the adult population; both total (blue) and diagnosed (red) prevalence are shown. Prediabetes prevalence rises only gradually, from 22% to 25% of the adult population. Diagnosed prediabetes is zero until testing for prediabetes starts in the late 1990s.

In considering the prediabetes simulation, the one useful data point we have to compare against is from the NHANES III analysis described above (Kahn, Genuth et al., 2003), which found prediabetes in about 40% of the age 40-74 population for the survey period 1988-1994; a total of 40 million people. Using other documents (notably, Honeycutt, Boyle et al., 2003) we

extrapolate this to a prevalence for the full adult population of 24.7%, which corresponds to a total of 46 million people. (That is, we estimate another 6 million prediabetics among those age 18-39 or age 75-plus.) The model produces a prediabetes prevalence of 24.4% in 1988 rising to 25.1% by 1994, in agreement with the extrapolated data.

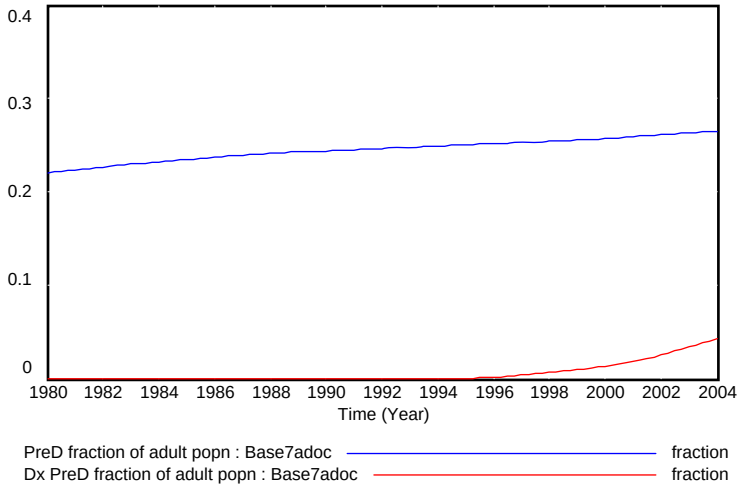

Figure 21. Simulated total and diagnosed prediabetes prevalence 1980-2004

Figure 22 presents simulated results for the diagnosed fraction of all people with diabetes (blue) and compares them with corresponding data from NHANES (red line, through 2000). The very close fit between simulation and data seen here is attributable to fine-tuning of the time series for testing of high-risks seen previously in Figure 16.

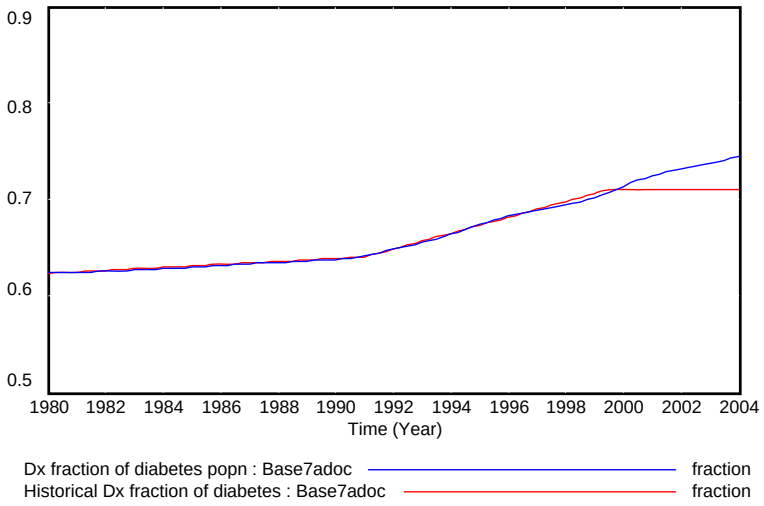

Figure 22. Simulated diagnosed fraction of diabetes 1980-2004, and comparison with NHANES data through 2000 (flat line indicates no data for 2001-2004)

Figure 23 presents simulated results for the four components of the diabetes population, as defined by presence or absence of complications and presence or absence of diagnosis. These are expressed as fractions of the total diabetes population, the four of which sum to 1 (100%). These components are:

- Diagnosed complicated (blue line): starts at 34.4% and ends at 34.7% of the diabetes population;
- Undiagnosed complicated (red): starts at 8.6% and declines to 3.7%;
- Diagnosed uncomplicated (green): starts at 27.9% and climbs to 39.6%;
- Undiagnosed uncomplicated (black): starts at 29.1% and declines to 22.0%.

By combining and comparing these components, one may draw some conclusions about how their mix has changed from 1980 to 2004:

- The uncomplicated fraction of diabetes has increased from 57% to 62%. Growth in diabetes onset, particularly during the 1990s and driven largely by the growth of obesity, has increased the "front-loading" of the diabetes chain, and much of the cascading of this growth through to complications has not yet occurred.
- The diagnosed fraction of the diabetes population overall (as seen above in Figure 22) has increased from 62% to 74%. The diagnosed fraction of uncomplicated diabetes has grown from 49% to 64%. The diagnosed fraction of complicated diabetes has grown from 79% to 90%.
- The complicated fraction of undiagnosed diabetes has decreased from 23% to 14%. Some of the clinical literature suggests that up to 22% of people with newly diagnosed (and thus, until recently, undiagnosed) diabetes have measurable retinopathy, which means that their diabetes should be considered complicated. (See, for example, Wang, Ip, and Lam, 1998.)

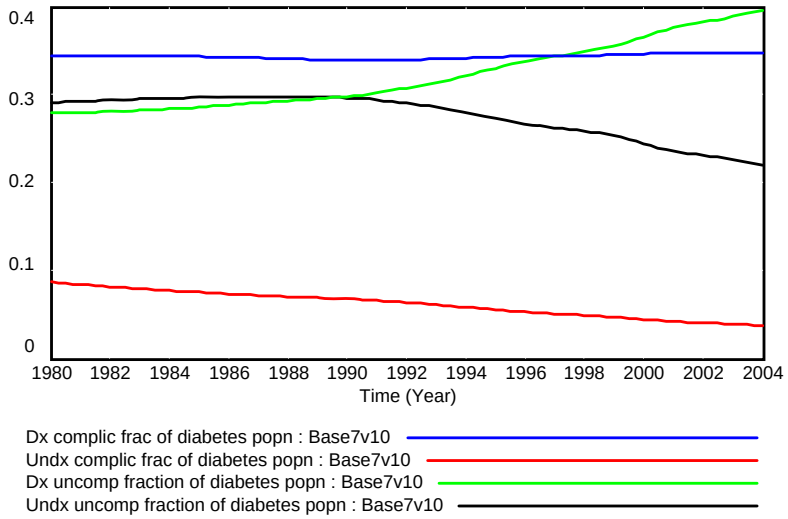

Figure 23. Simulated four component fractions of diabetes population 1980-2004

4. Control of Diabetes and Prediabetes

4.1 Factors Affecting the Controlled Fraction

We know from the clinical literature that the control of blood glucose, as well as blood pressure and lipids, is critical for reducing deaths from complications of diabetes (see Figure 8), progression to diabetes from prediabetes (Figure 12), and progression to complicated diabetes from uncomplicated (Figure 13); the magnitudes of those beneficial effects of control are also fairly well established. Moreover, we know something about the fraction of (diagnosed) diabetes patients who are under control: An estimated 37% of diabetes patients in 1999-2000 had their blood glucose level under optimal control, defined as an HbA1c level under 7% (DHHS/AHRQ, 2003). We also have information on the behavioral factors that can contribute to achieving control, which typically requires a combination of good nutrition, exercise, glucose self-monitoring, and the use of drugs.

Figure 24 presents the causal structure for the controlled fraction of diagnosed diabetes and prediabetes. The controlled fraction is formulated as the product of two factors: (1) the fraction of hyperglycemics (people with diabetes or prediabetes) under proper clinical management, that is, receiving medical examinations regularly according to guidelines; and (2) the controlled fraction of those patients under management. Three factors, in turn, contribute to the ability of hyperglycemics under clinical management to maintain control: (1) the ability to self-monitor one's condition and report any changes to one's healthcare providers, (2) the ability to adopt a healthy lifestyle conducive to the maintenance of control, and (3) the ability to afford prescribed medications needed for maintaining control.

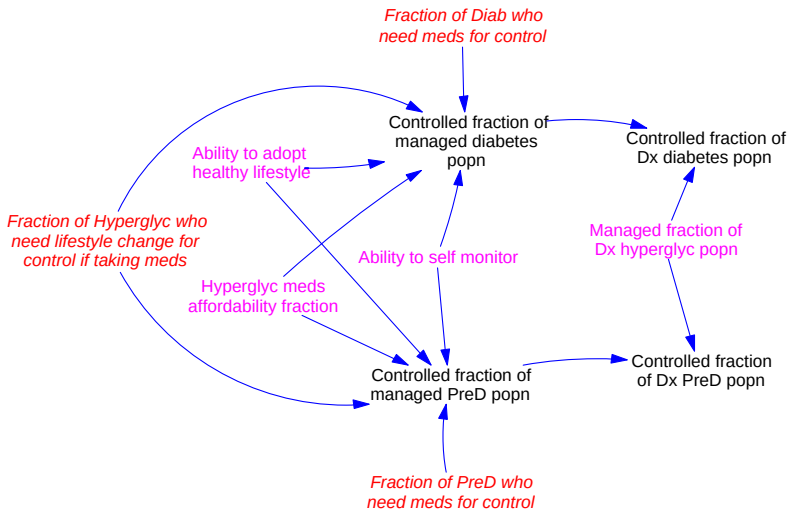

Figure 24. Controlled fraction of diagnosed diabetes and prediabetes

Figure 25 shows our assumption (blue line) for the fraction of diagnosed hyperglycemics who are receiving professional care that would give them the opportunity to stay under control. This assumed curve rises from 20% in 1980 to 66% in 2004. The 1994-2002 portion of our assumed curve is based on data (red line) from the Behavioral Risk Factor Surveillance System (BRFSS). From available BRFSS measures, we have settled upon the average of "dilated eye exam last year" and "foot exam last year" as a stable, representative measure of the management fraction. (Another relevant measure, "at least two A1c tests last year", is available only for 2000-2002. Its values for these years are in the same range as the eye and foot measures. For the sake of having a consistent metric over all years, we have not factored in the A1c data.)

