Are All Indicators Created Equal?
Alternatives to An Equal Weighting Strategy in the Construction of A Composite Index of Child Wellbeing*

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Kenneth Land and his colleagues at Duke University have developed a Child Wellbeing Index (CWI) for the United States with support from the Foundation for Child Development in New York City (Land, 2006; Land, Lamb, & Mustillo, 2001; Land, Lamb, Meadows, & Taylor, 2005). The purposes of the CWI are to permit monitoring of changes in the wellbeing of American children and youth over time and to draw press and public attention to the situation of young people.

The CWI is based on 28 statistical data series on children that are regularly available from federal statistical agencies or university-based survey programs that are supported by the federal government (see Table 1 for a list of the indicators). The series cover such topics as child health and disability, educational achievement, preschool enrollment, financial wellbeing of families, teen crime victimization and criminal offending, teen substance abuse, teen religious observance, and young adult voting participation. Most of the indicators have been available on an annual basis since the mid-1970's.

As currently constituted, the CWI project uses an equal-weighting strategy for constructing composite indices from the component child indicator data series. Each of the 28 component indicators is indexed by a base year (usually 1975). The base year value of the indicator is assigned a value of 100 and subsequent values are transformed into a percentage change from the base year. The directions of the indicators are oriented so that values greater than 100 mean that conditions have improved and values less than 100 indicate deterioration.

The 28 indexed indicator time series are grouped into seven "quality-of-life domains:" family economic well-being, health, safety/ behavioral concerns, educational attainment, community connectedness, social relationships, and emotional/spiritual well-being. These domains are described as having been "well-established as recurring time after time in over two decades of empirical research in numerous subjective well-being

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studies. They also have been found, in one form or another, in studies of the well-being of children and youth" (Land, 2006, p.19). The indexed indicators within each domain are combined with equal weighting to form domain-specific index values for each year. Then the seven domain-specific indices are combined with equal weighting to form the overall CWI for that year.

Land and colleagues present two reasons for employing the equal-weighting strategy in constructing the composite wellbeing indices (Land, 2006, p. 19). The first is that it is the simplest and most transparent strategy and can easily be replicated by others. The second reason is that statistical research done by the project suggests that, in the absence of a clear ordering of the indicators of a composite index by their relative importance, an equal-weighting strategy will achieve the greatest level of agreement among members of the relevant population.

The purpose of this paper is to draw attention to problems that may arise with regard to the validity and acceptance of the CWI because of the use of the equal-weighting procedure. The paper describes several methods that might be used to corroborate or cast doubt on the notion that equal weighting is the optimum combinatorial strategy. The methods described could be used to produce an ordering of the child indicators in terms of their relative importance, as well as to foster important advances in the field of child indicators research.

Problems That May Arise From Equal Weighting of Indicators

A problem that can arise from giving each component the same weight in the composite index is that all components may not be equally important as indicators or determinants of children's overall wellbeing in contemporary U.S. society. A significant change in some components may have far more profound and long-lasting implications for child well-being than a significant change in other components. Giving them equal weight may result in misleading conclusions regarding the extent and direction of change in children's overall wellbeing. Likewise, some components may have more salience than others in terms of public perceptions regarding the overall state of children's well-being. Giving all components equal weight may result in the CWI being at odds with general understandings of how things are going for children, making the index less credible and less apt to capture public attention.

Thus, equal weighting of index components may be problematic for *causal* reasons, for perceptual reasons, or both. There are several methods that could potentially be used to generate weights for different components of the CWI. The work necessary to apply these methods would provide insights along the way into just how problematic the equal-weighting strategy really is. Therefore, it seems desirable to try out one or more of these methods on an exploratory basis and see where the results lead.

An illustration of the anomalies that may created by equal weighting of indicators may be found in the CWI domain of child health. The CWI health sub-index of the CWI has shown deterioration in recent years, primarily because of an increase in the proportion of young people who are deemed to be overweight (Land et al., 2006). Yet other fundamental indicators have been showing continued improvement in children's health status. For example, the infant mortality rate declined from 8.9 deaths per thousand live births in 1990 to 7.0 deaths in 2002, a 21 percent improvement in this basic indicator (National Center for Health Statistics, 2004, p. 131). Death rates among preschool-aged children declined 33 percent, 28 percent among elementary-school-aged children, and 23 percent among adolescents over the same time span (Federal Interagency Forum on Child and Family Statistics, 2005, pp. 140-142). Likewise, the proportion of U.S. children and youth under 18 rated as being in fair or poor health declined from 2.6 percent in 1991 to 1.9 percent in 2002 (National Center for Health Statistics, 2004, p. 217), a 27 percent improvement.

There have also been improvements in several indicators of health care and parental behavior that have been shown to be related to children's health outcomes. For example, the proportion of pregnant women receiving prenatal care in the first trimester of pregnancy increased from 75.8 percent in 1990 to 83.7 percent in 2002, a 10 percent improvement (National Center for Health Statistics, 2004, p. 113). And the proportion of pregnant women who reported smoking during pregnancy showed a dramatic 38 percent decline, from 18.4 percent in 1990 to 11.4 percent in 2002 (National Center for Health Statistics, 2004, p. 82).

