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# Models and Indicators\*

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## *Abstract*

*Returning to themes of Land (1971a) and Land (1971b), this article addresses topics in formal sociological models and the definition, construction, and interpretation of social indicators. I show how standard classes of formalisms used to construct models in contemporary sociology can be derived from the general theory of models. This demonstrates, at a high level of abstraction, the isomorphism of many formal sociological models to the formal models used in virtually every scientific discipline today. I also review recent model-building and model-evaluation efforts in which I have participated on the estimation of active life expectancy of the U.S. elderly population, an assessment of the robustness of a recently proposed adjusted total fertility rate, and the construction of a new index of child and youth well-being. These studies show how formal models help us to see patterns in data that otherwise are not detectable, improve social measurement, and, in particular, define and interpret social indicators.*

In these remarks, I revisit two aspects of sociological research that I initially addressed some 30 years ago — the uses of formal models in sociology and the definition of social indicators. I first (Land 1971a) explicated some aspects of the role of formal models in sociology. I especially focused on the interplay of the processes of formal model specification, model solution, reduced-form and structural parameter estimation, and model testing or evaluation with the traditional processes of theorizing and data collection. In Land (1971b), I took on the problem of developing and interpreting social indicators and argued that this was best done when the indicators are components of social system models. In revisiting these matters, I will sketch some aspects of the modern theory of models and show how

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the classes of formal models used in contemporary sociology fit within that general theory, describe some uses of models in sociology, and discuss some of my recent modeling work on topics in demography and social indicators research to show the progress that has been made developing social indicators as components in models of social systems.

## Models, Formal Models, and Theory

I first describe some elements of the modern theory of models. This theory defines formal models in generic terms and shows the universality of the uses of formal modeling systems across the sciences. The objective of my presentation is to show that many common formalisms used in contemporary sociology fit within this general framework. Thus, despite the many varied subject matters and theories embodied in sociological models today, there is more commonality among the approaches to modeling than might otherwise be apparent.

To frame the discussion that follows, it will be helpful briefly to review and adapt the general theory of models (Casti 1992a, 1992b; Land 1971a) to the sociological context. I begin with definitions of models, formal models, and theories motivated by some simple questions. To begin with, how are “models” conceptualized in the contemporary theory of models? Following Casti (1992b:380), I adopt a very general and encompassing definition:

- *models* are tools by which individuals order and organize experiences and observations.

But experiences/observations vary among individuals and can be organized in many different ways. Even if the observations are common and shared, as in the case of a single set of observations on specific social phenomena summarized in a data set, they can be organized in different ways. It follows that there can be many different models of the same experiences/observations. Hence, as Casti notes, there can be many alternative realities — at least to the degree that we see reality in models.

Note that one implication of this generic definition of models is that virtually every functioning person in a society can be presumed to be a modeler. Beginning with the characterization of natural language as a tool for ordering and describing experiences (see, e.g., Whorf 1956), one can regard much of linguistic, popular, and material culture as providing the “tools” by which individuals, on a day-to-day basis, model their experiences (cf. Swidler 1986). And, of course, it is the objective of long traditions of ethnographic research in sociology and anthropology to record and study the structure of such “natural” models.

Another implication of this definition is that many of the verbal characterizations of social phenomena that we use in sociology are properly regarded and respected as models. Many of these *verbal models* have stimulated much

research over many years and will continue to do so. As but two examples, Frank Notestein's (1945) verbally stated *demographic transition model* stimulated demographers to focus their research attention on a host of historical and contemporary questions about trends in birth and death rates and their relationship to economic development and improvements in health and longevity. Similarly, the verbally stated *life-course model* that has been developed over the years by many sociologists and articulated succinctly by Glen Elder (2000) has stimulated the work of researchers with many diverse substantive interests.

If models most generically are tools for ordering our experiences, what are "formal models"? Briefly:

- *formal models* encapsulate some slice of experiences/observations within the confines of the relationships constituting a formal system such as formal logic, mathematics, or statistics (cf. Casti 1992a:1).

Thus, a *formal sociological model* is a way of representing aspects of social phenomena within the framework of a formal apparatus that provides us with a means for exploring the properties of the social life mirrored in the model. Why construct formal sociological models? Why not just use verbally stated models? Basically, we construct formal models to assist in bringing a more clearly articulated order to our experiences and observations, as well as to make more precise predictions about certain aspects of the social world. Since most of the remaining discussion pertains to formal sociological models, I will drop the "formal" adjective and simply use the term "models."

Some notation will be useful. Consider a particular subset  $S$  of social life, and suppose that  $S$  can exist in a set of distinct *abstract states*  $\Omega = \{\omega_1, \omega_2, \dots\}$ . The set  $\Omega$  defines the *state space* of  $S$ . Whether or not the sociological observer can determine the state of  $S$  in a particular moment of study depends upon the experiences, observations, or measurements (*observables*) at the sociologist's disposal. As a simple example, suppose  $S$  is a human population in which the sociological observer has distinguished two sexes. Then a reasonable set of abstract states might be

$$\Omega = \{\omega_1 = \text{male}, \omega_2 = \text{female}\}.$$

Next, let's look at the notion of an observable. An *observable* of  $S$  is a rule  $f$  associating a real number with each  $\omega$  in the state space  $\Omega$ , i.e., an observable is a measuring instrument. More formally, an observable is a map  $f: \Omega \rightarrow R$ . Using our example of a two-sex population and the usual "dummy variable" coding rule, we might define

$$f(\omega_1) = 0 \text{ and } f(\omega_2) = 1$$

as observables.

Generally, for a full accounting of social life, many sociologists feel that we need an infinite number of observables  $f_\alpha: \Omega \rightarrow R$ , where the subscript  $\alpha$  ranges over a possibly uncountable index set. Thus, the complete slice of social life  $S$  is

described by  $\Omega$  and the possibly infinite set of observables  $F = \{f_\alpha\}$ . But it is impossible to deal with such a large set of observables, and it is not necessary to do so in order to build useful sociological models and/or theories. As Smith-Lovin (2000) has argued:

social life is very complex. To be completely described, any historical event or current interactional situation requires a virtually infinite catalog of contextual, historically specific information to be conveyed. . . . But the fact that social life is complex does not imply that we need complex descriptions of it. . . . Indeed, I think that the most successful theories often focus on just one basic process, while most situations involve the simultaneous occurrences of many different processes. (302)

In brief, in model construction, we boldly throw away most of the possible observables in social life, and focus our attention on a proper subset  $A$  of  $F$ . It is, of course, the case that this means that our models may poorly capture the full complexity and nuances of social life. This, again, reinforces the position that models are worth constructing and dealing with only if they assist in bringing a more clearly articulated order to experiences and observations, and in making more precise predictions about certain aspects of the social world. And baseline, over-simplified models often can be criticized and improved.

We now can characterize a social system model  $S^*$  as an abstract state-space  $S$  together with a finite set of observables  $f_i : \Omega \rightarrow R, i = 1, 2, \dots, n$ . Symbolically,

$$S^* = \{\Omega, f_1, f_2, \dots, f_n\}.$$

But there is more to the notion of a social system model than just the list of observables by which it is characterized. The essential "systemness" of  $S^*$  is contained in relationships that link the observables. These relationships are termed the *equations of state* for  $S^*$ . Formally, the equations of state can be written as

$$\Phi_i(f_1, f_2, \dots, f_n) = 0, \quad i = 1, 2, \dots, m,$$

where the  $\Phi_i(\cdot)$  are mathematical relationships expressing the dependency relations among the observables. This can be more compactly written as

$$\Phi(f) = 0. \quad (1)$$

Now suppose that the last  $m$  observables  $f_{n-m+1}, \dots, f_m$ , called *endogenous* (or determined within the system under consideration), are functions of the remaining observables  $f_1, f_2, \dots, f_{n-m}$ , where the latter are termed *exogenous* (or determined outside the system under consideration). In other words, suppose we can define  $m$  functional relations, with some finite number  $r$  of numerical parameters,  $\beta_1, \beta_2, \dots, \beta_r$ , for determining values of the endogenous observables as a function of the exogenous observables. Then, if we introduce the notation