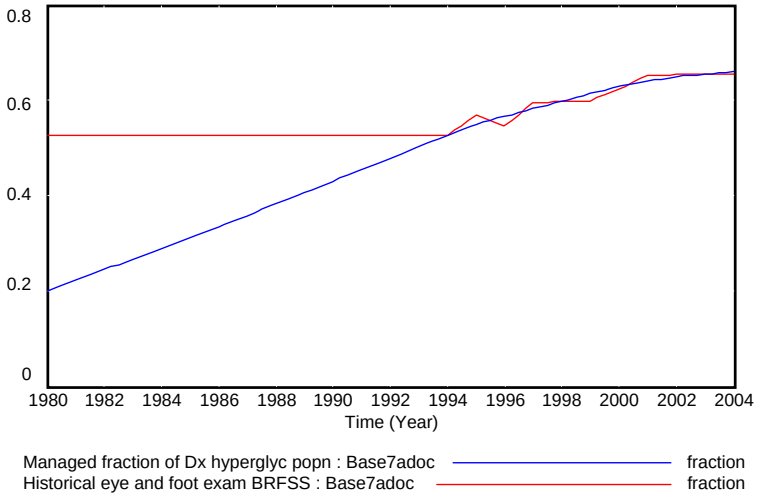

Figure 25. Assumed managed fraction of diagnosed diabetes 1980-2004, and comparison with BRFSS data averaging eye exam and foot exam measures 1994-2002
(flat line indicates no data for 1980-1993 nor for 2003-2004)

The equations for the controlled fractions of managed diabetes and prediabetes are a bit complex. We will present the first of these equations, for diabetes control; the equation for prediabetes is identical to that for diabetes except for the substitution of the parameter "Fraction of PreD who need meds for control" for the parameter "Fraction of Diab who need meds for control".

Controlled fraction of managed diabetes popn =

(1-Fraction of Diab who need meds for control) * Ability to adopt healthy lifestyle

+

Fraction of Diab who need meds for control * Ability to self monitor * Hyperglyc meds affordability fraction *

(1 - Fraction of Hyperglyc who need lifestyle change for control if taking meds + Fraction of Hyperglyc who need lifestyle change for control if taking meds*Ability to adopt healthy lifestyle)

The equation combines the three factors mentioned above affecting the ability of managed patients to maintain control—self-monitoring, healthy lifestyle, and drug affordability—by taking into account the fraction of people who need drugs to achieve and maintain control and the fraction of drug-takers who also need to change their lifestyle (nutrition and exercise) for control. We assume that **95%** of people with diabetes require medications to achieve control, while only **33%** of prediabetics (whose blood glucose is only moderately elevated and who do not yet have irreversible insulin resistance) require medications to do the same. The first line of the equation says that for those people who do not need drugs for control, the controlled fraction is equal to the ability to adopt a healthy lifestyle, as drug affordability and self-monitoring (which is important primarily for determining the need to adjust a drug regimen) are assumed not relevant for such people. The remainder of the equation relates to people who do need drugs for control, for whom all three factors affecting control come into play.

Figure 26 presents our assumed curve for the ability of hyperglycemics to adopt a healthy lifestyle including good nutrition and exercise. The curve rises from 40% in 1980 to 60% in 2004. The BRFSS contains information on weight control and physical activity for the population at large, but we have not seen such data for people with diabetes and prediabetes specifically. From 1996-2000, the fraction of the population eating fewer calories to control weight rose from 40% to 43%, while the fraction doing more physical activity to control weight rose from 59% to 61%. The BRFSS also reports for people with diabetes that the fraction who have ever attended a diabetes self-management class rose from 51% in 2000 to 56% in 2002; such classes include information on lifestyle change. From these various BRFSS data we surmise that 60% is a reasonable current estimate for adherence to lifestyle change guidelines among hyperglycemics, a number that is undoubtedly greater than it was in 1980.

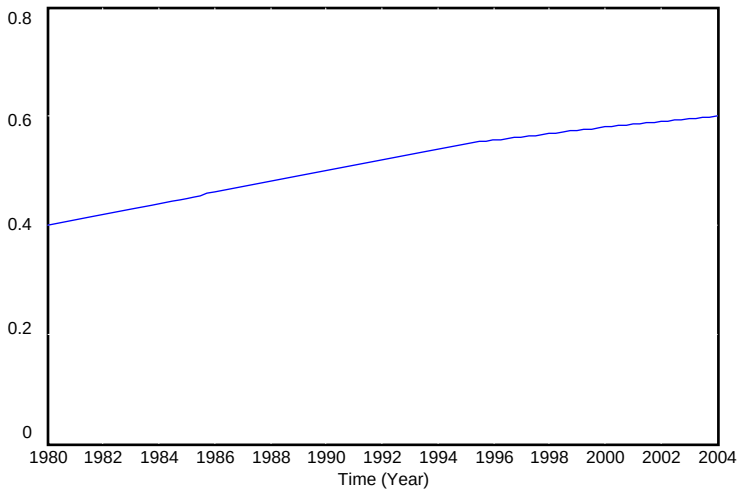

Figure 26. Assumed ability of hyperglycemics to adopt a healthy lifestyle 1980-2004

Returning to the equation above, the second part says that, for those hyperglycemics who do need drugs for control, two requirements for control are the affordability of those drugs, and the ability to self-monitor to assess the effectiveness of the drugs and perhaps other interventions. A third possible requirement for control among such people is the ability to adopt a healthy lifestyle, but that applies only if the drugs are not sufficient by themselves to accomplish control. We assume that, for hyperglycemics who need drugs for control, the fraction for whom this is sufficient to achieve control without lifestyle change is only **33%**.

Figure 27 shows our assumption (blue line) for the fraction of diagnosed hyperglycemics under professional management who are also able to self-monitor. This assumed curve rises rather steeply from 45% in 1980 to 91% in 2004. The 1994-2002 portion of our assumed curve is based on BRFSS data (red line) on the fraction of people with diabetes who do daily glucose self-monitoring. But among those who do not do daily glucose self-monitoring are people are not even under professional management. To calculate self-monitoring *as a fraction of those under professional management*, we construct the ratio of the BRFSS self-monitoring measure to the measure discussed above in connection with Figure 25, that averages the fractions getting annual eye and foot exams. It is this ratio that is presented as the red line in Figure 27.

Note that, because of how it has been defined in relation to the data, the affordability of self-monitoring supplies is implicitly included in our fraction describing the ability to self-monitor.

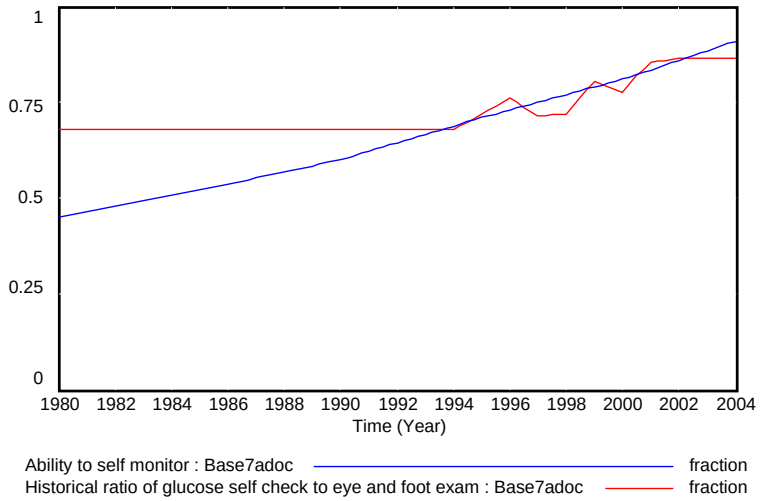

Figure 27. Assumed self-monitoring fraction of hyperglycemics 1980-2004, and comparison with ratio of BRFSS data on glucose self-checking to the average of eye and foot exam measures 1994-2002 (flat line indicates no data for 1980-1993 nor for 2003-2004)

Figure 28 shows our assumption for the fraction of hyperglycemics able to afford the drugs they need to stay under control. The assumed value (blue line) starts at 79% for 1980-1990, rises to 84% by 2000, and remains at 84% thereafter. The 1997-2000 portion of our assumed curve is based on BRFSS data (red line) on the fraction of people with diabetes who say they use diabetes medication. To assess affordability, we divide this usage metric by the 95% of people who we assume need drugs to achieve control. It is this ratio that is presented as the red line in Figure 28.