To be sure, there is still room for improvement in the health status of children and youth in the U.S. And there are still dismaying gaps across social-class and racial and ethnic groups in access to health care, health-related behaviors, and health status indicators of children. But should the increase in youthful obesity outweigh the positive trends in other child health indicators in a composite index of the health status of children and youth? One way to go about answering this question is by gathering evidence on the relative importance of obesity and other health indicators as markers or determinants of longer-term health outcomes, such as average life expectancy in the U.S.

In a recent issue of the New England Journal of Medicine, Olshansky et al. (2005) estimated that the current life expectancy at birth in the United States would be one third to three quarters of a year longer if all overweight adults were to attain their ideal weight. They argue that because of the increase in obesity and other negative health trends, current generations of children may have lives whose duration is shorter, on average, than those of today's adults.

But in an invited editorial reply in the same journal issue, Samuel Preston (2005) argues against this gloomy outlook. He points out that, "The effect of an increase in the prevalence and severity of obesity on the longevity of U.S. citizens is already embedded in extrapolated forecasts made in recent periods [in life expectancy tables] (Preston, 2005, pp. 1135-1136)." Yet these tables continue to show greater life expectancy at birth and other ages for U.S. citizens than was projected and obtained in the past. This suggests that the negative trend in childhood obesity should *not* outweigh the positive trends in other child health indicators. This is especially true because the relationship between overweight in childhood and adulthood has yet to be clearly established.

Preston goes on to note that, "Hundreds of factors affect a population's rate of death in any particular period, and it is their combined effect that establishes the trend…many factors are at work to maintain a steady pace of advance…Younger cohorts are better educated than older cohorts, and mortality is profoundly influenced by education…Younger cohorts have had lives less scarred by infectious disease, which influences the development of many chronic diseases of adulthood…Younger cohorts have consumed fewer cigarettes at a given age than older cohorts, and the effect of smoking is clearly manifested in the rates of death of the general population…The fact that the U.S. population has already shown the ability to shift to healthier lifestyles is [also] encouraging" (Preston, 2005, p. 1136).

Gathering and analyzing evidence on the relative importance of different component indicators of child health and wellbeing would not only help to resolve issues such as the conflict between the obesity trend and other child health trends. It would also help to advance the general field of social indicators research and help make child indicators more informative for child policy.

Methods for Generating Relative Weights for Different Indicators

The following methods could be used to generate relative weights for different component indicators of a composite Child Well-Being Index:

1. ***Factor analysis*** of the component indicators as they vary and covary across geographic units or over time;
2. ***Scaling*** based on expert or lay judgments of the relative importance of different indicators; and,
3. ***Regression analysis of longitudinal data*** examining how significant each near-term indicator is in predicting to longer-term child outcomes.

What follows is a brief description of each of these approaches and what would be required in the way of data and analysis in order to implement it. Examples of previous applications of the methods are presented and the advantages and drawbacks of each approach are discussed.

1. Factor Analysis of Component Indicators

Factor analysis is a statistical technique whose objective is to explain most of the variability among a number of observable variables in terms of a smaller number of unobservable variables called "factors" (Hair, Anderson, Tatham, & Black, 1998, Chapter 3). The observable variables are modeled as linear combinations of the factors, plus error terms. The technique is widely used in social science applications involving large numbers of variables and substantial quantities of data, such as in market research, test construction, operations research, and product management. For example, Filmer and Pritchett (2001) used factor analysis to create a household wealth index for India based on questionnaire items about specific household possessions.

Factor analysis provides insight into the dimensionality of a data set, i.e., the number of separate dimensions or factors that are required to adequately describe the observable variables. If a large first factor emerges from the child indicator analysis, accounting for the majority of the variation in the data set, with most or all of the component indicators contributing to or "loading" on this factor, then the notion of developing a single composite CWI would receive empirical support. The linear model underlying the factor solution would furnish the weights that each child indicator should receive in deriving the composite factor score. If the derived weights are fairly similar from one indicator to the next, that result would support the current equal weighting strategy. On the other hand, if some indicators have much higher loadings than others on the first factor, then differential weighting of the components or even the dropping of some indicators would clearly be in order.

If the factor analysis shows that two or more dimensions or factors are needed to adequately describe the observable indicators, that result would mean that more than one composite index may be needed to monitor child well-being. The linear model would then provide the weights that each observable indicator should receive in deriving both the first and second composite index scores (as well as additional factor scores, if necessary).

Data requirements. In order to apply factor analysis to the task of modifying the CWI, one would need values for each of the 28 component child indicators in a given year or group of years, across a set of geographic units, such as states of the United States or nations of the world. Factor analysis of the FCD child indicator data for a set of 50-100 nations is not currently practicable, for many of the 28 indicators are not available for countries other than the U.S., or are available in forms that are not directly comparable to the American statistics. More feasible is a factor-analytic study with child indicator data from the different states of the U.S.A.