$$\beta \doteq (\beta_1, \beta_2, \dots, \beta_r)$$

to denote the vector of parameters and the notations

$$x \doteq (f_1, f_2, \dots, f_{n-m})$$

and

$$y \doteq (f_{n-m+1}, f_{n-m+2}, \dots, f_n)$$

to denote vectors of the exogenous and endogenous observables, henceforth *variables*, respectively, then the equations of state become

$$y = \Phi_\beta(x). \quad (2)$$

This last expression now is beginning to take on a form similar to the sociological models we see in practice. In particular, suppose we define an additive vector

$$\epsilon = (\epsilon_{n-m+1}, \epsilon_2, \dots, \epsilon_n)$$

of error terms (with the usual specifications on the error terms, namely, that the expected value of each  $\epsilon_i$ ,  $E(\epsilon_i) = 0$  with constant variance,  $E(\epsilon_i \epsilon_j) = \sigma^2_i$ ,  $i = 1, 2, \dots, m$ ), one for each endogenous variable, to take explicitly into account the fact that there may be stochastic shocks to the equations of state due either to factors unaccounted for in our system model or to an intrinsic random element in the behavior of the endogenous variables. Then the equations of state, equation 2, become

$$y = \Phi_\beta(x) + \epsilon, \quad (3)$$

Equation 3 now is in a form such that many of the common formalisms used in model construction in sociology can be recognized as special cases. For instance:

- If  $m = 1$ , so that the vector  $y$  of endogenous variables contains a single element, then the equations of state, equation 3, reduce to the form of a *conventional regression model*. If, in addition,  $y$  is a continuous variable, equation 3 becomes a *classical regression model*, either linear or nonlinear, depending on the functional form of  $\Phi_\beta$ , whereas a dichotomous  $y$  and a logistic form for  $\Phi_\beta$  yields a *logistic regression model* (Neter et al. 1996). Other specifications of measurement and functional formats yield other types of regression models, including the *multilevel* or *hierarchical models* for the analysis of contextual effects and growth models that have been developed and widely applied in recent years (e.g., Bryk & Raudenbusch 1992).
- In the case that  $y$  contains  $m$  endogenous variables, equation 3 is in a form similar to that of the reduced form of a *classical econometric/structural equation model*. If the functional form  $\Phi_\beta$  incorporates recursive or nonrecursive dependencies among the endogenous variables, then the equations of state, equation 3, are in the structural-equation form of a classical econometric/structural equation model (Christ 1966). If explicit measurement models taking into account random measurement errors of the exogenous variables and/or endogenous variables are specified in addition to structural equations linking

latent variables, then the equations of state, equation 3, take the form of contemporary *structural equation models with latent variables*, of which LISREL models are the most widely known (Bollen 1989; Hoyle 1995).

- The characterization of formal models given above and the notions of observables and equations of state also can be applied to many other types of modeling formalisms used in sociology. For instance, the equations of state can be given a *dynamic formulation* by specifying in *differential or stochastic differential equation form*. If the endogenous variables then are defined in terms of duration time to a transition of some type, the equations of state then may yield *hazard or event history regression models*, as will be illustrated below.

One question has been avoided to this point: What differentiates models from theories? These terms sometimes are distinguished and sometimes are used interchangeably. Usually, however, scientific theories are regarded as more general than scientific models:

- a *theory* is a *family of related models*, and a *model* is a formal manifestation of a particular theory (cf. Casti 1992b:382).

A key defining characteristic of models, as noted above, is that they are constructed relative to a given set of observables. Theories, on the other hand, are more generally applicable to numerous sets of observables. For example, *game theory* (Fudenberg & Tirole 1992) can be construed as a family of models of the behavior we observe when rational decision makers interact. The game theory family of models is more general than, say, a *game-theoretic model* of crime control policies and criminal decision making (de Mesquita & Cohen 1995). As another example, *functionalism* as a sociological theory can be regarded as a family of functionalist models of social structures and processes (e.g., Turner 1991). And functionalist sociological theory is more general than, say, a *functionalist model* of how organizations try to reduce uncertainty in their environments (Thompson 1967).

From sociological theories and theories in other social and biological sciences sociologists develop ideas about what observations and measurements of social life to make, generative mechanisms (Smith-Lovin 2000) with which to build and choose models, and hypotheses to be tested. But since sociological theories are typically stated in very general terms, they leave measurement instruments and functional forms of models to be specified. At this point models become relevant. They develop linkages of theory to observations and data (Land 1971a). Indeed, Skvoretz (1998) has forcefully argued that *theoretical models* — models that represent the generative mechanisms and processes embodied in sociological theory — are the missing or underdeveloped link in the discipline today.

Yet sociological theory sometimes does not provide complete guidelines for model building, which often leads to controversies about the adequacy of models constructed and applied in sociology. Two important issues of this kind are:

- the *endogenous-exogenous distinction*, and
- *model completeness*.<sup>1</sup>

Sometimes there is no disputing that certain variables are appropriately specified as exogenous or determined outside of a particular set of functional relationships. At other times, however, questions certainly can be raised, and disputes over the “endogenous/exogenous” distinction often are at the heart of disagreements over the “correct” model specification. There also is little doubt that many regression and structural equation models estimated in sociology over the past few decades have arbitrarily taken certain variables as exogenous that should have been regarded as jointly endogenous with one or more dependent variables. The inclusion of jointly endogenous variables — variables that are at least partially determined by the “dependent” variable(s) of a model — as “explanatory variables” in a regression and/or structural equation model leads to biased parameter estimates as well as to false inferences about the phenomenon being modeled.

Questions about model completeness also are often sources of dispute concerning the adequacy of sociological models. An analyst, in an effort to be complete, may extend the list of exogenous variables to a very large number. This can produce models with so many explanatory variables that the interpretation of results becomes difficult, if not impossible. On the other hand, some of the most damaging critiques of models are the claims that the modelers omitted variables (observables) that were centrally important to understanding the behavior of the observables employed. A dividing line on this issue also often depends on one’s theoretical versus empirical orientation towards modeling. Those who approach the construction of sociological models from a theoretical perspective tend to emphasize parsimony in model specification (e.g., Smith-Lovin 2000). Empirically oriented modelers, on the other hand, often feel that many explanatory variables are necessary for model completeness (e.g., in discussing the complications in sociological modeling due to multiple causation, Blalock [1984:40] stated that “upwards of 40 or 50 factors [may be] at work” in the determination of a social phenomenon).

Finally, it should be noted that, while most of the foregoing exposition has emphasized the *quantitative uses of models*, there are important *qualitative uses of models* as well. Models often provide convenient metaphors for thinking about social processes. An example is Wallerstein’s (2000:249) use of the mathematics of nonlinear dynamics and chaos to qualitatively characterize the modern world-system as in structural crisis and experiencing “a period of chaotic behavior which will cause a systematic bifurcation and transition to a new structure whose nature is as yet undetermined.”

## What Good Are Models?

Let me turn in more detail to some uses of models in sociology. What good are they? One list of the benefits of models that I like was presented by Nathan Keyfitz some three decades ago (Keyfitz 1971). While the subject of Keyfitz’s article pertained



to the benefits of models in demography, the list he developed appears to apply more generally. Keyfitz began by noting that the development of demography had been greatly influenced by the demand for prediction of future population. Furthermore, this demand for population prediction had stimulated the development of demographic models such as the life table and stable population models. Keyfitz then identified the following benefits of models:

- *Models focus research by identifying theoretical and practical issues.*
- *Models help us to assemble and explain data.*
- *Models permit the design of experiments, simulations, and other research studies out of which we can obtain causal knowledge.*
- *Models systematize comparative study across space and time.*
- *Models reveal formal analogies between problems that on their surface are quite different.*
- *And models help us to make predictions.*

The case for the significance of these contributions of models was well illustrated by Keyfitz (1971) and will not be replicated here. Rather, I would like to emphasize the following additional benefits of models:

- *Models provide a “lens” through which we can see patterns in some social data that otherwise cannot be perceived.*
- *Models help to improve social measurement.*
- *And, in particular, models provide a locus for defining, developing, and interpreting social indicators.*

### **Improving Social Measurement and the Construction of Social Indicators**

In brief, models make important contributions to social measurement, even to the point of facilitating the perception of patterns in data that otherwise might not be detectable. The construction and interpretation of social indicators is a specific instance of this, a point that was made in my three-decade-old (Land 1971b:323) definition:

I propose that the term *social indicators* refer to social statistics that (1) are components in a social system model . . . or of some particular segment or process thereof, (2) can be collected and analyzed at various times and accumulated into a time-series, and (3) can be aggregated or disaggregated to levels appropriate to the specifications of the model. Social system model means conceptions of social processes, whether formulated verbally, logically, mathematically, or in computer simulation form. The important point is that the criterion for classifying a social

statistic as a social indicator is its *informative value*, which derives from its empirically verified nexus in a conceptualization of a social process.

