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"Good Life Time" (GLT): Health, Income and the Time to Enjoy Them

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"Good Life Time" (GLT): Health, Income, and the Time to Enjoy Them

Indicators Based on a New Integrated Microanalytic Framework for Socio-Economic Statistics

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Abstract

Contemporary public policy increasingly takes an integrated view of individuals – in their family contexts, in their time spent in leisure and unpaid as well as paid work, and in their interactions with major government institutions such as schooling, health care, taxes and cash transfers. Moreover, policy-related information needs, as well as those of the general public, include both broad summary indices and detailed distributional patterns. However, there is no widely accepted integrated framework for socio-economic statistics that spans these domains, particularly one based on explicit and coherent microanalytic foundations. LifePaths is a prototype of such a framework under development at Statistics Canada. It builds on ideas developed for the UN's (1975) System of Social and Demographic Statistics, and Juster and Land's (1981) discussion of demographic versus time-based systems of social accounts. This paper extends earlier work sketching the initial LifePaths prototype (Wolfson, 1997) from a cross-sectional or period framework to an historical cohort, or equivalently an overlapping generations, framework. New illustrative results provide initial working estimates of the extent and distribution of "good life time", defined as spells of leisure time over the life cycle that are coincident with adequate disposable income and health.

Introduction

There is a pervasive interest in contemporary societies to know how well things are going, to have indicators of performance. These range from the commonplaces of sports scores and blockbuster movie revenues, to financial market indices, and to measures for entire societies like GDP per capita and life expectancy. However, there is also a continuing malaise with regard to the standard national-level indicators. The predominance of GDP and related measures, while useful for economic matters, lacks balance as a reflection of the diversity of social activity, and what is generally considered important in life. Similarly, the ubiquity of national health measures based only on mortality rates, taking no account of health status among the living, is increasingly seen as inadequate for social measurement.

As a reflection of this dissatisfaction with conventional socio-economic indicators, there is almost as long a history of search for alternatives. Among the various proposals, there is a resurgence, certainly in North America, of work in developing specific indicators, or *ad hoc* collections (e.g. OECD 1982; Sustainable Seattle, www; Federation of Canadian Municipalities, www; Redefining Progress, www). Indeed, the OECD (1998b) recently brought an illustrative collection of indicators together for social affairs ministers because "the need for a system of social indicators has recently become more pressing" (p2).

The most ambitious social indicator proposals involve more than *ad hoc* collections of indicators. These are proposals for an integrated framework for socio-economic statistics – such as Juster and Land's discussion of time-based and demographic systems of accounts (1981), Richard Stone's System of Social and Demographic Statistics (Stone, 1973; UN, 1975), the System of National Accounts and others' discussions of Satellite Accounts and Social Accounting Matrices or SAMs (e.g. UN et. al, 1993; Vanoli, 1994; Keunig,1994; Pyatt, 1990)

Such integrated frameworks – when compared to *ad hoc* collections of a few diverse indicators – have the disadvantages that their indicators, because they are also part of a framework, may be more difficult to understand; and they also have at least the appearance that they are far more costly to implement. On the other hand, indicators embedded in a statistical framework have the benefits of a well articulated conceptual foundation and logical consistency. They may also, if properly designed, yield more reliable statistical measures. And in the end, they may be no more costly than a wide-ranging collection of *ad hoc* indicators, especially when account is taken of the range of underlying data collection vehicles required.

This paper describes one such integrated framework that has been under development at Statistics Canada, generically called LifePaths. Here we focus on one incarnation, where the emphasis is on social indicators relating to time, money and health, hence LifePaths TMH. In a parallel paper (Wolfson and Rowe, 1998), we focus on inter-generational equity and generational accounting (GA) using another variant called LifePaths GA. LifePaths TMH is still a prototype, so the results are very much initial estimates. In line with the practice of "rapid prototyping" in the software industry, the LifePaths TMH results to be discussed here should be seen as early worked examples, and not the more definitive set of results that will be produced once more of the underlying data analysis has been completed, and richer data become available.