State-level measures for most but not all of the 28 FCD component child indicators can be obtained, especially for recent years. Many of the state indicators have been compiled and tabulated in convenient form by the Annie Casey Foundation's Kids Count project (state-level versions of 17 of the 28 FCD child indicators can be found in the 2005 edition of the Kids Count Data Book).

Indicators that were formerly available for only a limited subset of states, such as state-level reading and math achievement test scores or youth risk behavior estimates, are now available for all or nearly all states. The 2001 reauthorization of the Elementary and Secondary Education Act, also referred to as "No Child Left Behind" legislation, required states that receive Title I funding to participate in state versions of the National Assessment of Educational Progress (NAEP) in reading and mathematics at grades 4 and

8 every two years. As a consequence, state NAEP data in reading and math are available for all 50 States in 2003 and 2005.

The number of States participating in the U.S. Center for Disease Control's Youth Risk Behavior Survey System (YRBS) has also been growing. As of 2003, YRBS data on teen risk behaviors were available for some 43 of the 50 states (although in 11 of these states participation rates were not sufficiently high to justify development of weighted state-level population estimates).

There are several national survey-based statistics in the FCD child indicators set that are not now available in state-level versions. These include statistics from the National Health Interview Survey on children with activity limitations and children rated as being in "excellent" or "very good" health. Also, state statistics are not available from the National Crime Victimization Survey on violent crime victimization and violent crime offending among teenagers. As well, state-level statistics are not available from the "Monitoring the Future" annual survey of high-school seniors on weekly religious attendance and perceived importance of religion among 12th Graders. Some of these indicators might become available at the state level if several years of national survey data were combined to produce state subsample sizes that were sufficient for stable estimates.

Example. Even with the incomplete set of child indicators currently available, factor analysis of state-level indicators from the FCD set seems like a relatively low cost, useful, and potentially informative exercise. In 1991, as part of a review of the Kids Count Data Book done at the request of the Annie Casey Foundation, Zill (1991) carried out a principal components analysis with a more limited set of 8 state-level child indicators that were then being used in the Kids Count reports. (Six of the eight indicators are among the 28 in the FCD child indicators set).

The results of the principal components analysis showed that six of the eight child indicators that were used in the KIDS COUNT report at that time did indeed "hang together" in a sensible pattern of interrelationships. These indicators were births to unmarried teens, infant mortality, low birth-weight births, child poverty, child death rate, and (in reverse) the high school graduation rate. The variables formed a first factor that accounted for 48 percent of the cross-state variation in the Kids Count indicators. Moreover, giving these six indicators equal weighting in an overall child wellbeing composite score was supported by the analysis. However, the other two indicators correlated only weakly with the first factor. These two indicators, the teen violent death rate and the juvenile incarceration rate, required a separate factor of their own, one to which the child death rate also contributed. Giving these two indicators equal weighting with the other six indicators in a composite index was not justified. Instead, what the analysis suggested was that the two indicators should either be dropped from the summary index or a second composite index should be developed that contained these or other, better indicators of youthful violent death and injury and juvenile delinquency and crime. The Annie Casey Foundation subsequently modified the list of indicators contained in their child wellbeing composite, dropping the juvenile incarceration statistic and replacing the teen violent death rate with the teen total death rate.

Zill and Alva (2006) repeated the principal components analysis of state-level child indicators data, using numbers from the latest Kids Count Data Book (2005). Seventeen component indicators for each of the 50 States of the U.S. were entered into the analysis. The component indicators were either exactly equivalent or closely related to the national indicators that figure into the FCD/Land et al. CWI. Note, however, that not appearing in this state-level analysis are several distinctive indicators that might well have formed separate factors. These include a child obesity measure, juvenile crime victimization and offending rates, a measure of voting participation by young adults, and measures of high school seniors' frequency of attendance at religious services and the perceived importance of religion in their lives.

The results of the principal components analysis are summarized in Tables 2 - 4. The analysis found that much of the cross-state variation in the available indicators could be represented by three dimensions or factors. Together, the three factors accounted for more than three-quarters of the overall variation in the 17 indicators. The first factor was by far the largest, accounting for 58 percent of the variance. Ten of the seventeen indicators had sizable loadings (.75 or higher) on this factor, and five more had moderate loadings (.64 to .74). The child poverty rate and teen birth rate had the highest loadings. Also highly correlated with this factor, but in the reverse direction, were NAEP achievement test scores for 4th Graders and 8th Graders in math and reading. (Table 2).

States whose factor scores gave them low rankings on the first factor were those with high child poverty rates, high teen birth rates, low achievement test scores, high proportions of teens who were neither working nor in school, high proportions of families in which neither parent had full-time, year-round employment, and low median income levels for families with children. They included Mississippi, Louisiana, New Mexico, and West Virginia, states that year after year come out at or near the bottom of the Kids Count composite rankings. States scoring very favorably on this factor included New Hampshire, Minnesota, Massachusetts, and Vermont, states that dependably come out at or near the top of the Kids Count rankings.