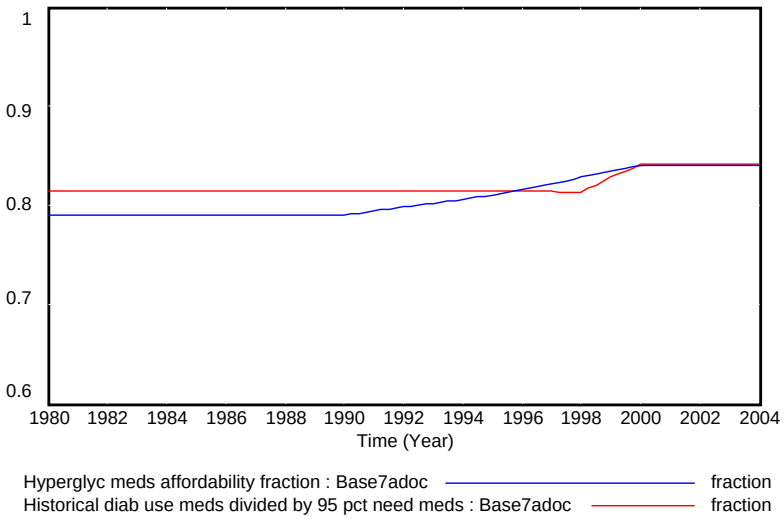

Figure 28. Assumed drug affordability for managed hyperglycemics 1980-2004, and comparison with ratio of BRFSS data on diabetes medications use 1997-2000 to the 95% assumed to need medications for control (flat line indicates no data for 1980-1996 nor for 2001-2004)

In addition to the BRFSS data, we have done an alternate calculation of diabetes drug affordability based on data and estimates from a system dynamics modeling study of diabetes in Whatcom County, Washington (Homer, Hirsch et al., 2004). The salient numbers are as follows:

- Elderly fraction of people with diagnosed diabetes in year 2000: 43%
- Fraction of insured non-elderly able to afford diabetes drugs: 99%
- Fraction of elderly with Medigap plans providing drug coverage: 41%
- Fraction of those with Medigap plans who can afford co-payments for diabetes drugs: 80%
- Fraction of those without Medigap plans who can afford to pay out of pocket: 50%

Putting all of these numbers together gives 84% as the fraction of the insured who can afford diabetes drugs, which is identical to the number we have assumed based on BRFSS. Using those with insurance coverage as the denominator is appropriate, as it seems extremely unlikely that an uninsured person with diagnosed diabetes would remain under regular management (for which visits they have to pay out of pocket) but not be able to afford the prescribed medications.

4.2 Simulation of Historical Diabetes and Prediabetes Control

In concluding this section, we present model output on diabetes and prediabetes control for the period 1980-2004. Figure 29 presents simulated controlled fractions of the diagnosed, and also controlled fractions of the subset of the diagnosed who are being managed. (That subset, the managed fraction of diagnosed hyperglycemics, was presented above in Figure 25.) These fractions are calculated based on the combination of factors shown in the causal diagram presented above as Figure 24.

For the diagnosed diabetes population, the controlled fraction (blue line) starts at 6% in 1980 and rises to 44% by 2004. It is equal to 37% in 2000, matching the value cited in the previous section (DHHS/AHRQ, 2003). The controlled fraction of the managed subset of diabetes (red line) starts at 29% and rises to 66%. The sources of increase in control among the managed are (1) increased ability to adopt a healthy lifestyle, as seen in Figure 26, (2) increased self-monitoring, as seen in Figure 27, and, to a lesser degree, (3) increased drug affordability during the 1990s, as seen in Figure 28.

For the diagnosed prediabetes population, these three factors cause similar increases in the controlled fraction (green line), and in the controlled fraction of the managed (black line). Recall, however, that that the prevalence of diagnosed prediabetes was zero until the late 1990s (see Figure 21), so that the controlled fractions seen below are inactive and have no beneficial impact on diabetes onset until that time.

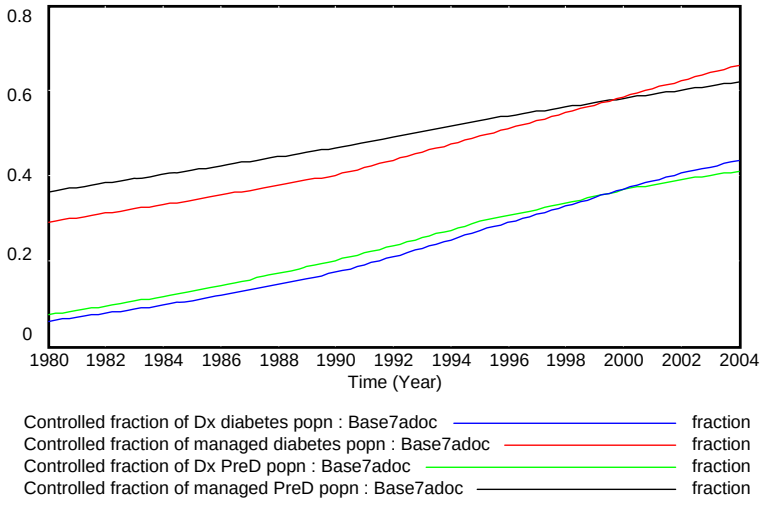

Figure 29. Simulated controlled fractions of diagnosed or managed diabetes and prediabetes populations 1980-2004

5. Obesity as Affected by Caloric Intake and Physical Activity

5.1 Modeling Obesity by Way of Average Weight and BMI

In the model, obese population fractions affect the onset of prediabetes (see Figure 9), recovery from prediabetes (Figure 10), and onset of diabetes (Figure 12). Figure 30 presents the dynamic structure used to model the obese fraction of the adult population by way of modeling average body weight and body mass index (BMI). Body weight (averaged across all adults) is formulated as a stock which accumulates net changes over time; see the two-way flow, *Change in body weight*. The equations used for modeling weight change are shown below.

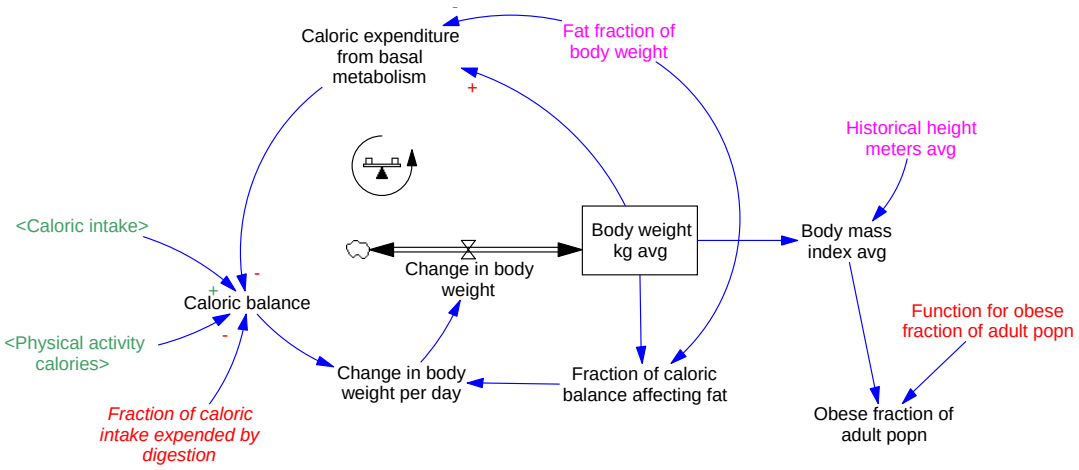

Figure 30. Average body weight and BMI, and Obese fraction of adult population

Change in body weight per day =

Caloric balance * (Fraction of caloric balance affecting fat/9300 + (1-Fraction of caloric balance affecting fat)/4100)

where:

(a) Fraction of caloric balance affecting fat = 1/(1 + ((10.4/(Body weight kg avg * Fat fraction of body weight))*(4100/9300)))

(b) Caloric balance = Caloric intake – Physical activity calories – Caloric expenditure from basal metabolism – (Caloric intake * Fraction of caloric intake expended by digestion)

(c) Fraction of caloric intake expended by digestion = **10%**

(d) Caloric expenditure from basal metabolism = (Body weight kg avg * (0.024*Fat fraction of body weight + 0.102*(1-Fat fraction of body weight)) + 0.85) * 238.7

(These equations are based on Abdel-Hamid, 2002. Note that 9300 is Kcal/kg fat; 4100 is Kcal/kg muscle; and 238.7 is Kcal/megajoule of energy.)

Note that a balancing feedback loop going through Body weight average (and marked with a balancing loop symbol in Figure 30) is formed by virtue of equations (b) and (d). An increase in weight, due to a caloric balance temporarily greater than zero, leads to an increase in metabolic expenditure (equation d), which, in turn, tends to bring caloric balance back toward zero (via equation b). This balancing loop will cause the body weight eventually to reach a new equilibrium level to adjust for any changes in caloric intake or physical activity. Simulations of this sector of the model by itself suggest that this adjustment process can take one to two years.

A time series for the Fat fraction of body weight (required for equations (a) and (c) above), was developed starting from skinfolds data from all four of the NHANES surveys going back to the early 1970s. (All data presented in this section come from NHANES and were provided by the CDC's Edward Gregg.) Long-established empirical equations (Durnin and Womersley, 1974) were used to translate the skinfolds data to a fat fraction, applied to male and female data separately and then averaged together. The derived data for fat fraction remains in a very narrow band of 30.0-30.5% from the early 1970s through 2000; we have assumed the average fat fraction of body weight will remain at **30%** into the future.

Average BMI is calculated in the model as the ratio of average body weight (kilograms) to the square of average height (meters). Average height is a time series input based on NHANES data, which rises from about **1.68** meters in 1980 to about **1.69** meters in 1990 and beyond; we have assumed the average height will remain at 1.69 meters into the future.

In regard to Average BMI, one may note that we have taken what is actually the population mean of a ratio and modeled it instead as the ratio of population means for weight and height (squared), and that those calculations are not identical. This may call into question our approach to modeling BMI. Figure 31 may put these concerns to rest, as it shows that there is very little difference between our calculation (using historical data on mean weight and mean height) and historical mean BMI throughout the 1980-2000 period. Moreover, note that BMI is used in the model only as an intermediate calculation in the modeling of the obese fraction, and for no other purpose.