This definition of social indicators is entirely consistent with the contemporary theory of models as discussed above.

With the hindsight of three decades, however, it also is apparent that this characterization was extravagantly out of step with the state-of-the-art of sociological models in 1971. Today, we are closer to realizing the ambitions set forward in this definition. Some illustrations will help to make this case. I will briefly describe three efforts in model construction in which I recently have participated — one from an article that was published last year (Manton & Land 2000), one from an article that appeared this year (Zeng & Land 2001), and one from a soon-to-be-published article (Land, Lamb & Mustillo 2001).<sup>2</sup> Each illustrates how models help to provide contexts in which indicators can be interpreted and, thus, lend meaningfulness and interpretability to the indicators. I discuss them in the order of the complexity of the underlying mathematical model, from most to least.

#### EXAMPLE 1: THE MEASUREMENT OF ACTIVE LIFE EXPECTANCY

This first example shows how the application of an elegant mathematical model of human survival and aging to a longitudinal panel data set yields a refined social indicator of health among the elderly. This is an example of the type of model-embedded social indicator called for by Land (1971b). It also illustrates how models help us to see patterns in data that otherwise are not discernible. And it shows how models can be used to improve social measurement.

Demographers and public health scientists have focused attention in recent decades on developing and applying of health measures that combine mortality and disability data. Building on work on community and national health measures, and focusing on the elderly population, Katz, Branch, Branson, Papsidero, Beck, and Greer (1983) operationally defined *active life expectancy* (ALE) as the period of life free of disability in activities of daily living (ADL). ADL's are personal maintenance tasks performed daily, such as eating, getting in/out of bed, bathing, dressing, toileting, and getting around inside. Freedom from disability in any ADL means the person is able to perform each self-maintenance function without another person's assistance or "special" equipment. Since the Katz et al. (1983) article, the concept of ALE also has been generalized to include not having limitations in instrumental activities of daily living (IADL), which are household maintenance tasks such as cooking, doing the laundry, grocery shopping, traveling, and managing money as well as to physical performance limitations and impairments, disabilities or social handicaps.

In assessing deviations from the intact or "active" health state, however, there has been controversy in selecting metrics to differentially weight specific physical and cognitive dysfunctions. Obtaining responses directly from affected individuals

and whether they perceive that they are *chronically* functionally limited in an ADL or IADL in the manner initiated by Katz et al. (1983) is a preferred approach — probably better than only making physical measurements because physical independence at late ages also involves psychological factors, such as the self-perception of health, general morale, and the level of motivation to preserve functions. To move from responses about the ability to perform specific ADLs or IADLs to ALE estimates (sometimes called disability-free life expectancy, DFLE) requires the use of state-dependent life table methods to estimate the average number of years of life remaining free from ADL or IADL impairment at specific ages. The life table methods used for this purpose have evolved from the prevalence-rate method of Sullivan (1971), to double-decrement models (Katz et al. 1983), and to multistate, or increment-decrement, models (e.g. Rogers, Rogers & Branch 1989; Land, Guralnik & Blazer 1994). Because of the relative scarcity of national panel studies, however, these models usually are applied to synthetic-cohort, or “period” data in which general (i.e., non-disability-state-specific) age-specific mortality rates (from vital statistics), and disability rates (measured in health surveys) experienced by a population during a period (e.g., a calendar year), are concatenated across ages to simulate the “experience” of a cohort. The prevalence-rate method remains the most frequently applied technique because of data limitations at the national level (e.g. Crimmins, Saito & Ingegneri 1997).

In addition to a paucity of applications of dynamic ALE concepts to national longitudinal studies, applications of increment-decrement models have often been limited to highly aggregated or “coarse” disability states to define health changes — for example, transitions from not at all disabled, to disabled with any ADL or IADL impaired; or transitions from not being disabled, to severely disabled where a minimum number of ADL (or IADL) limitations are present. While coarse state classifications provide ALE estimates, they do not represent the detailed gradations in levels and types of disability that can be extracted from multiple ADL, IADL, or physical performance responses. In addition, the use of a “not at all disabled/disabled” criterion defined by any ADL or IADL impairment defines a heterogeneous disabled group, containing, for example, individuals with one IADL partly limited (e.g., cooking) as well as individuals completely limited in all ADLs (e.g., bedfast persons).

A recent article by Manton and Land (2000) addresses these limitations by developing an increment-decrement stochastic process model of transitions among highly-refined functional status profiles interacting with a disability-specific mortality process. The model used to make ALE estimates by Manton and Land (2000) builds upon multidimensional stochastic process models previously developed to analyze risk factor processes (Woodbury & Manton 1983). This model of human mortality and aging, as originally specified by Woodbury and Manton (1977, 1983), begins with the specification of two equations of state:

$$dz_i(t) = u(z_i, t) + d\xi(z_i, t), \quad (4)$$

$$dP_i(z_i) = \mu(z_i, t) P(z_i) dt. \quad (5)$$

These stochastic differential equations are defined for a panel of individuals  $i = 1, \dots, N$  who are presumed to be followed longitudinally over time  $t$  as they age and eventually die. For each individual  $i$ , an array of  $n$  risk factors (i.e., observables) for mortality (such as blood pressure, serum cholesterol, health maintenance practices, etc.) is presumed to be measured repeatedly over time (say every year or two). The risk factors for each panel member  $i$  then are collected and placed in the vector  $z_i$ , which enters into both of equations 4 and 5. The first of these equations defines a stochastic diffusion process governing the movements of individuals within the state space defined by the risk factors. Equation 4 represents the change (or diffusion over time) for individual  $i$  on each of the  $n$  risk factor dimensions,  $z = (z_j, j = 1, 2, \dots, n)$ , at time  $t$ . Movement or change in the vector of risk factors of individual  $i$ ,  $dz_i(t)$ , during a short time interval  $dt$ , is specified by equation 4 to be a sum of two effects. The first of these two effects,  $u(z_i, t) dt$ , is deterministic and depends on  $i$ 's prior position on the risk factors. The second effect,  $d\xi(z_i, t)$ , is a random walk term (i.e., a sequence of mutually independent random variables with a common distribution) that is the probabilistic component of the change in the risk factor vector over time.

The second stochastic differential equation, equation 5, describes the change in the probability of survival of  $i$ ,  $dP(z_i)$ , during a short time interval  $dt$ . Equation 5 specifies that this change in survival probability is equal to the probability of mortality ( $\mu[z_i, t]dt$ ) for individual  $i$  with a risk factor profile as represented by  $z$  at time  $t$  times the probability of  $i$  surviving to attain  $z$ , i.e.,  $P(z_i)$ . In this specification,  $\mu(z_i, t)$  denotes the instantaneous intensity, hazard, or force of mortality for an individual with risk factor profile  $z_i$  at time  $t$ .