Thus far, the factor analysis results seem fairly consistent with and supportive of an equal-weighting strategy. But note that one of the child indicators, the proportion of children with special healthcare needs that limit employment of a family member, had only a low loading on the first factor (.26). This variable loaded much more highly (.76) on a second factor, a factor which accounted for 11 percent of the overall cross-state variance. Also showing moderate loadings on this factor were the proportion of low-birth-weight births in each state (.61) and the state infant mortality rate (.50). This factor was uncorrelated with child poverty rates and negatively correlated with a lack of health insurance coverage for children. States with unfavorable scores on this factor included

Delaware and Maryland, states that were toward the middle of the Kids Count rankings. Thus, the analysis may be signaling significant variation across states in child health and disability status that is not merely a matter of the general socio-economic wellbeing of families with children.

The third factor that emerged from the analysis was defined by moderate loadings for the child death rate (.62) and the teen death rate (.56). This factor accounted for eight percent of the overall variance. It was also uncorrelated with child poverty rates and negatively correlated with the proportion of single-parent households in the state. States with unfavorable scores on this factor were predominantly rural Midwestern and Western states, such as South Dakota, Wyoming, Montana, and Nebraska. These states were in or above the middle in the Kids Count composite rankings. Again, the analysis seems to be signaling appreciable variation across states in the risks that children and adolescents face, variation that does not simply covary with the socio-economic wellbeing of families with children.

It is possible that the smaller factors emerging from the principal components analysis may be partly artifactual, reflecting variations in registration, tabulation or reporting procedures across states. But it is also possible that the factors represent genuine variability in facets of child health, safety, and wellbeing, variability that might actually be more responsive to policy differences across states than the large-scale, socio-economic-related variation tapped by the first factor. In any event, the results would seem to warrant further exploration, as well as posing at least a modest challenge to the equal-weighted composite approach to indexing child wellbeing.

2. Scaling of Subjective Judgments

Scaling is the use of one of several statistical techniques to express human comparative judgments about a series of objects or organisms in numerical terms (Nunnally & Burnstein, 1994; Guilford, 1954; Torgerson, 1958). The judgments are typically about the degree to which each member of a set of objects or organisms possesses a given attribute or trait. The attribute may be one, such as loudness or fatness, for which a physical scale already exists. Or it may be one which is more abstract or subjective, such as beauty or shyness, where no physical method of measurement is available. The numbers that result from the scaling operation may have only weak measurement properties, being little more than a set of ordered categories (nominal or ordinal scales). Or, depending on statistical assumptions made by the scaling method and the degree to which the judgment data conforms to those assumptions, the numeric labels may behave like real numbers and have stronger measurement properties, such as having equal differences between adjacent numbers at two different points on the scale (interval or ratio scales).

There is also multidimensional scaling, where human observers are asked to make judgments about the similarities among a set of objects or organisms. Here statistical algorithms are used to cluster the items or convert the similarity judgments into distances between items in a two- or three-dimensional similarity space (Torgerson, 1958, Chapter 11).

Expert judgments. There are several ways in which scaling could be used to derive weights for use in combining the component child indicators into a composite index of child wellbeing. One is to ask a group of child development experts to compare each of the 28 child indicators against each of the 27 others in terms of their relative importance for overall child health or wellbeing. The comparative judgments would then be converted into a set of scale values, and those values could be used to give each indicator a weight when they are all combined into the composite index. If the scale values turned out to be fairly similar, the equal weighting strategy currently being used would be supported and could be continued. If, on the other hand, the weights turned out to be quite different from one another, a modified combinatorial procedure would be in order. Low-rated indicators might be dropped from the composite index altogether.

The set of indicators used in the scaling task could be broadened to cover domains or data series not presently included in the FCD indicator set. The judgment task could be made less burdensome by increasing the number of judges and asking each to rate only a subset of the indicator items. The degree of consistency in expert judgments could be determined, as could similarities and differences in the judgments of different groups of experts (e.g., pediatricians, teachers, child development psychologists, social workers, social policy analysts). These results would be of interest in their own right, as well as in helping to guide index construction efforts.

Public perceptions. A second way of using scaling is to ask a group of ordinary but well-informed citizens to compare the various component measures in terms of how indicative each is of the general state of child wellbeing. The resulting public salience scale could be used to weight the constituent indicators in a similar manner to that outlined above for the expert judgment scale. Again, the degree of consistency in public perceptions could be determined, as could similarities and differences in the perceptions of different groups of citizens (e.g., parents vs. non-parents, various age groups and education levels, different racial and ethnic groups, and those affiliated with different political parties and religions). If both expert and citizen judgments were obtained, it would be instructive to compare them. Points of divergence might be good topics for public education campaigns (or efforts to make experts more appreciative of “common sense”).

Multidimensional scaling. Experts or citizens could also be asked to sort the various indicators into groups or make judgments about the similarity of different pairs of indicators. The resulting judgments would then be used to build an empirical conceptual map of the child indicator space. This could be compared with the current domain grouping and might result in a set of component sub-indexes that is more meaningful from a child development standpoint, or more easily comprehensible from a public communication viewpoint.