Figure 32 presents the X-Y lookup function for converting Average BMI (X) to Obese fraction of the adult population (Y). (Obesity is defined as a BMI greater than or equal to 30.) This function was developed through estimation of a two-parameter logistical regression using BMI and obesity data from the four NHANES surveys spanning 1971 to 2000; over this time period, Average BMI rose from 25.3 to 28.0, and the Obese fraction rose from 15% to 31%. The function in Figure 32 has the S shape one would expect to see from the growing tail of a bell-shaped distribution (for BMI) as it moves to the right (with cut point at BMI=30). Also, in the lookup function an Average BMI of 30 corresponds to an obesity fraction of slightly less than 50%, which is what one would expect to see from a slightly skewed-to-the-right bell-shaped distribution with its mean greater than its median. We know from NHANES data that BMI has such a distribution (see Cutler, Glaeser, and Shapiro, 2003).

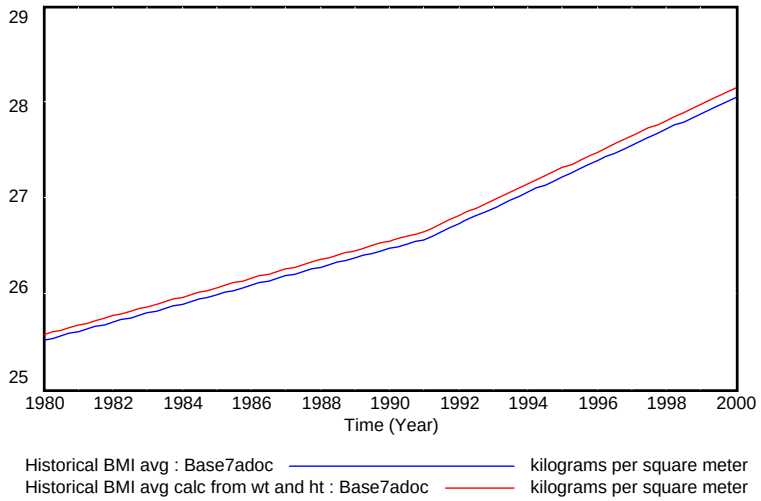

Figure 31. Average BMI 1980-2000 (blue), compared with the ratio (red) of average weight to the square of average height (data from NHANES II, III, 1999-2000)

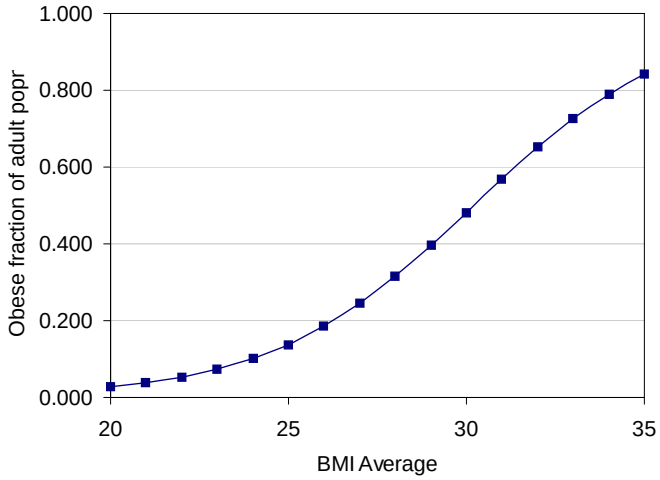

Figure 32. Model lookup function for Obese fraction of adult population as a function of BMI Average

Figure 33 shows that the lookup function can reproduce the 1980-2000 historical data for the obese fraction quite well, though the function creates a bit more upward curvature than is seen in the NHANES data to date. The fact that the green line (corresponding to the "ratio of means" approximation to Average BMI) does no worse than the red line (corresponding to actual Average BMI) in reproducing the historical obese fraction through the lookup function supports our use of the "ratio of means" approximation to Average BMI in the model.

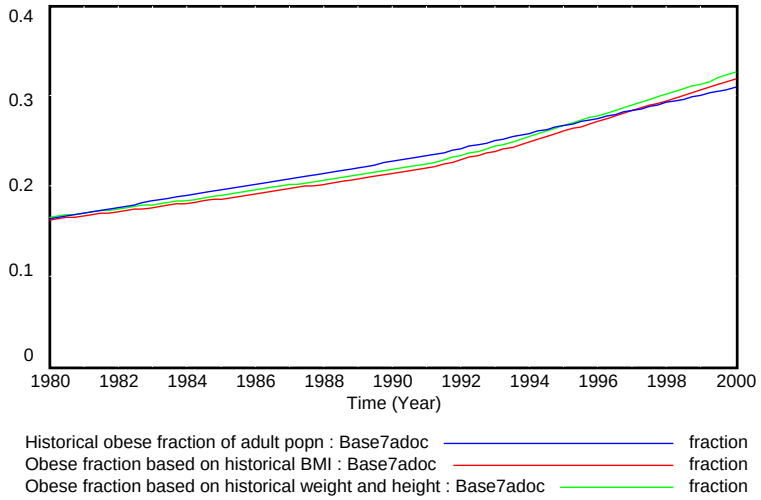

Figure 33. NHANES reported obese fraction of adult population 1980-2000 (blue), compared with lookup function calculations using historical average BMI as input (red) or historical ratio of average weight to average height squared as input (green)

5.2 Caloric Intake and Physical Activity

We have found various indicators of average caloric intake, including NHANES surveys, USDA food disappearance, USDA Continuing Survey of Food Intake for Individuals, and USDA pounds consumed. The first three of these (all expressed as Kcal/person/day) are presented in Figure 34 below, along with the assumed curve for caloric intake used in the model. This assumed curve is equal to the NHANES values (covering 1980 to 2000) plus an add-on fraction to adjust for underreporting by survey subjects, and to allow for a better model fit to the BMI data as shown above in Figure 31. The underreporting add-on fraction is set to 6.5% for 1980-1991, then rises gradually until it reaches 8.5% in 1999. The assumed growth in the add-on fraction reflects the observation that underreporting of caloric intake is greater among the overweight and obese than it is among individuals of normal weight, and accordingly should be expected to increase to some degree when the obese fraction increases. With the add-on fraction, the assumed curve for caloric intake grows from 2,130 Kcal in 1980 to 2,355 in 1991, to 2,425 in 1999. We have extended the slow growth trend seen in the 1990s to the period after 1999, so that our baseline curve climbs to 2,465 Kcal in 2004.

In contrast with caloric intake, we have found no solid indicators of physical activity-related caloric expenditure for the 1980-2004 period. The following data may be salient but still do not leave us with a clear and complete picture of what has happened:

(1) BRFSS “no leisure time physical activity” fractions for 1990-2002 seem to indicate a small improvement during the 1990s, followed by greater improvement more recently (28.7% in 1990, 26.9% in 2000, 24.4% in 2002);

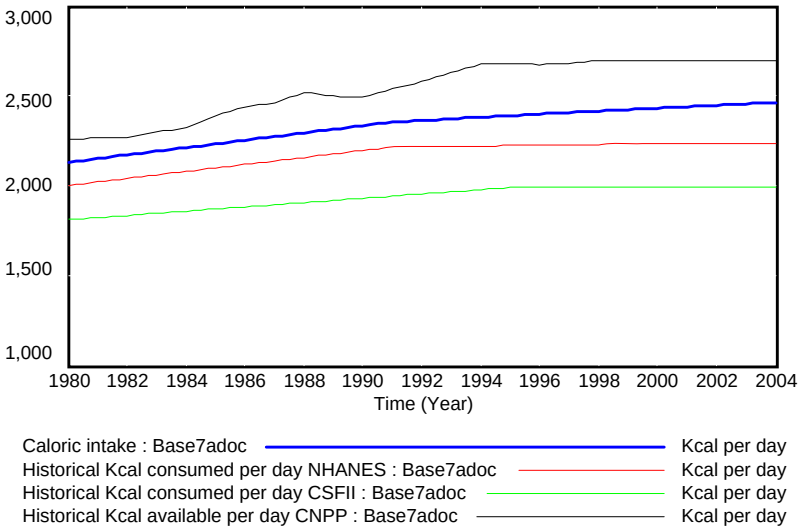

Figure 34. Assumed (blue line—through 2004) and reported caloric intake (NHANES: red—through 2000, USDA/CSFII: green—through 1989, USDA/CNPP: black—through 1998)

(2) Robinson and Godbey (1997) surveyed daily activity intensity, and found some improvement during 1975-1985, followed by some slackening during 1985-1995 (1.57 for 1975, 1.62 for 1985, 1.53 for 1995; as reported in Cutler, Glaeser, and Shapiro, 2003).

Following model experimentation, we have settled upon a pattern of average physical activity calories per day presented in Figure 35, which rises 35% during 1980-1990 from 355 Kcal to 480 Kcal, rises a bit more to 490 Kcal by 1995, then subsides back to 480 Kcal by 2000, staying constant thereafter. This assumed pattern of physical activity, in conjunction with the assumed NHANES-based pattern of caloric intake in Figure 34, helps make possible a good match of simulated BMI to historical BMI, as presented further below.

The ratio of assumed physical activity to assumed caloric intake is shown in Figure 36. This ratio rises from 16% to 21% and then subsides back to 19%. This range is typical of the physical activity ratio observed for people not engaged in heavy labor (Whitney and Rolfes, 1999; and see Abdel-Hamid, 2002, p. 435), and helps to establish that our assumed values for physical activity are in proper proportion to caloric intake.

Aside from its appropriate proportionality to caloric intake, is there any evidence that our assumed pattern of physical activity is a reasonable one? Lacking solid historical data, we can rely only upon historical anecdote in support of the pattern. Perhaps one may think of the 1980s of a decade during which a broad swath of society, but the baby boomers in particular (then in their 20s and 30s), took great interest in getting in shape, joining gyms and pursuing aerobic activities in droves. One may characterize the 1990s, in contrast, as a period during which the concern about fitness reached a plateau or perhaps even faded to some degree, as younger people got no more exercise than the baby boomers (then in their 30s and 40s).