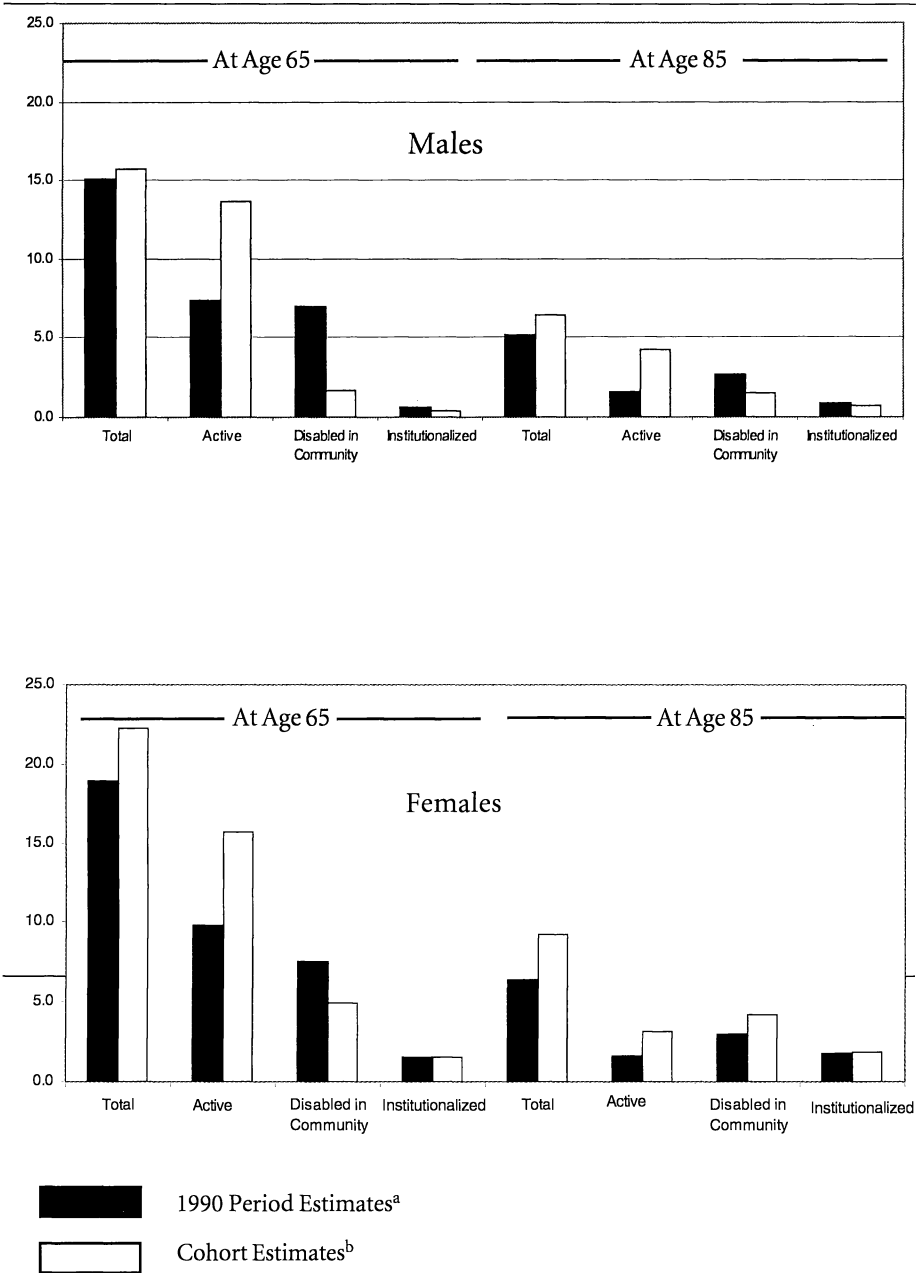
To apply this model, assume that the time span of the model is equal to that of the longest surviving individual  $i$  in a panel of  $N$  individuals followed longitudinally over time. Assume next that the random walk for  $T$  occurs in an  $n - m$  dimensional real numerical space,  $R^{n - m}$ , where  $m$  denotes the number of risk factors relevant to survival that have *not* been measured. Assume also that there are no interaction effects among the individuals in the panel so that the individuals in the panel can be treated as stochastically independent. Under these specifications, Woodbury and Manton (1977, 1983) first derived the Fokker-Planck-Kolmogorov forward partial differential equation describing the diffusion process specified by equations 4 and 5. Then, after specializing the model to the case of normally distributed risk factors (i.e., a Gaussian diffusion model), Woodbury and Manton (1977) derived the ordinary differential equations describing the time trajectories of changes in the average force of mortality for the cohort being followed over time, the panel-average risk factor vectors, and the panel-average variance-covariance

matrices for the risk factor vectors. This original Gaussian stochastic diffusion model has been suitably generalized (see, e.g., Manton, Stallard & Singer 1994; Manton et al. 1994) to deal with non-Gaussian diffusion processes to describe “lumpy,” sparsely populated, high-dimensional disability state spaces such as one obtains from data on ADLs and IADLS.

The latter version of the random walk model was applied by Manton and Land (2000) to data from a nationally representative longitudinal survey of elderly persons to produce ALE estimates for a finely partitioned state space representing individuals in terms of disabilities and disability intensities on multiple dimensions. The data are from the 1982, 1984, 1989 and 1994 National Long Term Care Surveys (NLTCSS). These surveys employ a two-stage sample design to focus interviewing resources on detailed assessments of persons with chronic disability (Manton, Corder & Stallard 1993). In the first stage of each NLTCSS, persons age 65 and older sampled from Medicare administrative lists are screened for chronic disabilities. If they report at least one chronic (lasting or expected to last 90 or more days) disability, or are living in a chronic care institution, they are given either a detailed in-person community or institutional instrument.<sup>3</sup> Because samples are drawn from an administrative list, the follow-up of persons between surveys is nearly 100%.<sup>4</sup> Response rates in all four surveys were 95% (Manton, Corder & Stallard 1997).<sup>5</sup>

Manton and Land (2000) made comparisons of their ALE estimates with prevalence-rate-based estimates from synthetic cohort life tables of the U.S. elderly population in 1990 (Crimmins, Saito & Ingegneri 1997). Results are summarized in Figure 1. It can be seen that the ALE estimates of Manton and Land (2000) are 1.8 and 2.6 times larger than the period estimates of Crimmins et al. for males at ages 65 and 85, respectively; 1.6 and 1.9 times higher at these ages for females. The larger multiples observed for males than for females are due to the fact that males are more likely to recover from some disability states than females. By demographic standards, these differences in ALE estimates are very large and have very important implications for the population burden of disability among the elderly. Additional research is called for to corroborate the accuracy of the Manton and Land estimates. Suffice it to say that the more refined state-space descriptions of disability dynamics permitted by the stochastic diffusion life table model they employ has yielded estimates of ALE that appear to be much improved over those produced by the application of the traditional prevalence life table model. If the Manton and Land (2000) ALE estimates continue to be replicated over time as additional updates of National Long Term Care Surveys become available, and if they are further refined to become cohort specific, they will become increasingly valuable social indicators of the health status of the ages 65 and older population in the U.S. Furthermore, and what is most important in the context of the present article, the ALE estimates of Manton and Land are interpretable within the context of a sophisticated mathematical model of human mortality and aging that has been developed, applied

**FIGURE 1:** Comparison of Period and Completed-Cohort Estimates of Life Expectancies, in Years, in Various Health States



<sup>a</sup> Based on Crimmins et al. (1997)

<sup>b</sup> Based on Manton and Land (2000)

empirically, and elaborated upon in dozens of research publications over the past two decades.

#### EXAMPLE 2: ADJUSTING THE PERIOD TOTAL FERTILITY RATE

This second example shows how simulation studies within the context of a well-defined model can be used to determine how robust a social indicator is to violations of the assumptions under which it was derived. In this case, the indicator derives from a mundane model in the conventional toolkit of demographers for the estimation of fertility levels and trends. Estimates of fertility are among the most widely used and monitored demographic statistics. Recent levels of fertility in many developing countries are closely watched by demographers, family planning program managers, and policy makers to determine whether and how rapidly fertility is changing and whether in a desired direction. These same statistics for much of the developed world, where fertility in recent years has been at historic lows, are examined for signs of an upturn in fertility back to the replacement level needed to prevent future absolute declines in population size.

Although the demographic literature contains many measures of fertility, the period total fertility rate (TFR) is now used more often than any other indicator. The TFR is defined as the average number of births a woman would have if she were to live through her reproductive years (usually taken as ages 15–49) and bear children at each age at the rates observed in a particular year or period. The actual childbearing of cohorts of women is given by the completed or cohort fertility rate (CFR), which measures the average number of births 50-year-old women had during their past reproductive years. Formally, let  $f_p(t, a)$  denote the age-specific fertility rates for women aged  $a$  at time  $t$ , and let  $f_c(T, a)$  represent the age-specific fertility rates at age  $a$  for cohorts of women born at time  $T$ . Then the *period total fertility rate* for time  $t$  is

$$\text{TFR}(t) = \int f_p(t, a) da$$

and the *cohort fertility rate* for the cohort born at time  $T$  is

$$\text{CFR}(T) = \int f_c(T, a) da.$$

In applications, the integrals are replaced by finite summations and the sums are taken over the reproductive ages. Note also that the TFR can be made specific to the order of births (i.e., first, second, and so forth), but to simplify the notation, subscripts for the order of births are omitted.