Data requirements. In order to apply the scaling approach to the task of modifying the CWI, one would need to gather comparative judgments of the sort outlined above from a sample of at least several hundred child development experts or informed members of the general public. The judgment task would take no more than an hour of each person's time. For definitive results, larger samples of judges are preferable, as are samples chosen with each member of a defined population having an equal probability of being selected. But gathering data from large probability samples would be expensive and time consuming. It seems best to pilot test the scaling procedures on data from relatively small samples of convenience in order to find out whether the preliminary results seem promising. If they are, larger-scale data collection and analysis efforts would be in order.

The promise of the scaling approach is that it would provide conceptual maps revealing the structure of perceived relationships among component child well-being indicators as well as among clusters of indicators or facets of well-being. The scaling approach would also provide optimal importance weights for combining each indicator into its appropriate cluster and then combining various cluster scores into one or more composite indicators of child well-being. As already mentioned, the conceptual maps and perceived importance scales would be of interest in their own right, as well as aiding in the process of index construction, evaluation, and communication. The results might also be useful in prioritizing public policies and services aimed at bettering children's lot.

Example. An example of the application of scaling methods to develop component weights may be found in studies of the influence of life stress on the development and course of physical disease or mental illness. Psychiatrists Thomas H. Holmes and Richard H. Rahe (1967; Holmes & Masuda, 1974) used scaling methods to develop a Social Readjustment Rating Scale. They asked human judges to produce numbers indicating how much life change is involved in adjusting to various life events, such as birth of a child, loss of a job, or death of a spouse. The emphasis was on the amount of life change involved, not whether the event was a positive or negative occurrence.

Each event was to be evaluated in comparison to the event of marriage, which was given an arbitrary value of 500. Holmes and Rahe originally collected these kinds of judgments from a sample of convenience composed of 394 adults of differing genders, age groups, education levels, social classes, races, religions, and marital statuses. They found considerable agreement among the 394 individuals (Kendall's coefficient of concordance W equaled .48) concerning the relative magnitude of the readjustment required by the different life events. There was greater agreement across the different groups in the sample concerning the relative order and magnitude of the mean readjustment ratings of the different items (most cross-group correlations exceeded .90).

The scale is applied as follows: individual adults participating in a study are asked to recall which events in the list of life events have occurred to them in the last year. A life stress score for an individual is obtained by multiplying each event that affected the individual by the value of that event in the Social Readjustment Rating Scale and then summing over all relevant events. The life stress index scores for different individuals or groups are compared and related to the occurrence, exacerbation, or improvement of various diseases or health conditions in those individuals or groups. The index has been used in numerous studies to test the hypothesis that persons with higher life stress scores are more prone to experience major illness or other stress-related conditions in the coming year (Dohrenwend & Dohrenwend, 1974).

The original Holmes and Rahe scale is shown in Table 5. The rating task was subsequently carried out with samples of individuals from other nations with generally similar results, but also some differences in mean scale values across countries (Holmes & Masuda, 1974). Other investigators have used somewhat different judgment tasks or scaling methods to come up with alternative stressful events scales, including a life change scale for children based on judgments by child development experts (Gersten, Langner, Eisenberg, & Orzeck, 1974).

3. Regression Analysis of Longitudinal Data

Multiple regression analysis of longitudinal data is a statistical technique whose objective is to account for variations in individual outcomes at a later time point based on a set of attributes of the individuals at one or more earlier time points. The expected value of the dependent variable or outcome for a given individual is derived from a linear or log-linear combination of the attribute values for that individual, each multiplied by a regression coefficient, plus an intercept term and error term. The regression coefficient for each attribute reflects the relationship of that attribute to the outcome, net of the relationships of all the other attributes in the model. Multiple logistic regression (Walker & Duncan, 1967; Morgan & Teachman, 1988) is especially suited for modeling dichotomous outcome variables and proportional hazards models take into account the special characteristics of event history data (Allison, 1984).

The statistical significance and relative size of the regression coefficient for each attribute may be taken as measures of the predictive importance of that attribute for the outcome in question. Of course, this assumes that there is not some other related attribute that has been overlooked in the model and which is causally more important than the attributes that have been included.

Such a regression model could furnish weights for a composite index of child wellbeing. What would be needed would be a large, representative sample of individuals who were followed from childhood into adulthood, with values on each of the set of child indicators obtained for each individual, as well as a later measure of how the child turned out on a generally-accepted measure of adult health, wellbeing, or accomplishment. A multiple regression model would be developed from this longitudinal data set, and the regression coefficient derived for each indicator would serve as the basis for weighting the equivalent indicator in a composite index of child wellbeing. What the weights would then represent is not expert judgment as to the relative importance of the indicators, but an evidence-based estimate of the developmental significance of the indicators for the outcome in question. And the value of the composite index would reflect the estimated probability that a child of today will become a healthy, self-supporting adult of tomorrow.