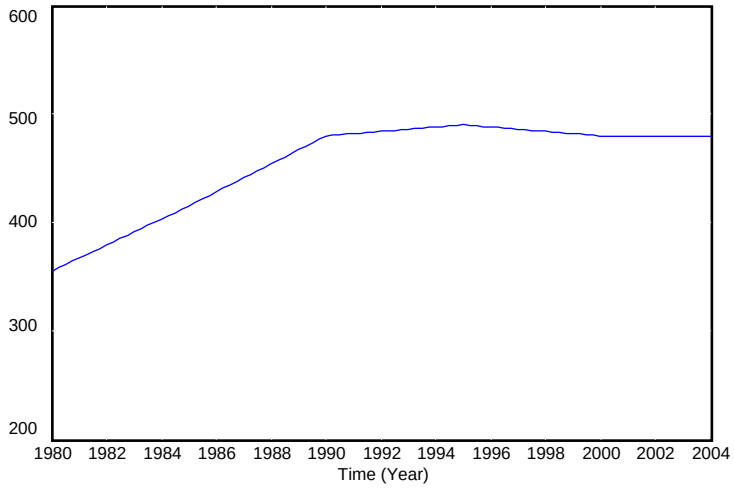

Figure 35. Assumed average physical activity caloric expenditure per day 1980-2004

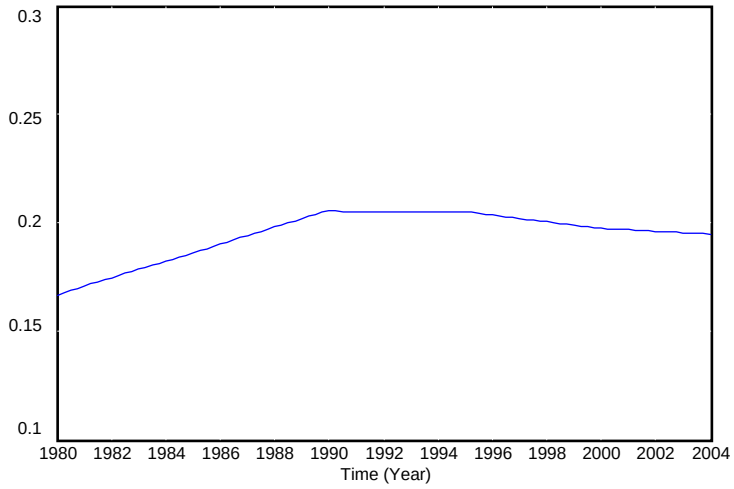

Figure 36. Ratio of assumed physical activity to assumed caloric intake 1980-2004

5.3 Obese Fractions of Normoglycemic, Prediabetes, and Diabetes Populations

We have described previously how (1) prediabetes onset is affected by the obese fraction of the normoglycemic population, (2) prediabetes recovery is affected by changes in the obese fraction of the prediabetes population, and (3) diabetes onset is affected by the obese fraction of the prediabetes population. These flows are affected by obesity among specific subsets of the adult population, not by obesity in the adult population overall. But the BMI/obesity calculations described earlier in this section are for the overall population, based as they are on population-wide NHANES data. Figure 37 shows how, starting from the overall obese fraction, obese fractions for the normoglycemic and prediabetes populations are derived; this also requires derivation of the obese fraction of people with diabetes.

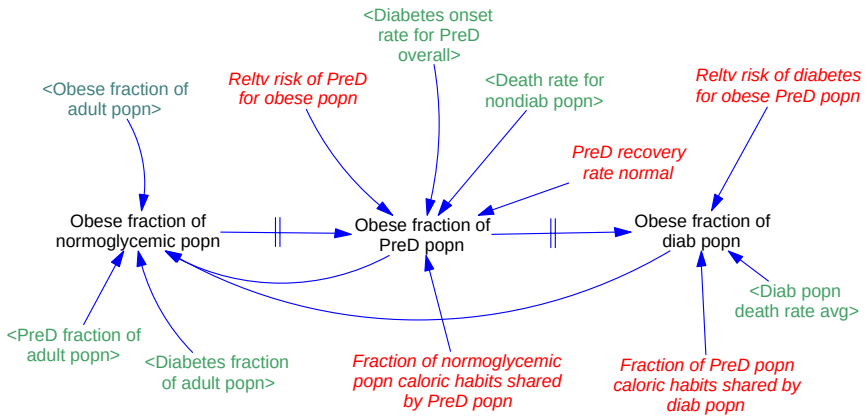

Figure 37. Obese fractions of normoglycemic, prediabetes, and diabetes populations

The equations used for these derivations are as follows:

Obese fraction of normoglycemic popn =

(Obese fraction of adult popn - Obese fraction of PreD popn*PreD fraction of adult popn - Obese fraction of diab popn*Diabetes fraction of adult popn) /

(1 - PreD fraction of adult popn - Diabetes fraction of adult popn)

Obese fraction of PreD popn =

SMOOTHI((Reltv risk of PreD for obese popn*Obese fraction of normoglycemic popn)/(Reltv risk of PreD for obese popn*Obese fraction of normoglycemic popn + (1-Obese fraction of normoglycemic popn)) ,

(1-Fraction of normoglycemic popn caloric habits shared by PreD popn)/(Diabetes onset rate for PreD overall+Death rate for nondiab pop + PreD recovery rate normal), Obese fraction of PreD popn initial)

Obese fraction of Diab popn =

SMOOTHI((Reltv risk of diabetes for obese PreD popn*Obese fraction of PreD popn)/(Reltv risk of diabetes for obese PreD popn*Obese fraction of PreD popn + (1-Obese fraction of PreD popn)),

(1-Fraction of PreD popn caloric habits shared by diab popn)/Diab popn death rate avg, Obese fraction of diab popn initial)

The obese fraction of the normoglycemic is—after setting its initial value in 1980—calculated algebraically from the other obese fractions. The first equation above takes those other obese fractions, and solves for normoglycemic obesity, based on the fact that overall obesity represents a weighted average of the obese fractions for normoglycemic, prediabetes, and diabetes. (An initialization is required because of the circular, though delayed, relationship among obese fractions for normoglycemic, prediabetes, and diabetes. We have found that setting the 1980 normoglycemic obese fraction to equal **67%** of the overall adult obese fraction leads to properly smooth and stable behavior of the obese fractions thereafter, given the model's other parameter values, and especially the relative risk parameters seen in the other two equations above.)

The second equation above indicates that the obese fraction of people with prediabetes is calculated, after a delay, from the obese fraction of the normoglycemic. (The delay is a first-order smooth, and is indicated in Figure 37 with a hash mark // symbol across the connecting arrow.) The parameter determining how much greater the prediabetes obese fraction will be in steady-state than the hyperglycemic obese fraction is the *Reltv risk of PreD for obese popn*, seen previously in Figure 9 and set to **2.6**. (If the relative risk parameter were 1, then the obese fraction of prediabetes would be equal to that of the normoglycemic.) The smoothing delay reflects the idea that some of the nutrition and physical activity habits of the normoglycemic population are shared by the somewhat older prediabetes population, while others are not. To the extent that these habits are shared, any change in normoglycemic obesity translates immediately, without delay, into a change in prediabetes obesity. The *Fraction of normoglycemic popn caloric habits shared by PreD popn* has been set to **80%**, a value that allows the model to reproduce NHANES data on the growth of prediabetes population obesity (described below). To the extent that the habits are not shared, the delay reflects the passage of people (and their associated obesity fraction) from normoglycemia to prediabetes. Given the dynamic behavior of attributes associated with stocks and flows (see Sterman 2000, Chapter 12, on the subject of coflows and aging chains), this delay may also be described as the average time spent in the prediabetes population stocks, and calculated based on rates of outflow due to death, prediabetes recovery, and diabetes onset.

The third equation above indicates that the obese fraction of people with diabetes is calculated, after a delay, from the obese fraction of those with prediabetes. The parameter determining how much greater the diabetes obese fraction will be in steady-state than the prediabetes obese fraction is the *Reltv risk of diabetes for obese PreD popn*, seen previously in Figure 12 and set to **2.6**. The smoothing delay reflects the idea that some of the nutrition and physical activity habits of the prediabetes population are shared by the often much older diabetes population, while others are not. To the extent that these habits are shared, any change in prediabetes obesity translates immediately, without delay, into a change in diabetes obesity. The *Fraction of PreD popn caloric habits shared by diabetes popn* has been set to **20%**, a value that allows the model to reproduce NHANES data on the growth of diabetes population obesity (described below). To the extent that the habits are not shared, the delay reflects the passage of people (and their associated obesity fraction) from prediabetes to diabetes. This delay may also be described as the average time spent in the diabetes population stocks, and calculated based on the death rate for people with diabetes.

5.4 Simulation of Historical BMI and Obese Fractions

In concluding this section, we present model output on BMI and obesity fractions for the period 1980-2004, and compare these simulated results with the historical record where possible.

Figure 38 presents simulated results (blue line) and a curve interpolating NHANES-reported values (red line, previously seen as the blue line in Figure 31) for average BMI. The simulated values demonstrate a close fit to the data. The simulated values start from an average BMI of 25.5 in 1980 rising to 28.6 by 2004.