The key goals of LifePaths include :

- providing a useful and broadly based set of summary socio-economic indicators, for example various decompositions of life expectancy such as "good life time";
- producing indicators with "construct validity" – that reasonably reflect what are widely agreed to be major socio-economic outcomes and attributes of the level of well-being in society;
- helping to "conceptualize, measure and understand social change" (p xiv, Juster and Land, 1981), thereby allowing representations not only of socio-economic outcomes, but also their underlying causal pathways;
- providing a framework for integration and coherence – more than mere juxtaposition or arbitrary aggregation to form overall indicators (as in the Genuine Progress Index, Cobb, 1996); Fordham Index of Social Health (1995); and the UNDP's (1997) Human Development Index); and
- tightly coupling the resulting indicators, and the system of socio-economic statistics within which they are embedded, with a simulation capacity – the capacity to pose carefully and answer a series of "what if" questions, both for research and for policy analytic purposes.

In order to motivate the LifePaths TMH results to be presented, we begin in the next section with a review of a few indicators already extant in the literature. All of these turn out (not accidentally) to be nested within LifePaths TMH. (They also provide an introduction to some of the methods underlying LifePaths.) An overview of the structure of LifePaths TMH is then given, followed by brief discussions of validation, and the relationships between LifePaths TMH and the System of National Accounts (SNA). We then present an initial set of estimates building up to a set of measures relating three major socio-economic domains – namely time, money, and health. In particular, we use LifePaths TMH to provide estimates of the *joint* availability of a minimum level of leisure or discretionary time, adequate money income, and good health – adequate TMH, or "good life time" (GLT). The LifePaths framework allows us to generate estimates of GLT and its components over the entire life course by birth cohort in Canada. Moreover, realistic heterogeneity within cohorts is included.

Since the foundations of the analysis are explicitly microanalytic, with richly heterogeneous cohorts of individuals, the underlying data are highly multivariate. Such detail is essential to the construction of the summary socio-economic indicators of interest, but is also complex. Fortunately, with the spectacular improvements in computing, we need not suppress this underlying detail. Instead, we can draw on computer graphics and data visualization to show considerably more of the underlying detail than is possible with the usual tabular presentations.

Components of the Vision

In order to motivate LifePaths TMH, and its vision of an integrated framework for socio-economic statistics, it is useful to review a number of (up to now) disparate examples. However, there is one unifying theme. All the examples build on measures of the time individuals spend in various situations or socio-economic states, or the rates at which they make transitions between the various states. There is, as a result, a common numeraire in all these examples, other than money – namely time, measured in hours, days, weeks and years as appropriate.

Population Age Structure – The first example, shown in Figure 1, is a series of well-known population pyramids. In this case, there are three pyramids, showing the Canadian populations in 1961 and 1991, and as projected for 2031. In addition, the more darkly shaded area indicates those individuals classified by the census (1961 and 1991) or projected by Canada's Chief Actuary (2031 – OSFI, 1995) as in the paid labour force.

Such population pyramids are a very widely used form of social indicator. In this case, they show clearly several major phenomena:

- the post-war baby boom and bust, and as a result the expected aging of the population,
- the increase in female labour force participation, and
- the growing ratio of the non-working population (mainly elderly) to the working population.

It is important to note that the three pyramids represent cross-sectional or "period" views of the population. An alternative view is that of a birth cohort or generation. This kind of view would be built up by following, those born in a given year over time. In Figure 1, this is illustrated by the dashed horizontal line at about age 17 in the 1961 pyramid, age 47 in the 1991 pyramid, and age 87 in the 2031 pyramid, which shows where individuals in a given birth cohort would appear in each of these successive cross-sectional period views of the population. This distinction between period and cohort views is fundamental to much of what follows.