Data requirements. In order to apply regression analysis to the task of modifying the CWI, one would need longitudinal data sets that follow representative samples of children into adulthood and contain suitable outcome measures as well as values for independent variables that correspond to each of the 28 component child indicators in the FCD set. No single longitudinal study based on U.S. children or youth and containing all these variables is currently available. There are, however, several longitudinal data bases containing substantial subsets of the FCD indicator variables or reasonable approximations thereto. These include the National Education Longitudinal Study beginning in 1988 (NELS:'88), the National Longitudinal Study of Youth beginning in 1979 (NLSY:'79) and the one beginning in 1997 (NLSY:'97), as well the Child Supplement to the NLSY:'79. These data sets and others could be used to make a start at applying regression analysis to the tasks of evaluating the equal-weighting strategy currently being used in the CWI and, if necessary, of modifying the weights to better reflect developmental realities.

Example. One possible adult outcome might be whether the child grows into an adult who at age thirty is alive, in good health, gainfully employed at some non-criminal occupation or pursuit, and earning enough to avoid poverty or welfare dependency. Longitudinal data sets would enable us to observe how this adult outcome relates to childhood attributes like growing up in a single-parent family, living in a family whose income is below the official poverty level, being in "excellent" or "very good" health as a child, having a childhood disability, achieving a "proficient" score on a standardized test of reading ability in Grade 8, being overweight as an adolescent, dropping out of high school, and having a baby as a teenager. Multiple linear or multiple logistic regression models based on these data would provide coefficients for each of the independent predictor variables or child attributes. Those coefficients could provide the basis for weighting component indicators of the CWI that correspond to the independent variables in the model.

Special provision would have to be made in order to incorporate child indicators based on death events, such as the infant mortality rate, the child death rate, or the teen death rate, into the regression analysis framework. Obviously, a child who dies as an infant, toddler, or preschool child has zero probability of growing up into a healthy, productive adult, as well as zero or near-zero probability of being included in a longitudinal study that begins in or after the early years of school. We could use current mortality statistics to insert proxy cases for an appropriate number of such children into the longitudinal data base and include dummy variables representing "died in infancy," "died in childhood," or "died in adolescence." But these cases would have missing data on most or all of the other independent variables. So suitable procedures for imputing values for the other variables would have to be developed and applied, or forms of regression analysis that allow for missing cases would have to be employed.

Fortunately, relatively few children die in infancy or childhood nowadays. So even though the regression coefficients for dummy variables representing childhood death would have large, negative values, the number of children to whom those coefficients applied would be quite small. Thus, the net effect of childhood mortality on the average probability of a child growing up into a healthy, productive adult would be relatively modest. Nevertheless, it would be important to develop and apply defensible procedures for including childhood mortality into the regression framework so that the mortality-based indicators would get appropriate weightings in the CWI.

A regression analysis strategy like this one holds the promise of leading to a composite wellbeing index with a readily interpretable real-world meaning. For example, using the kind of adult outcome described above, the index could be interpreted as the expected proportion of all children born in the current time period who will live and grow into healthy, self-supporting adults. Using available cross-sectional survey data and vital statistics, this figure could be contrasted with the equivalent proportions for earlier generations of U.S. children and youth (i.e., current and recent cohorts of U.S. adults). One could also compare the predicted probability that an "average" child would attain the outcome of interest across successive generations. This would provide an additional measure of progress over longer time spans.

Thus, a regression-based CWI and changes in such an index over time would have concrete and easily communicable meanings, as opposed to representing percent change in a relatively arbitrary index number. And the predictive validity of the index could be tested and refined over time, as the current generation of children and youth progresses into adulthood.

An added benefit of a program to use longitudinal child data to improve the CWI is that it would provide a useful framework for summarizing and synthesizing information that is often looked at more narrowly. Typical studies using these data sets focus on one or two explanatory factors, treating other child attributes as control variables. The effort to evaluate the relative predictive power of each element in an extensive set of child indicators would bring a more holistic perspective to the life-course data. It would help bring public attention to the important findings of these landmark studies and might even lead to wiser decisions regarding policies and programs aimed at benefiting children. Finally, the effort is likely to stimulate further longitudinal research to fill in gaps in the life-course models.

Summary and Conclusions. Kenneth Land and his colleagues (2006) have developed a composite index of child wellbeing in the United States. The index uses an equal-weighting strategy for combining a number of component indicators of child health, achievement, behavior, and living conditions. This paper argues that such a strategy may be problematic for both causal and perceptual reasons. Changes in some component indicators may have – or may be seen to have – more profound implications for children's longevity and development than changes in other indicators. Before continuing to generate and publicize the index, research should be done to evaluate the soundness of the current approach. Three methods for generating and evaluating relative weights are: 1. factor analysis of component indicators as they vary and covary across geographic units or over time; 2. scaling based on expert or lay judgments of the relative importance of different indicators; and, 3. regression analysis of longitudinal data on the life-course of representative samples of children. Evidence using the first and third methods can be obtained through secondary analysis of existing data. The second method requires the collection of new judgment data from samples of child development experts or informed members of the lay public. The paper presents examples of each approach. Studies using any of the methods will advance the field of child indicators research, as well as aiding in the construction of a sounder and more easily understood child wellbeing index.