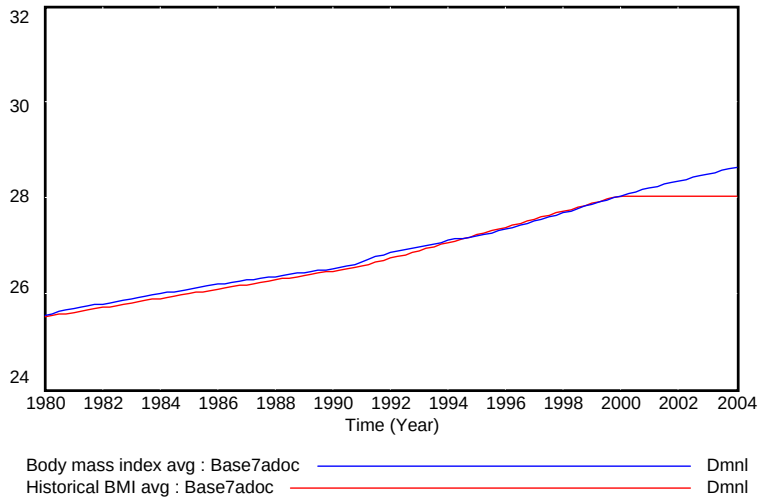

Figure 38. Simulated average body mass index 1980-2004, and comparison with NHANES data through 2000 (flat line indicates no data for 2001-2004)

Figure 39 presents simulated results (blue line) and a curve interpolating NHANES-reported values (red line, previously seen as the blue line in Figure 33) for the obese fraction of the adult population. The model shows a rather good fit to the data, though the 1990s growth in obesity is somewhat faster in the model than it is in the data. The simulated values start from an obese fraction of 16% in 1980 rising to 37% by 2004.

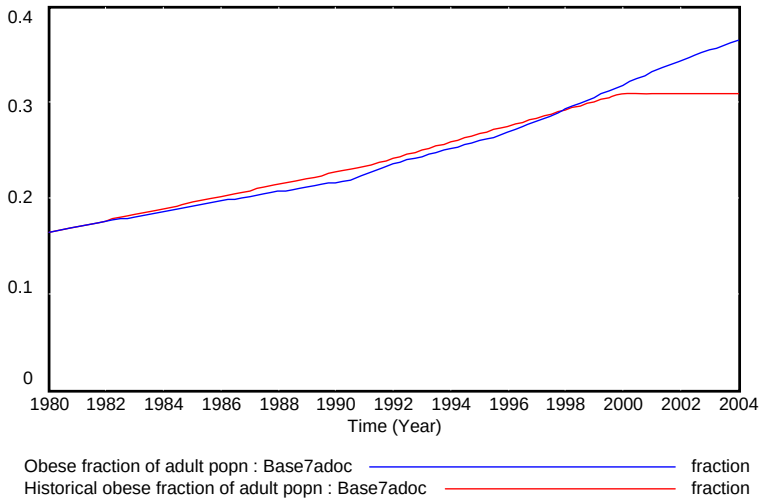

Figure 39. Simulated obese fraction of adult population 1980-2004, and comparison with NHANES data through 2000 (flat line indicates no data for 2001-2004)

Figure 40 presents simulated results for obese fractions of the normoglycemic (blue line), prediabetes (red line), and diabetes populations (green line). Also shown in this figure is the simulated obese fraction of the overall adult population (black line, previously seen as the blue line in Figure 39), which may be understood as the weighted average of the three other fractions. From 1980 to 2004, the obese fraction for the entire adult population increases by 123%, but this increase is not uniform across the three sub-populations: obesity in normoglycemics increases by 155%, obesity in the prediabetes population increases by 103%, and obesity in the diabetes population increases by only 23% over the 24-year time period.

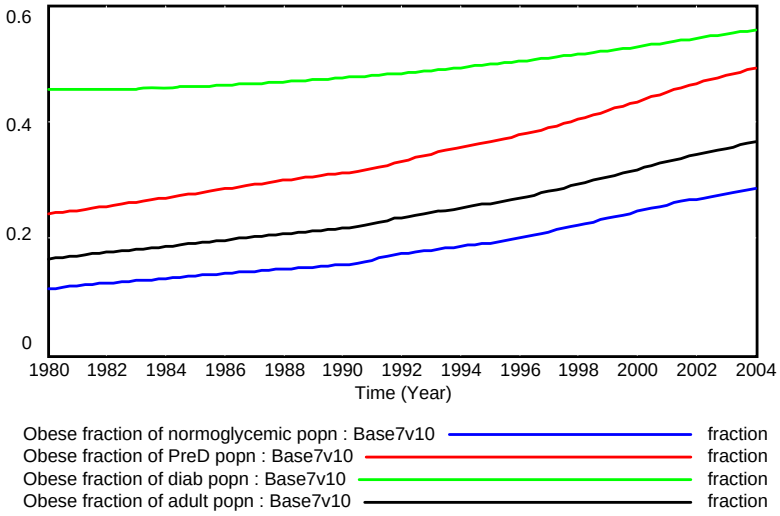

Figure 40. Simulated obese fractions of normoglycemic, prediabetes, and diabetes population, and adult population overall, 1980-2004

We mentioned above that the model's parameters affecting the average delays in changes in obesity fraction for prediabetes and diabetes were set so that the model could reproduce NHANES data on such changes. The unpublished data described above in Sections 3.2 and 3.3 indicate that from NHANES III (1988-1994) to NHANES 1999-2000, the obesity fraction for prediabetes increased from 32% to 42%, and for diabetes increased from 48% to 52%. The model as calibrated reproduces these values for 1991 and 1999, respectively.

The steep 1990s rise in normoglycemic obesity seen in Figure 40 still has some way to go in percolating its way through to the prediabetes population and, much more so, to the diabetes population. Given the simulated normoglycemic obesity fraction of 29% in 2004 (and assuming no further increase), and applying the equations for the other two obesity fractions presented in the previous section, one may calculate steady-state values for the prediabetes and diabetes obesity fractions and compare them to the 2004 simulated values. For prediabetes the simulated obesity fraction in 2004 is 49% compared with a steady-state 51%; for diabetes the simulated obesity fraction in 2004 is 56% compared with a steady-state 73%.

6. Health Care Costs

6.1 Health Care Costs of Diabetes and Prediabetes

We have modeled health care expenditures attributable to diabetes and prediabetes by using two broad categories: urgent and extended care costs, and preventive care costs. These categories may be related to the more detailed breakdown assembled by the American Disease Association in looking at diabetes costs for 2002 (ADA, 2003). The urgent and extended care costs include: Hospital inpatient stays and outpatient and emergency room visits, ambulance services, and nursing home and hospice care stays. The preventive care costs include physician office visits, medications, and supplies for glucose testing and insulin delivery. The ADA estimated total diabetes-related costs for 2002 at $91.9 billion, of which $23.2 billion was what we would call preventive, and the remaining $68.7 billion for what we would call urgent and extended care.

Figure 41 presents the causal structure of urgent and extended care costs, and also shows where preventive care costs are added in to produce total healthcare cost measures (for diagnosed diabetes, for all diabetes, and for all hyperglycemia). Urgent and extended care costs apply only to people with complicated, that is, symptomatic, diabetes. As discussed above in Section 3.1, the three categories of complicated diabetes and our assumptions for their average HbA1c levels are: undiagnosed (10.5), diagnosed and managed but uncontrolled (9), and controlled (7). We further assume that each point drop in HbA1c reduces the costs associated with complications by 40% (DHHS/AHRQ, 2003). Accordingly, the relative costs per capita for these three categories are, respectively: 100%, 46.5%, and 16.7%. (The second figure is supported by Menzin et al., 2001, where patients under "fair" control had costs 46% of those under "poor" control.)

Figure 41 shows three parameters determining urgent and extended care costs, each expressed as a dollar cost per year per person with complicated diabetes. For the undiagnosed, that figure is **$30,669**; for the diagnosed but uncontrolled: **$14,261**; and for the controlled, **$5,134**. The second and third of these estimates are based on: (1) the estimated $68.7 billion in urgent and extended care expenditures for diagnosed diabetes in 2002, (2) the assumed relative per-capita costs cited above, and (3) the simulated 2002 population sizes for the two categories of diagnosed complicated diabetes. After estimating the second parameter value, the first is then estimated from it, again using the assumed relative per-capita costs cited above: ($14,261 / .465) = $30,669.

Figure 42 presents the causal structure of preventive care costs for diagnosed diabetes and prediabetes. For each of three main categories—complicated diabetes, uncomplicated diabetes, and prediabetes—two parameters are required describing preventive cost per year per person. In the case of diabetes, one parameter is for the diagnosed but "low-prescription" (not using drugs or not self-monitoring), and the other for the "high-prescription" (using drugs and self-monitoring). In the case of prediabetes, one parameter is for the diagnosed but uncontrolled and the other for the controlled. These estimates of annual per-capita preventive care costs are as follows:

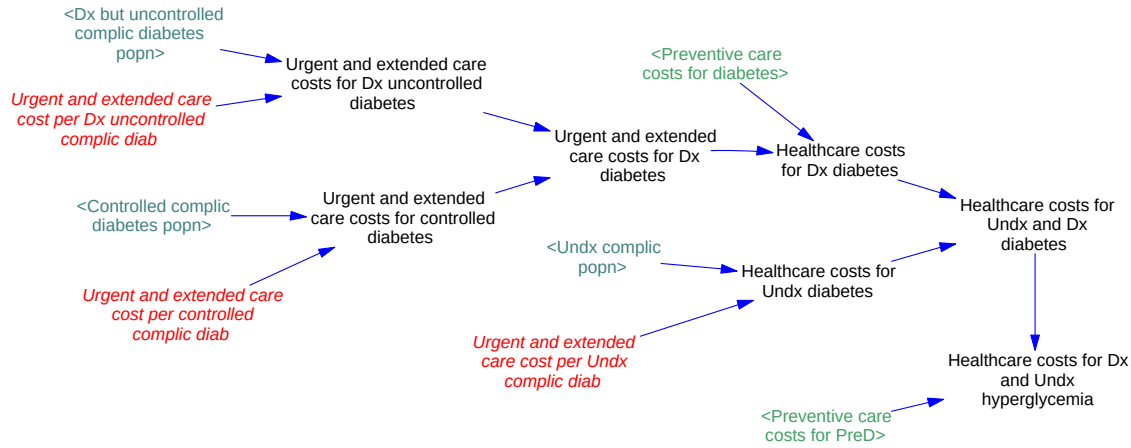

Figure 41. Urgent and extended care costs, and total health care costs, for diabetes and prediabetes