The CFR measures the true reproductive experiences of a well-defined group of women. But it has the disadvantage of representing past experience, as women currently age 50 did most of their childbearing two to three decades ago when they were in their 20s and 30s. The advantage of the TFR is that it measures current fertility and therefore gives up-to-date information on levels and trends in fertility.

The TFR also has a conventional metric (births per woman) that nondemographers can readily understand.

However, the TFR has been widely subjected to criticism among demographers. Demographers interpret the conventional period total fertility rate ( $TFR[t]$ ) as the total number of births an average member of a hypothetical cohort would have for whole life if this hypothetical cohort *exactly* (with no changes in quantum or level, tempo or timing of births across the ages, and shape of the fertility schedule) experienced the observed period age-specific fertility rates. This interpretation is equivalent to imagining that the observed period age-specific fertility rates are *constantly* extended sufficiently many years into the future (e.g., 35 years), so that a hypothetical cohort would have gone through the whole reproductive life span (e.g., from age 15 to 49) during this imagined extended period. This unadjusted conventional period total fertility rate is the total number of births an average member of the hypothetical cohort would have for her whole life in such a static situation, in the absence of mortality throughout the reproductive ages. Note, however, that the assumption of no changes in tempo or timing of births inherent in the conventional period  $TFR(t)$  is violated when the timing of fertility is changing. This violation results in well-known distortions of the conventional period  $TFR(t)$ .

For this reason, Bongaarts and Feeney (1998) recently proposed an adjusted version of the period total fertility rate to minimize tempo effects — distortions in the observed  $TFR(t)$  due to changes in the tempo or timing of births. Specifically, based on the underlying assumption that the shape of the period age-specific fertility schedule does not change and its implied assumption about equal changes in timing of births at all reproductive ages, Bongaarts and Feeney (1998) derived the following *quantum adjustment formula*:

$$TFR'(t) = TFR(t) / (1 - r[t]) \quad (6)$$

where  $TFR'(t)$  is the adjusted order-specific Total Fertility Rate in year  $t$ ,  $TFR(t)$  is the observed period order-specific Total Fertility Rate in year  $t$ , and  $r(t)$  is the *annual change in the order-specific period mean age at childbearing in year  $t$* . The annual change  $r(t)$  is defined as the difference of the mean age at childbearing of a particular birth order between two successive years. The unit of  $r(t)$  is “years old/per year.”

Although the Bongaarts-Feeney (B-F) quantum adjustment formula in equation 6 looks like a relatively simple and straightforward adjustment to a long-standing fertility indicator used by demographers, its reception by the demographic discipline has been anything but ordinary. Rather, it has been the subject of extensive critical review and commentary by several highly respected mathematical demographers (see Kim & Schoen 2000; van Imhoff & Keilman 2000 with responses by Bongaarts & Feeney 2000). One of the main points of contention in these critiques is that the simplifying assumption under which it is derived — that the shape of the period age-specific fertility schedule does not change over time and its implied assumption about equal changes in timing of births at all reproductive



ages — is not valid empirically. Indeed, the fact that the shape of the fertility schedule and not just its tempo can change over time is the basis of a recent mathematical and empirical analysis by Kohler and Philipov (2001). These demographers propose an extension to the B-F formula that includes so-called variance effects, i.e., changes in the variance of the fertility schedule over time. If these variance effects are ignored, then Kohler and Philipov (2001) deduce that the B-F  $TFR'(t)$  is biased. Kohler and Philipov (2001) also derive approximations for these biases and extend the  $TFR'$  formula to fertility schedules with changing variance.

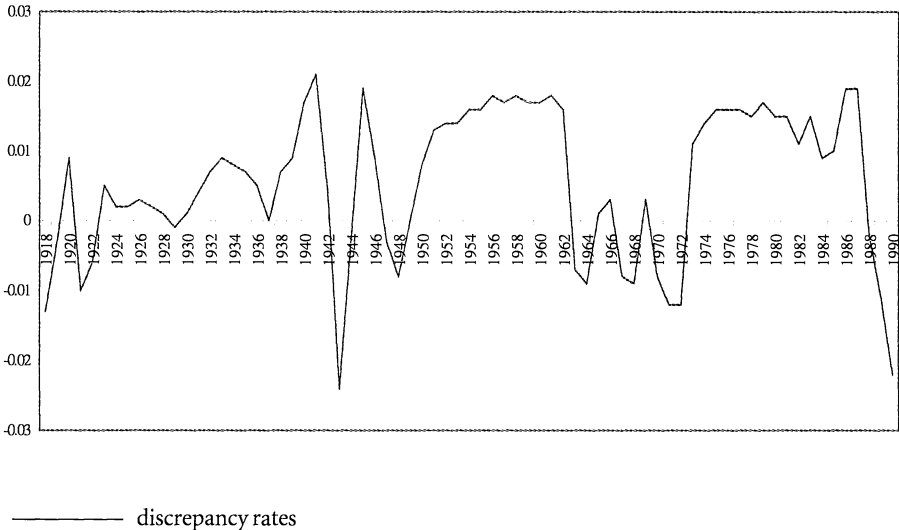
Thus, we have the following situation. The B-F  $TFR'(t)$  has the advantage of simplicity as a demographic indicator of what is happening to the fertility of a population and thus to the ability of a society to maintain itself in terms of numbers. Yet, in the presence of a fertility schedule that is changing in shape (variance) as well as tempo, the adjustment formula may be biased. But how much bias is the  $TFR'(t)$  likely to encounter empirically? It is precisely this question that led Zeng and Land (2001) to address the following question: Does the B-F formula (1998) work when its underlying assumption about invariant shape of the fertility schedule and its implied equal changes in timing of births across reproductive ages do not hold, as is likely the case in the real world?

To study this question, Zeng and Land (2001) carried out a sensitivity analysis of the B-F method. Their analysis is based on the fertility data in the U.S. from 1918 to 1990 and in Taiwan from 1978 to 1993, and the Brass Relational Gompertz fertility model and its extension. Figure 2 illustrates a small part of the findings from the Zeng and Land sensitivity study of the  $TFR'$ . Specifically, for first births in the U.S., 1918–90, this figure displays rates of discrepancy between the B-F  $TFR'(t)$  computed without allowing the shape of the fertility schedules to change and an alternative adjusted  $TFR''(t)$  that takes into account changes in the shape of the schedules. It can be seen that the discrepancy rates are almost always quite small.

This finding, in addition to several related results from their simulation study, led Zeng and Land (2001) to conclude that the B-F adjusted  $TFR'(t)$ , which assumes invariant shape of the fertility schedule, usually does not differ significantly from an adjusted  $TFR''(t)$  that allows the shape of the fertility schedule to change at a constant annual rate. This conclusion is consistent with a result in the mathematical analyses by Kohler and Philipov (2001) that shows that the biases in the B-F formula are quite small if a constant rate of increase in the variance of the fertility schedule prevails over time.

In brief, Zeng and Land (2001) found that the B-F  $TFR'(t)$  is generally and empirically robust for producing reasonable estimates of adjusted period  $TFR'(t)$  to reduce the distortion caused by the tempo changes, except under unusual conditions. The B-F method is sensitive to substantial nonsystematic changes (i.e., large and time-varying changes in the tempo and shape of the schedule). But, at least in the historical experience of the U.S. and Taiwan over much of the twentieth century, these nonsystematic changes are relatively rare. It also must always be kept

**FIGURE 2: Rates of Discrepancy between the B-F Adjusted TFR for First Births without Changing Shape of the Fertility Schedules and the Adjusted TFR with Changing Shape of the Schedules, U.S. 1918-1990**



in mind that the adjusted  $TFR'(t)$  using the B-F method neither represents any actual cohort experiences in the past nor forecasts any future trend. Rather, as compared to the conventional  $TFR(t)$ , it only provides an improved reading of the period fertility measure that reduces the tempo distortion, and is a hypothetical cohort measure similar to period life table measures. As such, the B-F  $TFR'(t)$  provides a second example of a social indicator of the type called for in Land (1971), namely, a component of a social system model within which it has a clear interpretation.