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Table 1. Twenty-Eight Component National Indicators of Child Well-Being in the FCD Child Wellbeing Index. (Land, 2006).

Family Economic Well-Being Domain
1. Poverty Rate (All Families with Children)
2. Secure Parental Employment Rate
3. Median Annual Income (All Families with Children)
4. Rate of Children with Health Insurance

Health Domain
1. Infant Mortality Rate
2. Low Birth Weight Rate
3. Mortality Rate (Ages 1-19)
4. Rate of Children with Very Good or Excellent Health (as reported by parents)
5. Rate of Children with Activity Limitations (as reported by parents)
6. Rate of Overweight Children and Adolescents (Ages 6-19)

Safety/Behavioral Domain
1. Teenage Birth Rate (Ages 10-17)
2. Rate of Violent Crime Victimization (Ages 12-19)
3. Rate of Violent Crime Offenders (Ages 12-17)
4. Rate of Cigarette Smoking (Grade 12)
5. Rate of Alcohol Drinking (Grade 12)
6. Rate of Illicit Drug Use (Grade 12)

Educational Attainment Domain
1. NAEP Reading Test Scores (Ages 9, 13, and 17)
2. NAEP Mathematics Test Scores (Ages 9, 13, and 17)

Community Connectedness
1. Rate of Persons who have Received a High School Diploma (Ages 18-24)
2. Rate of Youths Not Working and Not in School (Ages 16-19)
3. Rate of Pre-Kindergarten Enrollment (Ages 3-4)
4. Rate of Persons who have Received a Bachelor's Degree (Ages 25-29)
5. Rate of Voting in Presidential Elections (Ages 18-20)

Social Relationships Domain
1. Rate of Children in Families Headed by a Single Parent
2. Rate of Children who have Moved within the Last Year (Ages 1-18)

Emotional/Spiritual Well-Being Domain:
1. Suicide Rate (Ages 10-19)
2. Rate of Weekly Religious Attendance (Grade 12)
3. Percent who report Religion as Being Very Important (Grade 12)

Note: Unless otherwise noted, indicators refer to children ages 0-17. Data sources may be found in Land (2006).

Table 2. Principal Components Analysis of Kids Count 2005 State-Level Child Indicators

	Eigenvalue	Proportion Variance	Cumulative Proportion
Factor One	9.82	0.58	0.58
Factor Two	1.84	0.11	0.69
Factor Three	1.38	0.08	0.77

Loadings of Component Indicators on First Factor

Child Well-Being Indicator	Loading
Pct. children in poverty	0.91
Teen birth rate	0.90
Proficient scores on NAEP Grade 8 math	-0.89
Proficient scores on NAEP Grade 8 reading	-0.86
Proficient scores on NAEP Grade 4 math	-0.86
Proficient scores on NAEP Grade 4 reading	-0.85
Pct. teens not in school & not working	0.79
Pct. with no parent employed full-time	0.78
Median income of families with children	-0.78
Teen death rate	0.77
Pct. in single parent households	0.74
Pct. high school dropouts	0.71
Infant mortality rate	0.71
Child death rate	0.65
Pct. low birth-weight babies	0.64
Children without health insurance	0.55
Children with special needs	0.26

Loadings of Component Indicators on Second Factor

Child Well-Being Indicator	Loading
Children with special needs	0.76
Pct. low birth-weight babies	0.61
Infant mortality rate	0.50
Children without health insurance	-0.50
Pct. in single parent households	0.40
Proficient scores on NAEP Grade 4 reading	0.29

Loadings of Component Indicators on Third Factor

Child Well-Being Indicator	Loading
Child death rate	0.62
Teen death rate	0.56
Pct. in single parent households	-0.38
Median income of families with children	-0.37
Pct. with no parent employed full-time	-0.30

Table 3. States of U.S. Ranked By First Factor Scores*, Kids Count 2005 Child Indicators

1	New Hampshire	-1.74
2	Minnesota	-1.58
3	Massachusetts	-1.47
4	Vermont	-1.40
5	New Jersey	-1.36
6	Connecticut	-1.29
7	North Dakota	-1.06
8	Iowa	-1.02
9	Wisconsin	-1.01
10	Maine	-0.88
11	Utah	-0.79
12	Nebraska	-0.72
13	Virginia	-0.71
14	Kansas	-0.62
15	Washington	-0.55
16	South Dakota	-0.51
17	Wyoming	-0.43
18	Maryland	-0.39
19	Colorado	-0.36
20	New York	-0.34
21	Pennsylvania	-0.29
22	Michigan	-0.28
23	Ohio	-0.24
24	Oregon	-0.21
25	Rhode Island	-0.20
26	Illinois	-0.19
27	Idaho	-0.18
28	Indiana	-0.12
29	Delaware	-0.03
30	Missouri	0.02
31	Montana	0.10
32	Hawaii	0.24
33	California	0.29
34	Alaska	0.32
35	Florida	0.49
36	North Carolina	0.49
37	Nevada	0.76
38	Texas	0.77
39	Kentucky	0.89
40	Georgia	0.92
41	South Carolina	0.94
42	Oklahoma	0.95
43	Tennessee	1.02
44	Arkansas	1.09
45	Arizona	1.13
46	West Virginia	1.26
47	Alabama	1.67
48	New Mexico	1.68
49	Louisiana	2.40
50	Mississippi	2.55

* Negative scores reflect relatively favorable conditions for children, positive scores, unfavorable conditions.