Educational Progression – A second group of examples involve extensions to the ideas of life expectancy and the underlying life tables upon which such measures are based. For example the table at the top of Figure 2, based on Quebec's annual publication of indicators for their educational system, shows the amount of time children and youth have been spending in various stages of the education system, and in the bottom part, the corresponding rates of transition and drop out for the most recent year. It is important to emphasize that these two sets of figures are complementary. The average durations of various kinds of schooling in the table at the top of Figure 2 are the direct results of the transition rates in the bottom part.

These kinds of displays, and the data on which they are based, can illuminate widely used indicators like "the" high school drop out rate. In fact, there are many ways to measure this rate – for example the number of children leaving high school before graduating with a diploma (27% in Quebec according to Figure 2), or the number failing to attain a diploma by age 20 (only 13% in Quebec). Embedding these different rates in a framework like that in Figure 2 provides coherence. It also helps greatly in avoiding otherwise distracting controversy about which dropout rate is the "right one", by clearly displaying the reasons for the differences just noted – in this case because many drop-outs of the first kind return to school and do complete their courses within a few years.

Figure 1 – Period Populations Age 15+, Overall and Employed

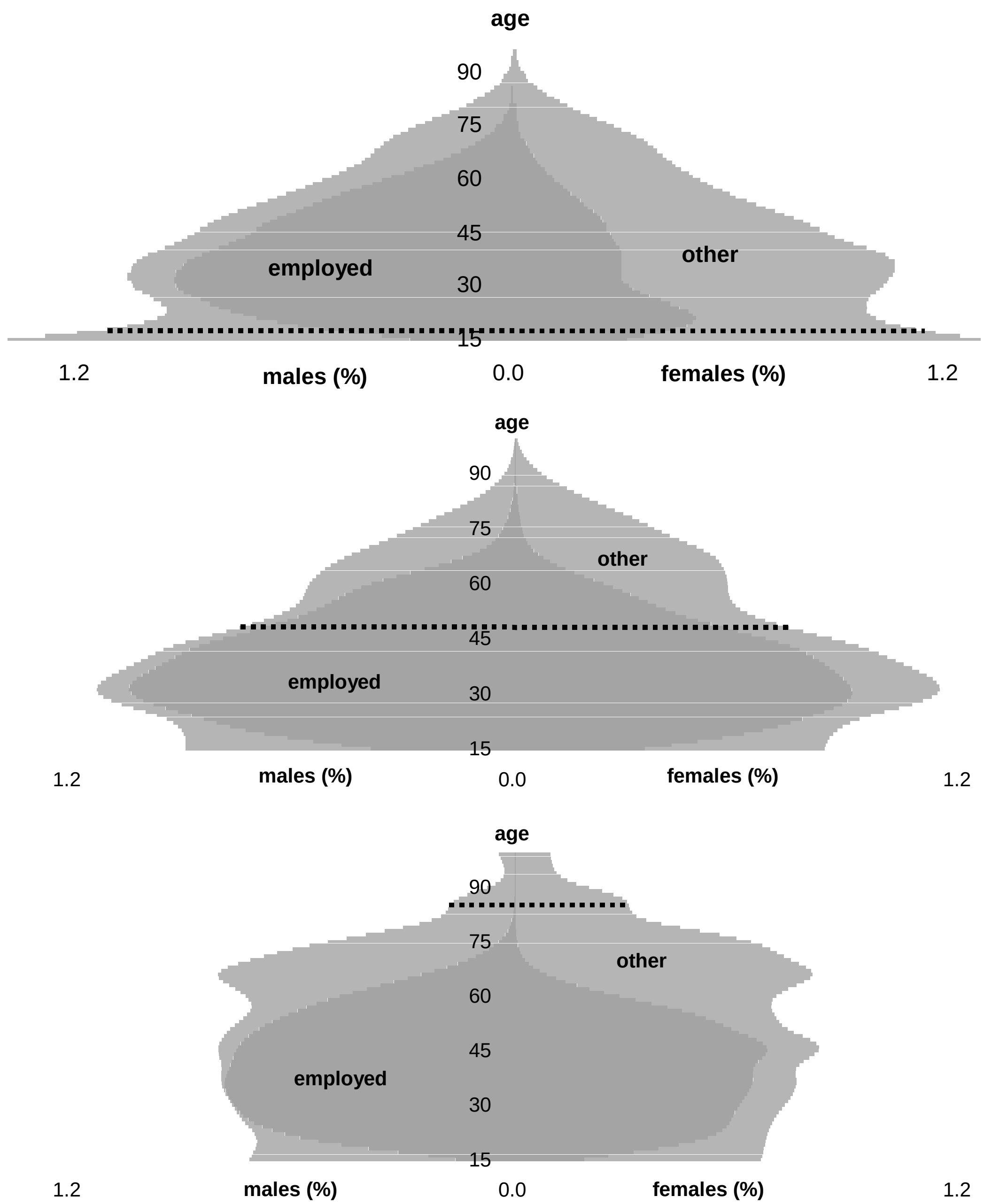
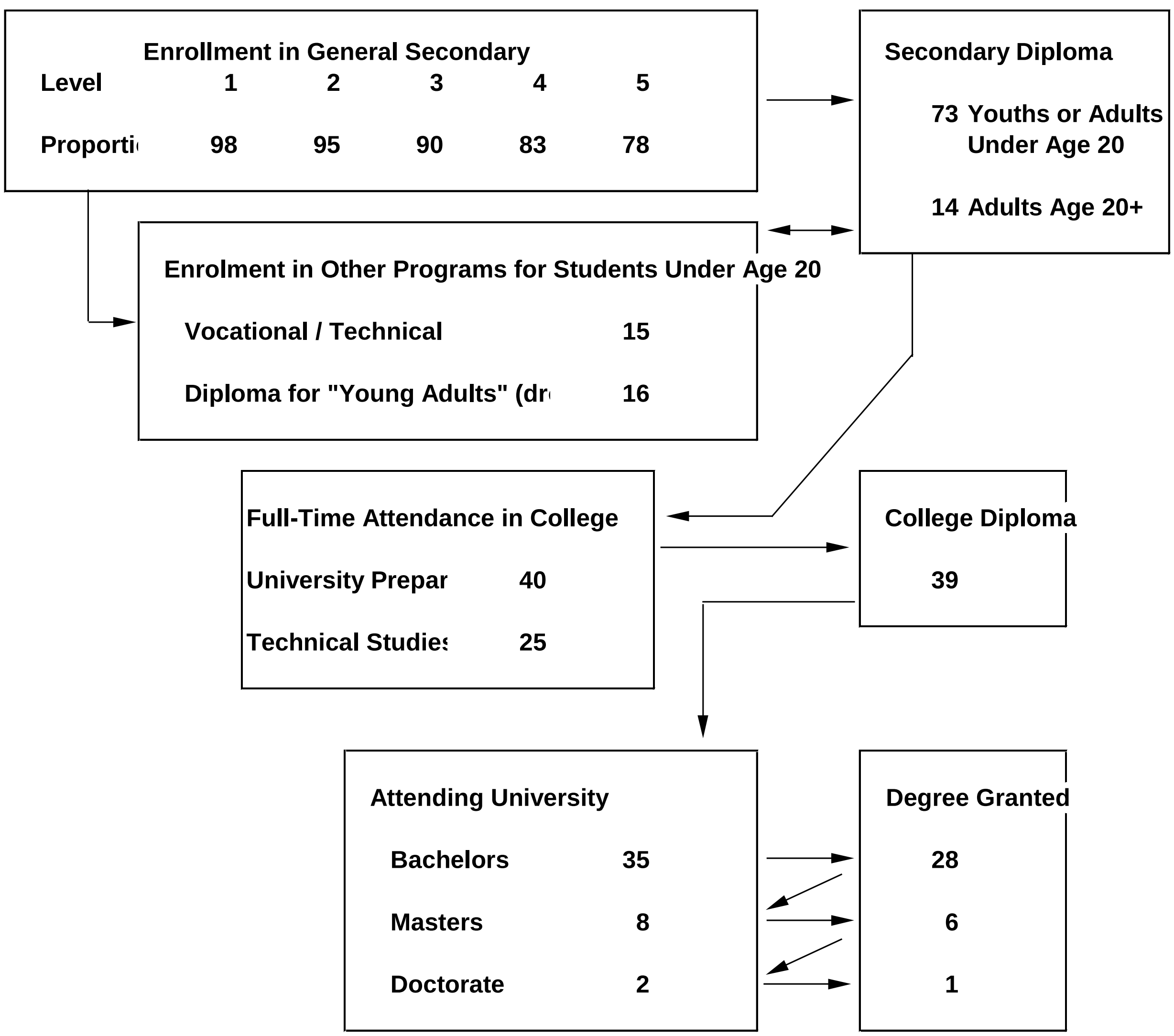