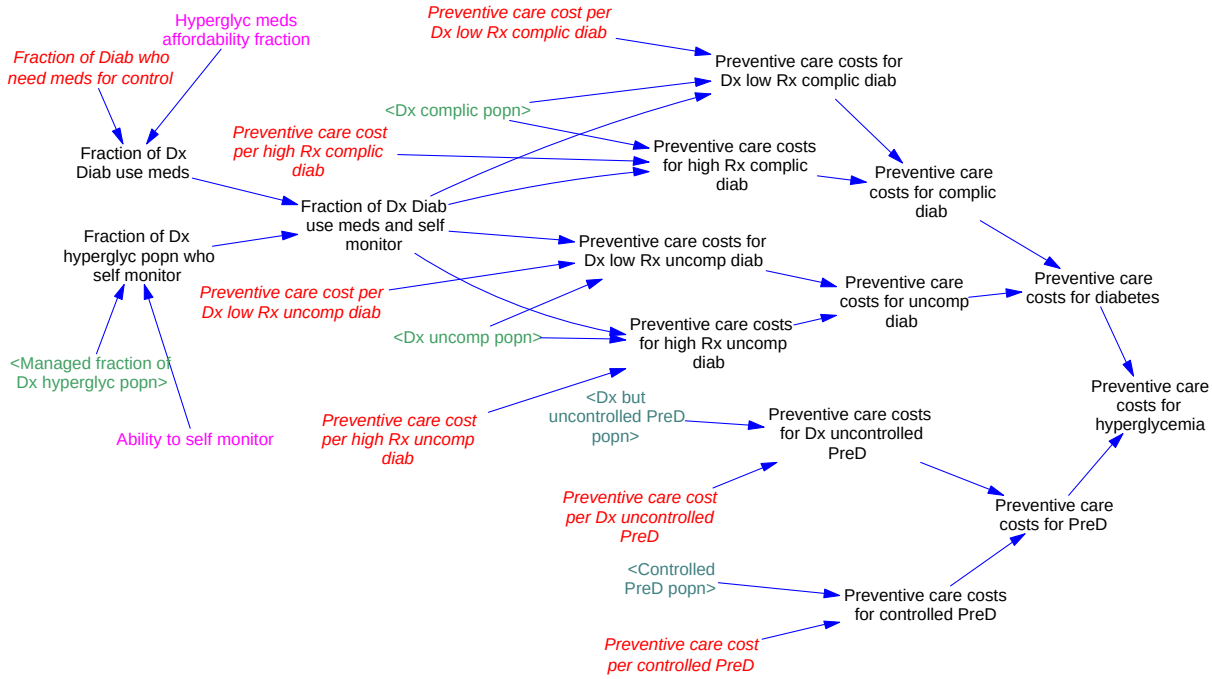

Figure 42. Preventive care costs for diabetes and prediabetes

Low-prescription complicated diabetes: **$1,254**
High-prescription complicated diabetes: **$2,612**
Low-prescription uncomplicated diabetes: **$925**
High-prescription uncomplicated diabetes: **$2,335**
Uncontrolled prediabetes: **$20**
Controlled prediabetes: **$1,000**

The four estimates for diabetes care are based on: (1) the estimated $23.2 billion in preventive care expenditures for diagnosed diabetes in 2002; (2) relative per-capita values drawn from Table 43 of the technical report for a Markov model dealing with diabetes costs (Hoerger, Hicks, and Bethke, 2004), and (3) the simulated 2002 populations sizes for the four categories of diagnosed diabetes.

The estimate of $20 per year for uncontrolled prediabetes care corresponds to the cost of an annual FPGT, but assuming no additional medications or office visits in the pursuit of disease control. The estimate of $1,000 per year for controlled prediabetes care is based on a cost of about $700 associated with lifestyle and medical interventions aimed at reduction of blood glucose among prediabetics (Hoerger, Hicks and Bethke, 2004; Herman, Brandle et al. 2003), plus $300 associated with drugs for the control of hypertension and hyperlipidemia (our estimate based on figures from Hoerger, Hicks, and Bethke, 2004; and ADA, 2003.)

6.2 Simulation of Historical Health Care Costs of Diabetes and Prediabetes

In Figure 43 we present model output on diabetes and prediabetes health care costs for the period 1980-2004. Four cost components are shown:

(1) The cost of urgent and extended diabetes care (blue line) starts at $52.5B in 1980 and rises to $71.1B in 2004. (A simulated cost for 2002 of $68.7 billion is identical to the ADA estimate cited above.)

(2) The cost of preventive care of diagnosed diabetes (red line) rises from $8.3 billion to $25.8 billion. (A simulated cost for 2002 of $23.2 billion is identical to the ADA estimate cited above.)

(3) The hidden cost of undiagnosed complicated diabetes (green line) declines from $29.3 billion to $22.5 billion. (As noted above in connection with Figure 23, undiagnosed complicated diabetes falls from 9% to 4% of the total diabetes population.)

(4) The cost of preventive care for prediabetes (black line) rises from zero, starting in the late 1990s, to $3.9 billion by 2004.

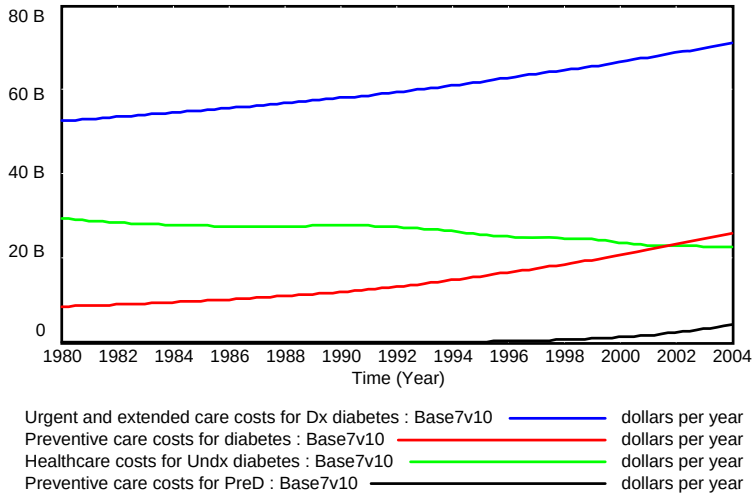

Figure 43. Simulated health care costs of diabetes and prediabetes, 1980-2004 (in billions of dollars per year)

7. Unhealthy Days

7.1 Unhealthy Days due to Diabetes

The CDC's Behavioral Risk Factor Surveillance System (BRFSS) contains a section that asks about the number of recent days when respondents were physically or mentally unhealthy. This "Healthy Days" approach has been extensively validated for measuring health-related quality of life (Moriarty, Zack, and Kobau, 2003). The average number of unhealthy days per month for the adult population has increased from 5.2 in 1993 to 6.0 in 2001, an increase of 15% in just eight years (CDC, 2004). For people with diagnosed diabetes, the number of unhealthy days is significantly higher than the overall average, and for the 1993-1997 period averaged 9.9 days per month (CDC, 2000).

Figure 44 presents the causal structure for unhealthy days due to the symptoms and complications of diabetes, in absolute terms and as a fraction of all unhealthy days for the adult population. We calculate unhealthy days attributable to both diagnosed and undiagnosed complicated diabetes; those attributable to undiagnosed diabetes constitute a problem that is not measured, but nonetheless should be recognized. Moreover, we recognize that morbidity is much greater for people with uncontrolled diabetes than for those with controlled diabetes. In particular, assuming that control reduces morbidity by a factor of two-thirds (similar to its effects on mortality and costs), we have set *Unhealthy days due to uncontrolled Complic diab* to **12.0**, and *Unhealthy days due to controlled Complic diab* to **4.0**.

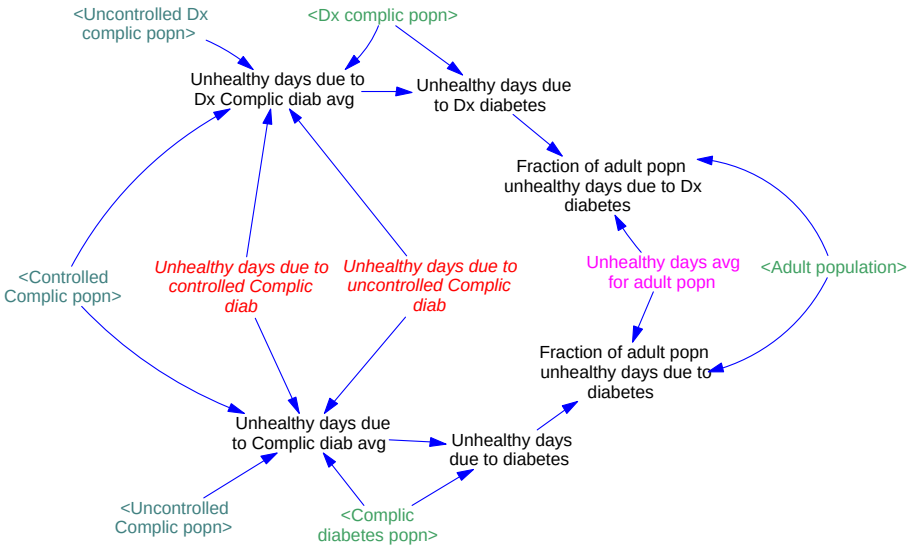

Figure 44. Unhealthy days due to symptoms and complications of diabetes

These parameter values were derived through a string of calculations. Based on the data presented above on unhealthy days data for all adults and for people with diagnosed diabetes, and using NHIS estimates of diagnosed diabetes prevalence, we calculated that, for the 1993-1997 period, approximately 4.7% of all unhealthy days were attributable to complications of diagnosed diabetes. Then, using a value of 50% for the complicated fraction of diagnosed diabetes (the model average for 1993-1997), we further calculated that, for people with diagnosed complicated diabetes, the average number of unhealthy days per month directly attributable to diabetes was 9.8. We then calculated the two model parameters described above, the one three times the other, that would give a weighted average of 9.8, using a value of 27% for the controlled fraction of diagnosed diabetes (the model average for 1993-1997).