Table 4. States of U.S. Ranked By 2nd & 3rd Factor Scores, Kids Count 2005 Child Indicators

2nd Factor			3rd Factor		
1	Nevada	-2.19	1	Hawaii	-2.47
2	Arizona	-1.95	2	Rhode Island	-1.81
3	California	-1.85	3	California	-1.70
4	Idaho	-1.80	4	New York	-1.40
5	Alaska	-1.72	5	New Hampshire	-1.32
6	Utah	-1.71	6	Massachusetts	-1.31
7	Texas	-1.64	7	Connecticut	-1.04
8	New Mexico	-1.20	8	Nevada	-1.01
9	Montana	-1.00	9	Washington	-0.83
10	North Dakota	-0.88	10	New Jersey	-0.81
11	Hawaii	-0.75	11	Florida	-0.77
12	Iowa	-0.73	12	New Mexico	-0.76
13	South Dakota	-0.55	13	Maryland	-0.64
14	Washington	-0.55	14	Oregon	-0.55
15	Oregon	-0.55	15	Alaska	-0.49
16	Nebraska	-0.49	16	Georgia	-0.47
17	Colorado	-0.29	17	Vermont	-0.36
18	Oklahoma	-0.21	18	Ohio	-0.35
19	Indiana	-0.11	19	Arizona	-0.31
20	Wyoming	-0.10	20	Maine	-0.30
21	Minnesota	-0.10	21	Illinois	-0.21
22	Illinois	-0.08	22	Michigan	-0.11
23	Wisconsin	0.14	23	Texas	-0.03
24	Maine	0.20	24	Louisiana	-0.01
25	New York	0.26	25	Pennsylvania	0.01
26	Kentucky	0.29	26	Virginia	0.05
27	Rhode Island	0.32	27	Kentucky	0.07
28	Georgia	0.44	28	Delaware	0.13
29	Pennsylvania	0.44	29	Oklahoma	0.14
30	New Hampshire	0.46	30	North Carolina	0.26
31	Michigan	0.47	31	Alabama	0.30
32	Florida	0.49	32	Mississippi	0.34
33	North Carolina	0.49	33	Colorado	0.35
34	Arkansas	0.50	34	Tennessee	0.37
35	Kansas	0.51	35	West Virginia	0.42
36	Alabama	0.53	36	Wisconsin	0.50
37	New Jersey	0.56	37	South Carolina	0.52
38	Tennessee	0.72	38	Iowa	0.53
39	Ohio	0.81	39	Idaho	0.58
40	Massachusetts	0.86	40	Indiana	0.62
41	West Virginia	0.88	41	Arkansas	0.76
42	Virginia	0.92	42	Minnesota	0.90
43	Connecticut	0.96	43	Utah	0.99
44	Missouri	1.04	44	Kansas	1.03
45	Vermont	1.08	45	Missouri	1.06
46	Mississippi	1.23	46	North Dakota	1.14
47	Louisiana	1.29	47	Nebraska	1.53
48	Maryland	1.37	48	Montana	1.54
49	South Carolina	1.41	49	Wyoming	2.07
50	Delaware	1.75	50	South Dakota	2.81

Table 5. Social Readjustment Rating Scale (Holmes & Rahe, 1967)*

Rating Scale Value	Life Event
100	Death of spouse
73	Divorce
65	Marital separation
63	Jail term
63	Dealth of close family member (except spouse)
53	Major personal injury or illness
50	Marriage
47	Being fired from work
45	Marital reconciliation
45	Retirement
44	Change in health of family member (not self)
40	Pregnancy
39	Sex difficulties
39	Gain of new family member
39	Business readjustment
38	Change in financial state
37	Death of close friend
36	Change to different occupation
35	Change in number of arguments with spouse
31	Mortgage over $40,000
30	Foreclosure of mortgage or loan
29	Change in responsibilities at work
29	Son or daughter leaving home
29	Trouble with in-laws
28	Outstanding personal achievement
26	Spouse begins or stops work
26	Begin or end school
25	Change in living conditions
24	Change in personal habits (self or family)
23	Trouble with boss
20	Change in work hours or conditions
20	Change in residence
20	Change in schools
19	Change in recreation
19	Change in church activities
18	Change in social activities
17	Mortgage or loan less than $40,000
16	Change in sleeping habits
15	Change in number of family get-togethers
13	Change in eating habits
13	Vacation
12	Christmas
11	Minor violations of the law

*The relative amount of life change required for each event is indicated by the number on the left. Values are based on mean magnitude estimation judgments of a diverse sample of 394 U.S. adults. To calculate index of life stress, list all the events from the table that have affected you in the last year and add up total life change scale values.