Figure 2 – Educational Progression in Quebec, Canada
(Adapted from Indicateurs de l'education, Ministere de l'Education, pp 7 and 45)

Expected Years of Schooling in Quebec for a Child Entering Primary School

Year	1988	1990	1992	1993	1994	1995
males	14.0	14.4	14.9	15.0	15.0	14.9
females	14.5	15.0	15.5	15.5	15.5	15.5
Total	14.3	14.8	15.2	15.3	15.3	15.2
primary	6.1	6.1	6.1	6.1	6.1	6.1
secondary	5.0	5.0	5.0	5.0	5.0	4.9
primary & seconc	0.2	0.6	0.8	0.8	0.8	0.9
college	1.6	1.6	1.8	1.8	1.8	1.8
university	1.3	1.5	1.6	1.6	1.6	1.6
Total	14.3	14.8	15.2	15.3	15.3	15.2

Pathways Followed by 100 Young Quebeckers Through the School System



Working Life – Analogous to education progression, life table methods have also been used to examine the working phase of the life course – how much of their lifetimes individuals can expect to spend in the paid labour force. The first such estimates for Canada were Denton and Ostry (1969), in turn updated by Gnanasekaran and Montigny (1975). More recently, Bélanger and Larrivée (1992) have developed more sophisticated estimates. Table 1 draws together these two sets of estimates, and shows ages at three major transitions: from school into the paid labour force, into retirement, and death. These demarcate three main phases of the life course – school, work, and retirement. Notwithstanding the various simplifying assumptions, this series of male working life table results vividly displays the long run trends of more time spent in schooling, ever earlier ages of retirement, a general reduction in working years, and hence a long run decline in the ratio of working to inactive or retired years. The last two columns in particular show a clear pincer-like trend toward shorter working lives and more years of retirement, with obvious implications for the "affordability" of public pensions.

Table 1 -- Historical Stationary Male Life and Working Life Expectancies at Age 15

	Average Age at			Number of Years	
Year	LF Entry	Retirement	Death	Working	Retired
1921	17.5	62.7	67.6	45.2	4.9
1931	18.0	63.0	68.4	45.0	5.4
1941	18.2	63.1	69.1	44.9	6.0
1951	18.5	62.9	70.4	44.4	7.5
1961	19.2	63.0	71.2	43.8	8.2
1971	19.8	62.3	71.3	42.5	9.0
1986a	20.0	65.5	73.8	44.6	8.3
1986b	20.0	60.3	73.8	39.4	13.5

Source: Adapted from Gnanasekaran and Montigny for decades 1921 to 1971 (Tables 2.1 and 12, 1975), and Bélanger and Larrivée for the two 1986 rows (Tables 1 and 2, 1992)

Notes: The Bélanger and Larrivée results were given only at age 16; age 15 results have been extrapolated. Working life expectancy is taken from their Table 2 for both the active and inactive populations for the 1986b row. Also, they have only estimated the average age at death, and the expected number of working years, so the average age at retirement and number of years retired were derived based on the simple assumption that the average age at labour force entry was exactly 20. There also appears to be an inconsistency in the Gnanasekaran and Montigny results for 1971 average number of years working in comparison to all their other estimates, so this figure has been adjusted. The Bélanger and Larrivée definition of "working" is having worked at least one hour in a reference week in September of each year. The Gnanasekaran and Montigny definition for 1971 was essentially working or looking for work in the week prior to census enumeration, but then excluding summer students.