### EXAMPLE 3: MEASURING CHANGES IN CHILD AND YOUTH WELL-BEING

This third example addresses the question of whether the social well-being of children in the U.S. has improved, deteriorated, or stayed about the same over the past couple of decades. From the stagflation and socially turbulent days of the 1970s through the decline of the rust belt industries and transition to the information age in the 1980s to the relatively prosperous *e*-economy and multicultural years of the late 1990s, Americans have fretted over the material circumstances of the nation's children, their health and safety, their educational progress, and their moral development (Moore 1999). Are their fears and concerns warranted? How do we know whether circumstances of life for children in the U.S. are bad and getting

worse, or good and improving? On what basis can the public and its leaders form opinions and draw conclusions?

Since the 1960s, researchers in social indicators/quality-of-life measurement have argued that well-measured and consistently collected social indicators provide a way to monitor the condition of groups in society, including children and families, today and over time (Ferriss 1988; Land 2000). The information thus provided can be strategic in forming the ways we think about important issues in our personal lives and the life of the nation. Indicators of child and youth well-being, in particular, are used by child advocacy groups, policy makers, researchers, the media, and service providers to serve a number of purposes. In three instances — to describe the condition of children, to monitor or track child outcomes, and to set goals — the use of indicators is well within the long-established “public enlightenment” function of social indicators. And while there are notable gaps and inadequacies in existing child and family well-being indicators in the U.S. (Moore 1999), there also literally are dozens of data series and indicators from which to form opinions and draw conclusions (e.g., Brown 1997).

In face of this surfeit of data, Land, Lamb, and Mustillo (2001) have taken on a crucial part of the public enlightenment function with respect to the well-being of America’s children, namely, the summarization question: Overall or on average, how well are children and youths in the America doing? Focusing on the last quarter of the twentieth century in particular, *did overall child and youth well-being — defined in terms of averages of social conditions encountered by children and youths — improve or deteriorate?*

Attempts to develop overall summary indices of trends in well-being often are dismissed as arbitrary. While there may be some irreducible element of arbitrariness in any summary social indicator, Land et al. (2001) attempt to reduce this element to a minimum by building upon a large body of research over the past three decades on the topics of subjective well-being and quality-of-life assessment. Recent reviews by Cummins (1996, 1997) of empirical studies of the quality of life have summarized several key findings from these studies. Based on his review of 27 definitions that have been used to identify domains or subject areas of the quality of life, Cummins (1997:118) drew three conclusions:

- First, the term *quality of life* refers to both the objective and subjective axes of human existence.
- Second, the objective axis incorporates norm-referenced measures of well-being (i.e., measures of life circumstances on which there is a consensus among the general public that they are significant components of better or worse life circumstances). Usually, *objective measures of well-being* are based on observable facts (e.g., infant deaths) or reports on behavior (e.g., victimization of a sample survey respondent in a violent crime incident within the last year).

- Third, the subjective axis incorporates measures of *perceived or subjective well-being* based on individuals' personal values, views, and assessments of the circumstances of their lives.

The norm-referenced approach mentioned in the second point dates back to the definition put forward by Mancur Olson. As the principal author of *Toward a Social Report* published on the last day of the administration of President Lyndon B. Johnson, Olson wrote: "A social indicator is a statistic of direct normative interest which facilitates concise, comprehensive and balanced judgements about the condition of major aspects of a society" (U.S. Department of Health, Education, and Welfare 1969, p. 97). The perceived or subjective well-being approach to quality of life measurement was initially explored in great methodological detail by Andrews and Withey (1976) and Campbell, Converse, and Rodgers (1976).

Both of the latter works also applied the two major approaches to quality of life measurement that have dominated the research literature. These are the measurement of assessments of life quality by individuals (1) as a single, unitary entity or (2) as being composed of discrete "domains" or areas of life. The former approach is tapped by the prototypical single, sample survey question "How do you feel about your life as a whole?" with responses typically obtained on a Likert rating scale of life satisfaction/dissatisfaction. The latter approach is typified by sample survey questions requesting satisfaction/dissatisfaction responses concerning a number of domain or subject area aspects of life such as work, income, family, friends, etc.

The literature reviews by Cummins (1996, 1997) of 27 subjective well-being studies offering definitions of the quality of life that identify specific domains suggests that there is a relatively small number of domains that comprise most of the subject areas that have been studied. Specifically, Cummins found that about 68% of the 173 different domain names and 83% of the total reported data found in the studies reviewed can be grouped into the following seven domains of life:

- *material well-being* (e.g., command over material and financial resources and consumption);
- *health* (e.g., health functioning, personal health);
- *safety* (e.g., security from violence, personal control);
- *productive activity* (e.g., employment, job, work, schooling);
- *place in community* (e.g., socioeconomic [education and job] status, community involvement, self-esteem, and empowerment);
- *intimacy* (e.g., relationships with family and friends); and
- *emotional well-being* (e.g., mental health, morale, spiritual well-being).

Cummins (1996) states that the weight of the empirical literature indicates that these seven dimensions are all very relevant to subjective well-being. Therefore, indices of the quality of life, whether based on objective or subjective data, should

attempt to tap as many of these domains as possible. Of course, these seven domains of well-being are derived from subjective assessments in focus groups, case studies, clinical studies, and sample surveys that cannot, by definition, be replicated in studies of the quality of life that use objective data. Nonetheless, the domains identified by Cummins (1996) can and should be used to guide the selection and classification of indices of the quality of life that are based on objective data, as will be illustrated from our study of child and youth well-being.

There are, however, considerable challenges in applying these domain areas to the measurement of the quality of life, and changes therein, of children and youths in the U.S. To begin with, most studies of subjective well-being have included (as participants in focus groups and respondents in sample surveys) only individuals who are 18 years and older. This raises the question of how applicable the domains of quality of life identified in existing empirical studies are to the quality of life of children and youths. Fortunately, the samples used in studies of subjective well-being have been quite diverse — ranging from general samples of adult populations to college students to various clinical populations. This variety of sampling frames suggests that the seven domains identified by Cummins have at least a fair level of robustness and applicability across different populations.

In addition, comparisons can be made with a few recent studies of subjective well-being that have focused on child and adolescent samples. For instance, Gilman, Huebner, and Laughlin (2000) found that the following domains of life related to general life satisfaction in a sample of American adolescents enrolled in grades 9–12 (ordered from greatest to lowest association with general life satisfaction): family (relationships), self (image), living environment (material well-being), friends (relationships), and school. While the survey questionnaires used by Gilman et al. do not contain questions on all of the domains identified by Cummins (1996) and cited above, several of these domains do have similar content.

In brief, Land et al. (2001) proceed on the presumption that the seven domains of well-being identified above are applicable — with some adaptations — to the measurement of the quality of life of children and youths. It is clear, for instance, that the main “productive activity” of most children up to age 18 is schooling or education rather than work. It also is evident that the income status of their parents or guardians is the principal way by which the command of children and youths over economic and material resources is measured in national data sources.