7.2 Simulation of Historical Unhealthy Days due to Diabetes

Figure 45 shows the behavior of three variables during the 1993-2001 period for which we have data on unhealthy days. The blue line shows *Unhealthy days avg for adult popn*, a time series input to the model, which has increased from 5.2 to 6.0 as noted above. The red line shows the simulated fraction of overall unhealthy days attributable to diagnosed diabetes, which declines from 5.0% in 1993 to 4.4% in 2001. The green line shows the fraction of unhealthy days attributable to all diabetes, both diagnosed and undiagnosed, which declines from 6.1% to 5.1%. The decline in the diabetes fraction of unhealthy days is a testament to the increase in the controlled fraction of diagnosed diabetes, seen as the blue line in Figure 29. Although the number of people with diagnosed complicated diabetes grew as rapidly as the diabetes population did in general in the 1990s, the steady increase in the controlled fraction has meant a relative improvement in health-related quality of life for those with the disease.

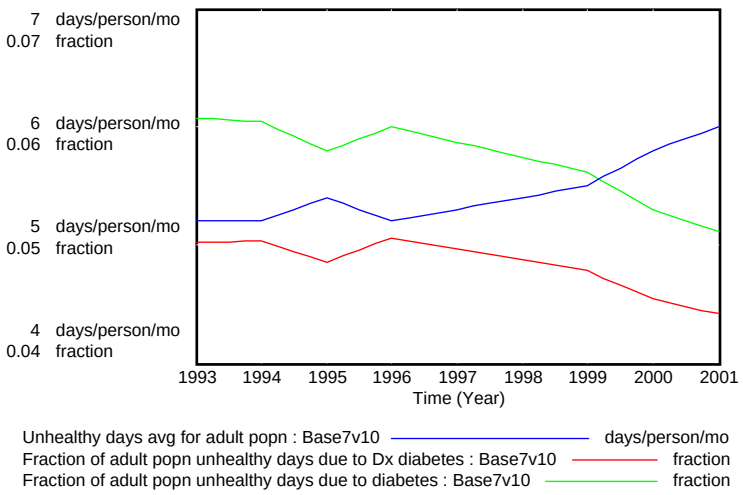

Figure 45. Average unhealthy days per month overall (blue line; source: BRFSS), and simulated fraction due to diabetes (red: diagnosed only; green: all diabetes), 1993-2001

Figure 46 shows for 1980-2004 simulated behavior of the number of unhealthy days per month due to diagnosed diabetes (blue line) and due to all diabetes, both diagnosed and undiagnosed (red line). Although Figure 45 indicates that these diabetes-related unhealthy days grew more slowly in the 1990s than unhealthy days did overall, the diabetes-related unhealthy days did nonetheless grow, and grew throughout the 1980s and 1990s. Unhealthy days due to diagnosed diabetes increased from 44.1 million per month to 58.9 million per month (a 34% increase in 24 years), while unhealthy days due to all diabetes grew from 55.6 million to 67.7 million (a 22% increase).

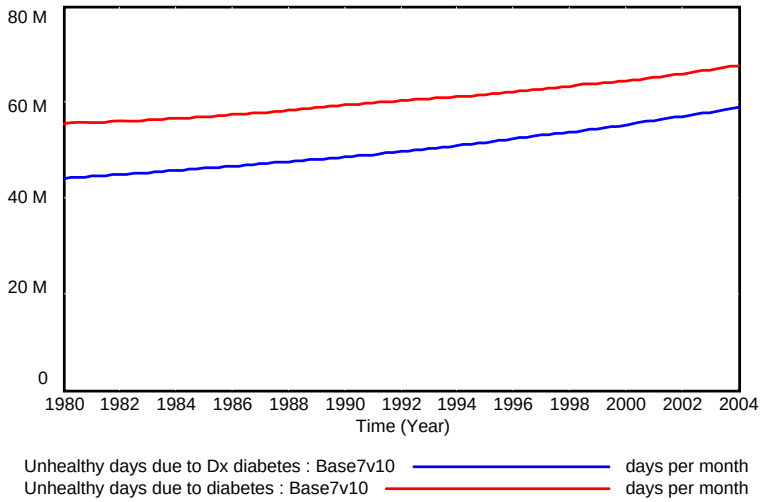

Figure 46. Simulated unhealthy days per month due to diabetes, 1980-2004

8. References

Abdel-Hamid TK. 2002. Modeling the dynamics of human energy regulation and its implications for obesity treatment. *System Dynamics Review* 18(4): 431-471.

American Diabetes Association (ADA). 2003. Economic costs of diabetes in the U.S. in 2002. *Diabetes Care* 26(3): 917-932.

American Diabetes Association and National Institute of Diabetes and Digestive and Kidney Diseases (ADA/NIDDK). 2002. The prevention or delay of type 2 diabetes. *Diabetes Care* 25: 742-749.

Centers for Disease Control and Prevention (CDC). 2000. *Measuring Healthy Days: Population Assessment of Health-Related Quality of Life*. CDC: Atlanta, GA, November 2000.

Centers for Disease Control and Prevention (CDC). 2004. Health-Related Quality of Life – Prevalence Data, 1993-2001. Available at http://apps.nccd.cdc.gov/hrqol. Last accessed October 4, 2004.

Cutler DM, Glaeser EL, Shapiro JM. 2003. Why have Americans become more obese? *National Bureau of Economic Research*, Working Paper 9446. Cambridge, MA. Accessed at: http://www.nber.org/papers/w9446.

Department of Health and Human Services, Agency for Healthcare Research and Quality (DHHS/AHRQ). 2003. *National Healthcare Quality Report*. Rockville, MD. Accessed at: www.qualitytools.ahrq.gov/qualityreport.

Durnin JVGA, Womersley J. 1974. Body fat assessed from total body density and its estimation from skinfold thickness: Measurements on 481 men and women aged from 16 to 72 years. *British Journal of Nutrition* 32: 77-92.

Forrester JW. 1961. *Industrial Dynamics*. MIT Press: Cambridge, MA.

Harris MI. 1995. Classification, diagnostic criteria, and screening for diabetes. In *Diabetes in America*, 2nd ed. National Institutes of Health: Bethesda, MD.

Harris MI, Flegal KM, Cowie CC, Eberhardt MS, and others. 1998. Prevalence of diabetes, impaired fasting glucose, and impaired glucose tolerance in U.S. adults. *Diabetes Care* 21(4), 518-524.

Herman WH, Brandle M, Zhang P, Williamson DF, and others in the Diabetes Prevention Program Research Group. 2003. Costs associated with the primary prevention of Type 2 diabetes mellitus in the Diabetes Prevention Program. *Diabetes Care* 26(1): 36-47.

Hoerger TJ, Hicks KA, Bethke AD. 2004. *A Markov Model of Disease Progression and Cost-Effectiveness for Type 2 Diabetes: Technical Report*. RTI: Research Triangle Park, NC.

Homer J, Jones A, Seville D, Essien J, Milstein B, Murphy D. 2004. The CDC diabetes system modeling project: Developing a new tool for chronic disease prevention and control. *22nd International Conference of the System Dynamics Society*, Oxford, England.

Homer J, Hirsch G, Minniti M, Pierson M. 2004. Models for collaboration: how system dynamics helped a community organize cost-effective care for chronic illness. *System Dynamics Review* 20(3).

Honeycutt A, Boyle J, Broglio K, Thompson T, and others. 2003. A dynamic Markov model for forecasting diabetes prevalence in the United States through 2050. *Health Care Management Science* 6:155-164.

Kahn R, Genuth S, and others (Expert Committee on the Diagnosis and Classification of Diabetes Mellitus). 2003. Follow-up report on the diagnosis of diabetes mellitus. *Diabetes Care* 26(11): 3160-3167.

Knowler WC, Barrett-Connor E, Fowler SE, Hamman RF, and others in the Diabetes Prevention Program Research Group. 2002. Reduction in the incidence of Type 2 diabetes with lifestyle intervention or Metformin. *New England Journal of Medicine* 346(6), 393-403.

Menzin J, Langley-Hawthorne C, Friedman M, Boulanger L, Cavanaugh R. 2001. Potential short-term economic benefits of improved glycemic control: A managed care perspective. *Diabetes Care* 24(1): 51-55.

Moriarty DG, Zack MM, Kobau R. 2003. The Centers for Disease Control and Prevention's Healthy Days measures: Population tracking of perceived physical and mental health over time. *Health and Quality of Life Outcomes* 1(1): 37.

Robinson JP, Godbey G. 1997. *Time for Life: The Surprising Ways Americans Use Their Time*. Pennsylvania State Press: University Park, PA.

Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin/McGraw-Hill: Boston, MA.

Wang WQ, Ip TP, Lam KS. 1998. Changing prevalence of retinopathy in newly diagnosed noninsulin dependent diabetes mellitus patients in Hong Kong. *Diabetes Res Clin Pract* 39: 185-91.

Whitney EN, Rolfes SR. 1999. *Understanding Nutrition*. West/Wadsworth: Belmont, CA.