The results in Table 1 for 1921 to 1971 are based only on cross-sectional age-specific labour force participation and mortality rate data, since these were the only data available over this period. As a result, the Gnanasekaran and Montigny (1975) life tables included just two living states – working, and not working. Transitions between these states were then based on two key assumptions: (1) that gross flows into and out of work exactly equaled net flows – an individual could only enter and leave the labour market once over their entire lifetime, and (2) that overall, labour force participation rates first rise monotonically to an age where they are at a maximum, and then fall monotonically. Thus, up to the age of the maximum participation rate a* (around age 30 in 1971), the rate of entry to the labour force at each age was assumed to equal the difference in the participation rate between ages a-1 and a (plus the mortality rate). After age a*, only exits from the labour force were assumed, again equal the difference in the participation rate between ages a-1 and a (also assuming mortality rates are independent of labour force status).

The more recent increment-decrement life table methods used by Bélanger and Larrivée (1992) allowed them to relax this restrictive assumption by using longitudinal microdata from Statistics Canada's Labour Market Activities Survey. These data allow *gross* flow transition probabilities to be estimated directly -- rather than inferring them based on an assumed equality with *net* flows, in turn derived by first-differencing age-specific participation rates. As a result, multiple exits and re-entries to the labour force over a lifetime are not ruled out *a priori*, as in the earlier working life tables.

Specifically, the last two rows in Table 1 give Bélanger and Larrivée's alternative working life estimates for 1986. The row labeled "1986a" used the older gross = net flow assumption, while the last row, 1986b, used an increment-decrement life table based on gross transition probabilities. Bélanger and Larrivée estimate an average of 2.6 labour force entries for men over their lifetimes using the gross flow approach, compared to 0.94 using the net flow approach (0.94 being the maximum participation rate at age a*). The rather large 5.2 year difference in expected working life in these last two rows further reflects the sensitivity of these kinds of results to detailed assumptions on transition rates.

However, strong simplifying assumptions are still embodied in the Bélanger and Larrivée increment-decrement life table analysis. In particular, transition probabilities into and out of the labour force are assumed to be first order Markov, depending only on age, sex, and labour force status in the year. This ignores the observed dependence of labour force participation in any given year on other factors like educational attainment, marital status, and fertility, as well as how long the individual has already been working. Moreover, both of the life table estimates in Table 1 take the calendar year as the smallest time period, and treat working within a given year as a dichotomous variable. There is no accounting for part-time or part-year rather than full-time full-year work, and nothing on unpaid work – points to which we return later.

Divorce and Lone Parents – As a fourth example, there is a long tradition in demography of interest in the dynamics of the family. One very well-known indicator is the fertility rate, while another is the proportion of marriages that can be expected to end in divorce. Both of these indicators are constructed using life table methods. Indeed, multi-state life tables can be used to construct families of related demographic and nuptiality indicators. For example, Table 2 from Wolfson (1989, Table 3) shows first how the period between age 25 and 64 is likely to be spent by women in various socio-demographic states, and then in the bottom portion of the table, how their children can expect to grow up.

In this case, the focus of the analysis was on the implications of different divorce rate scenarios. The first scenario assumes no divorce at all. The second and third scenarios assume that divorce is a function only of age, and use the observed age-specific divorce rates centered on the 1971 and 1981 censuses, a decade characterized by a rapid rise in divorce rates. In other words, they make the same first order Markov transition assumption as in the case of the working time estimates in Table 1. The last scenario draws on a more sophisticated hazard rate analysis of data from the 1983 Family History Survey (FHS; Rowe, 1989) where divorce was found to depend not only on age, but also on age at marriage, presence of pre-school children, and labour market history.