Even with conceptual adaptations of this kind, data sources available for the operationalization and measurement of child and youth well-being in the U.S. are limited. Using a number of available databases, Land et al. (2001) compiled some 25 indicators of child and youth well-being that date back at least to 1975.<sup>6</sup> They are grouped in Table 1 as much as possible according to the domains of well-being identified by Cummins (1996) reviewed above. In some cases, we have identified some of the key indicator series as jointly indicative of two domains of well-being.<sup>7</sup>

**TABLE 1: 25 Key National Indicators of Child Well-Being in the United States Available in Time Series Form, 1975–1998**

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Material Well-being Domain:	1. Poverty rate — all families with children
	2. Secure parental employment rate
	3. Median annual income — all families with children
Material Well-being and Social Relationships* Domains:	4. Rate of children in families headed by a single parent
Social Relationships Domain:	5. Rate of children who have moved within the last year
Health Domain:	6. Infant mortality rate
	7. Low birth weight rate
	8. Mortality rate, ages 1–19
	9. Rate of overweight children and adolescents, ages 6–17
Health Behavioral Concerns* Domains:	10. Teenage birth rate, ages 10–17
Safety/Behavioral Concerns Domain:	11. Rate of violent crime victimization, ages 12–17
	12. Rate of violent crime offenders, ages 12–17
	13. Rate of cigarette smoking, grade 12
	14. Rate of alcoholic drinking, grade 12
	15. Rate of illicit drug use, grade 12
Productivity (Educational Attainments) Domain:	16. Reading test scores, ages 9, 13, 17
	17. Mathematics test scores, ages 9, 13, 17
Place in Community* and Educational Attainments Domains:	18. Rate of preschool enrollment, ages 3–4
	19. Rate of persons who have received a high school diploma, ages 18–24
	20. Rate of youths not working and not in school, ages 16–19
	21. Rate of persons who have received a bachelor's degree, ages 25–29
	22. Rate of voting in presidential elections, ages 18–20
Emotional/Spiritual Well-being:	23. Suicide rate, ages 10–19
	24. Rate of weekly religious attendance, grade 12
	25. Percent who report religion as being very important, grade 12

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*Note:* A few key indicators can be assigned to two domains. For these, the \* denotes the domain-specific index to which the indicators are assigned for computation purposes. Explanations for the domain assignments are given in the text.

Unless otherwise noted, indicators refer to children ages 0–17.

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The child and youth well-being indicator series identified in Table 1 are most adequate with respect to the first five of the seven domains of the quality of life identified by Cummins (1996): material well-being, health, safety/behavioral concerns, productive activity/educational attainments (as measured by National Assessment of Educational Progress test scores), and place in community (as

measured by indicators of participation in school and work organizations). Only two indicators in Table 1, the rate of children in families headed by a single parent and the rate of children who have moved residences in the last year, can be construed as tapping the intimacy domain identified by Cummins. In fact, these two indicators can be construed only as imperfect measures (more commentary on this below) of the “relationships with family” and “relationships with peers” parts of Cummins intimacy domain, respectively. Thus, we henceforth will refer to these indicators as measures of a *social relationships* domain.

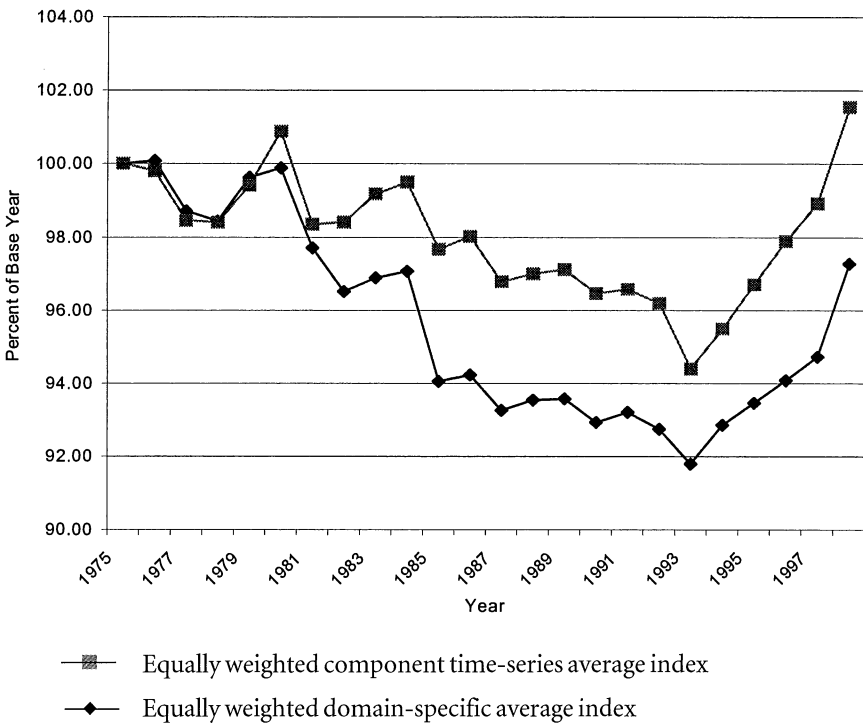
In addition, the single-parent indicator also measures, in part, the ability of families to command material resources. Hence, we separately identify the rate of children in families headed by a single parent as measuring both of these domains. Similarly, we separately identify the rate of children with health insurance coverage as measuring both the material well-being and health domains and the teenage birth rates as indicative of both the health and behavioral concerns domains. We also separately identify four of the schooling/work indicators as indicative of both the productive activity (educational attainments) and place in community domains.

Another limitation of our list of indicators is that none directly measure the emotional and spiritual well-being domain. Rather, we are limited to indirect indicators — suicide rates and religious attendance. Suicide is viewed in the mental health literature as indicative of extreme emotional stress (American Psychiatric Association 1994). Thus, an increase in the late childhood/adolescence (ages 10–14) and teenage (ages 15–19) suicide rates may indicate a greater prevalence of persons in these age groups who are suffering from very high levels of stress and, inversely, low levels of emotional well-being. Similarly, the rate of weekly attendance at religious ceremonies is, at best, an indirect indicator of spiritual well-being. However, the indicator identified in Table 1 pertains to teenagers who are enrolled in grade 12 and hence are about 17 years of age. It may thus be presumed that there is at least some volitional component of the religious attendance indicator. Accordingly, fluctuations up and down in the religious attendance time series may be indicative of trends in the spiritual well-being of American teenagers.

Note, finally, that none of the 25 indicators are based on subjective well-being responses. In sum, while the selection of indicators identified in Table 1 is guided by the recent statement on key domains of the quality of life by Cummins (1996), it also is highly constrained by available national data series, is almost exclusively based on objective indicators, and has relatively poor indicators to measure the intimacy and emotional well-being domains.

Land et al. (2001) explore various approaches to the construction of summary indices of well-being from these individual indicator series. In its broadest sense, an index number is a measure of the magnitude of a variable at one point (say, a specific year that is termed the *current year*) relative to its value at another point (called the *reference base* or *base year*). The index number problem occurs when the magnitude of the variable under consideration is nonobservable (Jazairi 1983).

FIGURE 3: Summary Indices of Child Well-Being, 1975-1998



In economics, where index numbers are widely used, this is the case, for example, when the variable to be compared over time is the general price level, or its reciprocal, the purchasing power of money. As noted, for example, by Ruist (1978), the index number problem arises in measuring the general price level due to the fact that there are multiple prices to be compared. Over any given historical period, the prices of some economic goods will have risen and some will have fallen.

In the present case, the variable to be compared over time is the overall well-being of children in the U.S. — defined in terms of *averages of social conditions encountered by children and youths*. In the case of overall child and youth well-being, there are multiple indicators of well-being to be compared. And as in the case of the general price level, over any period of years, some indicators of child and youth well-being likely will have risen and some will have fallen.

In the case of the general price level, the problem that arises is how to combine the relative changes in the prices of various goods into a single number that can meaningfully be interpreted as a measure of the relative change in the general price



level of economic goods. In the case of child and youth well-being, the problem similarly is how to combine the relative changes in many rates of behaviors pertaining to child and youth well-being into a single number that can meaningfully be interpreted as a measure of the relative change over time in a fairly comprehensive selection of social conditions encountered by children and youths. A key point is that in any given year no single consumer is likely to purchase all of the items that comprise the market basket of goods used in constructing the consumer price index. On the other hand, fluctuations over time in the consumer price index signal changes in general price levels that generally are encountered by consumers, and most consumers are interested in how the general price level is changing. Similarly, in any given year no single child encounters all of the social conditions that enter into the overall index of child and youth well-being that is developed in this article. Fluctuations over time in the index of child and youth well-being can be taken, however, as signaling changes in the overall context of social conditions encountered by children and youths. And many policy makers, officials, adults, and parents (and some children and youths as well) are interested in how the general level of social conditions faced by children and youths in a recent year, such as 1998, compares to the corresponding level in a previous year, such as 1975.