The results in this table are notable in several respects. First, they are based on a precursor of the LifePaths model, showing that a microsimulation approach can be used to generalize multi-state life table methods. Specifically, microsimulation nests, as a special case, increment-decrement life tables based on first order Markov transitions. In addition, the FHS results indicate the capacity to move beyond simple first order transition rates to draw upon more richly multivariate transition probability functions. In this case, Table 2 illustrates the differences between the implications of standard age-specific divorce rates on the one hand, and the more detailed FHS transition functions. These latter multivariate transition probability functions showed that marriage dissolution propensities depended not only on age, but also on the presence of pre-school children, which depressed age-specific divorce rates. Omitting this factor biases the results toward an impression that rising divorce rates have been associated with an even more rapid increase in the amount of time children can be expected to grow up in lone parent family settings. Specifically, comparing the last two columns, the number of years women could expect to spend divorced increases by about 50%, while the time children could expect to spend living with a lone parent actually drops.

Table 2 – How Individuals Can Expect to spend Parts of Their Lives Under Alternative Divorce Scenarios

	Divorce Scenario			
Average numbers of years spent by:	None	1970-1972	1980-1982	FHS
Females age 25 to 64				
Never-married	5.9	5.9	6.3	6.1
First Married	30.1	25.6	22.6	22.5
Working	17.5	15.0	12.9	12.9
Childless	2.3	2.3	2.0	1.6
One or more children	10.5	9.0	7.9	8.5
Empty nest	4.7	3.7	3.0	2.8
Not Working	12.7	10.6	9.7	9.6
Divorced	0	1.8	2.6	3.3
Widowed	2.1	2.0	2.1	2.1
Remarried	0.4	3.4	4.9	4.5
Total	38.6	38.6	38.6	38.4
Children growing up with				
Mother before marriage	1.9	2.1	2.1	2.1
Both natural parents	17.8	16.2	15.3	15.8
and mother is working	11.0	9.7	9.0	9.4
and father is working	15.6	14.3	13.5	13.8
A lone parent after marriage	0.4	1.1	1.5	1.3
A remarried parent or orphaned	0.2	1.0	1.5	1.1
Total	20.3	20.4	20.4	20.3

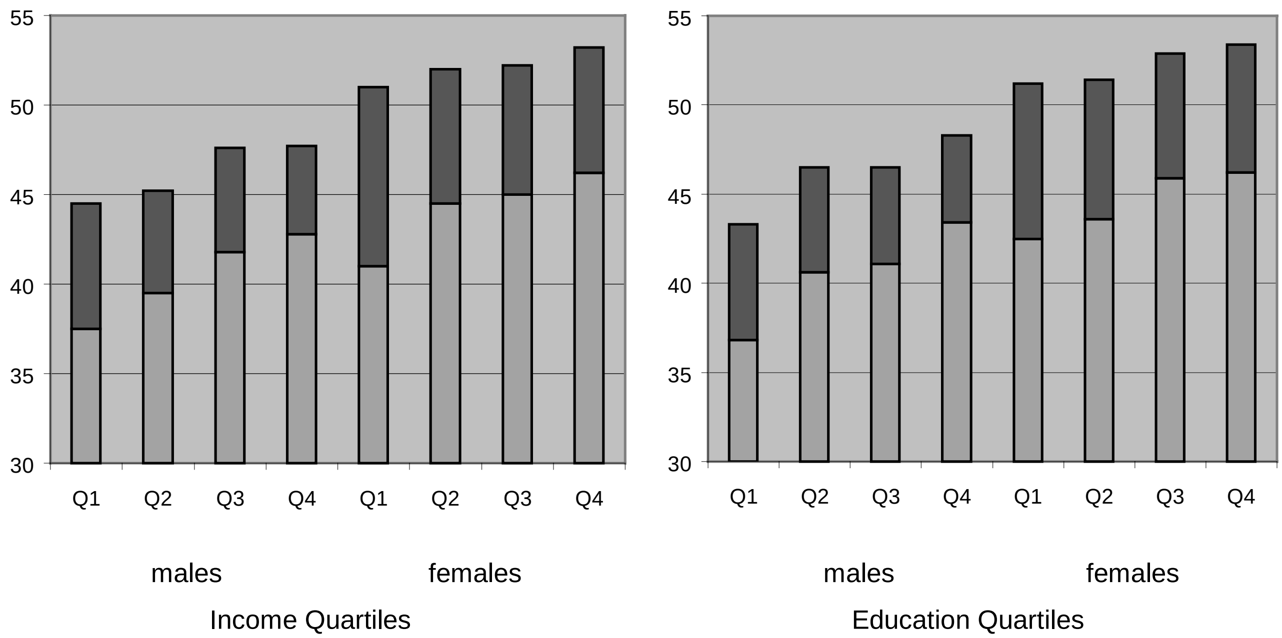
(n.b. Monte carlo error is such that the estimates should be treated as accurate to about 0.5 years.)