Figure 3 exhibits the results of one approach to the construction of an index of child and youth well-being studied by Land et al. (2001). In this case, the index is constructed as a percentage change index — wherein, for each year after the 1975 base year, changes in the values of each of the 25 component indicators from their values in 1975 are taken as a percentage of the 1975 values. These percentage change indices then are combined in two ways to obtain an overall summary index of child and youth well-being. One approach to index construction results in the time series labeled the *equally weighted domain-specific average index* of Figure 3. This summary index is computed by applying a percentage (of base year 1975) formula to each of the 25 component indicators and then computing an average of each of the resulting percentage change indices for each of the seven domains of well-being identified in Table 1. The second index in Figure 3, the *equally weighted component time series average index*, applies the percentage change index formula directly to all 25 indicator time series and then directly averages all 25 resulting percentage change indices. The first index weights the seven domain-specific indices equally, while the second weights the 25 component time series equally and, thus, weighs the seven domains unequally. Thus, the second index gives more weight to those domains for which we have more component time series, whereas the former treats the seven domains equally. A comparison of the two indices helps to ascertain the effects of the domain grouping on the overall summary well-being indices. Nonetheless, because the latter form of the index gives more weight to those domains of well-being for which we have more indicator time series, most quality-of-life researchers prefer to interpret the former, domain-specific, version as giving a more balanced representation of well-being.

What do these domain-specific trends imply for changes in overall child and youth well-being from the 1970s to the 1990s? It can be seen from Figure 3 that the two 1975 base year summary indices show different over-time behavior with respect to *levels*. The two summary index time series track closely together until about 1981 and then diverge substantially through the remainder of the 1980s and 1990s. Nonetheless, both summary index time series tell similar stories with respect to *trends* in child and youth well-being over this quarter century. Relative to 1975 base levels, overall child and youth well-being in the U.S. deteriorated substantially through the 1980s and early 1990s, reaching a low point in 1993, and rising to levels close to those of 1975 by the late 1990s. In numerical terms, both summary indices have levels in 1980 close to the 100 level of the 1975 base year. But the domain-specific average index drops to about 92% of the 1975 base at the low point in 1993 compared to just above 94% of the base year for the component-average index. Similarly, the domain-specific average returns to about 98% of the 1975 base year by 1998, the component-average index increases to nearly 102% of the base year index by that year.<sup>8</sup>

The key point for the present discussion is that the Land et al. (2001) analyses illustrate, in yet another way, how the use of models can inform the construction of social indicators. In this case, empirical findings from models of subjective well-being, as summarized in Cummins (1996), have been combined with existing social indicators time series data through the application of index construction theory to produce overall summary indices of child and youth well-being. This approach to summary index construction reduces considerably the arbitrariness of index construction in the sense that the choice of domains in the Land et al. (2001) indices is guided by prior research.

The Land et al. (2001) indices provide a tentative indication of how child and youth well-being has changed over the last quarter century in the U.S. In addition, the analyses provide a basis from which additional efforts to assess trends in child and youth well-being can be designed. In particular, the construction and analysis of an Index of Child and Youth Well-Being helps to identify major inadequacies and lacunae in the current indicator system for child and youth well-being in the U.S. Most obvious is the relative lack of reliable time series data with which to measure trends in the emotional well-being of children, especially adolescents and teenagers. Similarly, the index would benefit greatly from additional indicators for the social relationships domain of well-being, that is, of the relationships of children to family and friends. Social indicator analysts and social scientists and statisticians need to begin planning now for building an improved indicator system for child and youth well-being that will, in turn, facilitate improvements in indices of child and youth well-being in years to come.

## Conclusions

In sum, I have shown how standard classes of formalisms used to construct models in contemporary sociology can be derived from the general theory of models. This demonstration connects the structure of formalisms used in sociological modeling to those used in virtually every scientific discipline today.

I have noted how formal models attempt to encapsulate some slice of experiences/observations within the confines of the relationships constituting a formal system such as formal logic, mathematics, or statistics. Formal models, in this sense, are widely used in sociology today and have many benefits. What is most impressive with respect to the toolkit for model construction today as compared to three or four decades ago is the increased flexibility now available. Yet it probably is the case that few sociologists are content with the present state of model development in their subject of interest. Sociological models can be improved in various ways, and it is safe to predict that the twenty-first century will see many improvements in substantive sociological models along with increased flexibility in the modeling apparatuses available for use by sociologists.

I also have illustrated how formal models are particularly useful in helping analysts to see patterns in social data that otherwise are not detectable and in improving social measurement. In particular, models assist in the definition and interpretation of social indicators. I have illustrated the last point with brief reviews of recent research on the measurement of active life expectancy, adjusting the total fertility rate, and measuring changes in child and youth well-being. These studies lead to the conclusion that the goal of developing social indicators as components of social system models is closer to being realized today than when stated by Land (1971b) three decades ago.

## Notes

1. There are, of course, many additional issues of formal model building, estimation, and evaluation. Huge shelves of books have been written on these topics.
2. Many sociologists have developed excellent examples of the construction, evaluation, and use of models; virtually any issue of most sociological journals contains one or more instances. I choose to review these three examples of modeling from my own work mainly for convenience and because they fit into the overall themes of this article.
3. In addition, all persons chronically disabled or institutionalized in a prior NLTCS are automatically given a detailed interview at each subsequent wave (until death) to assess, in detail, persons regaining function as well as those who continued to lose function with their "disability" intensifying on one or more dimensions. In this sense, the NLTCSs represents a national longitudinal study of changes in defined "partial" cohorts.
4. To represent the entire population over 65, a new sample of 5,000 persons ("cohort") reaching age 65 in the survey interim is drawn at the next survey date from Medicare

lists and screened for chronic disability or institutional residence. Incidence cases in this group were given a detailed interview to supplement the cohort structure of the sample over time.

5. In each NLTCS, there were roughly 20,000 persons in the sample representing the U.S. elderly population age 65 and older. In the four surveys, 35,000 distinct elderly individuals were assessed one or more times. Roughly 17,000 deaths (from 1982 to 1996) were identified from Medicare records. Each NLTCS contains large numbers (> 2,000) of persons aged 85 and older. The survey records were also linked to a continuous history of Medicare Part A and B service use records. Questions on disability and morbidity have remained unchanged over the four NLTCS waves using the same field methods and survey organization (the U.S. Bureau of the Census). Thus, method effects on trend estimates are minimized.

6. Most of the series in Table 1 are reported annually. The exceptions are the reading and test scores (from the National Assessment of Educational Progress), the obesity prevalence rates (from the National Health and Nutrition Examination Surveys [NHANES]), and the voting in presidential election years percentages (which necessarily occur on four-year cycles). The NAEP test scores originally began on a five-year cycle in 1975 and then changed to a two-year cycle in 1985. Since these time series change quite smoothly, however, they quite easily can be interpolated to an annual basis. The obesity data from the NHANES studies were collected in cycles spanning the years 1971–74, 1976–80, and 1988–94. To fit with the annual spacing of the other time series in Table 1, Land et al. (2001) interpolated these data for the intervening years. And, similarly, the voting percentages were interpolated to an annual basis from the four-year cycles of presidential elections.

7. All of the indicator series, with the exceptions of median annual income and test scores, are reported in either of two forms. Many of the series are based on data on the prevalence of some identifiable characteristic or property. These are reported as *prevalence rates* (usually computed as the percentage of persons or the number per 1,000 with a given characteristic, e.g., good or excellent health, per year). However, some of the series are based on numbers of events that occur in a year. These are reported as *incidence rates* (usually computed as the number of events of some type, e.g., infant deaths, per population unit exposed to the risk of the incident, e.g., per 1,000 births, per year).

8. Land et al. (2001) note that the low point in the summary indices exhibited in Figure 3 in 1993 are due to downturns in the material well-being and safety/behavioral domain-specific components in the mid-to-late 1980s and early 1990s. And the rapid increases in the overall summary well-being indices over the years 1993 to 1998 are due to the fact that trends in the mid-to-late 1990s in 6 of the 7 domain-specific indices (and most of their component time series) were in concert and pointed upward — for the first time in the 23 years since 1975. Land et al. (2001) discuss many additional findings pertaining to trends over time in each of the seven domains of well-being, trends within infancy, childhood, and adolescence/teenage age groupings, and trends in race/ethnic-group-specific comparisons and disparities.

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