Finally, this analysis of divorce patterns and their consequences illustrates the utility of embedding the construction of social indicators within a simulation framework. In this case, we were able to draw out the implications of otherwise rather inscrutable hazard regressions in forms that are more practical and intuitively accessible (i.e. technically multi-state life table-style sojourn time results, and vernacularly how long people can expect to spend in different family situations). Moreover, in the spirit of Juster and Land's view that a framework of socio-economic statistics should help us to "conceptualize, measure and understand social change" (1981,p xiv), this kind of indicator plus modeling capacity points us toward much better frameworks for clarifying and presenting more richly textured views of the consequences and correlates of changing divorce rates.

Health Status – A final example is in the health domain. Life expectancy is a very well-known and widely used indicator. However, it suffers as a health indicator by making absolutely no distinction between person-years lived either in excellent or poor health. To address this concern, there is growing international interest (e.g. Mathers and Robine, 1993; OECD, 1998a) in a variant called health-adjusted life expectancy (HALE). In effect, this measure weights individual person-years by an index of health status (taking values between one for perfectly healthy, and zero for dead). There is considerable methodological work underway, particularly regarding the ways to assign a number in the zero-to-one interval to a person-year summarizing that individual's health status (e.g. Gold et al., 1996; Field and Gold, 1998).

Figure 3 presents results for the Manitoba population broken down into sub-groups based on two alternative socio-economic status (SES) variables, educational attainment and family income (Nault, Roberge, and Berthelot, 1996). One set of results is conventional life expectancy (LE), and the other is health-adjusted life expectancy (HALE). For both males and females, considerable differences across SES quartiles are clearly evident, with individuals in the highest education and income categories living longer, and in better health than those in the lowest categories. Also clearly evident for both the income and education groupings is a gradient. . In other words, the relationship is not a threshold phenomenon –steps up the socio-economic scale, even starting further up the scale, are generally associated with an increment in health status, measured either as LE or as HALE.

Figure 3: Life Expectancy (both bars) and Health-Adjusted Life Expectancy (lower bar) at age 30 Using Health Status Data for 1994



The magnitudes of the differences in HALE between high and low quartiles is 3.7 to 6.6 years for income and education, and men and women. These are wider than for LE, which differs by amounts ranging from 2.2 to 5.0 years between the high and low quartiles. Thus, estimates of SES differences in mortality may understate the magnitude of health inequalities when population health status is measured more broadly to encompass morbidity as well as mortality. In turn, these broader measures like HALE require a life cycle framework which can follow the shifting distribution of morbidity by age.

Figure 3 gives only a one-time set of estimates. However, if we had a time series of these HALE and LE estimates, we would also be able to shed light on one of the grand debates in epidemiology – the so-called “compression of morbidity”. The basic issue is whether or not increasing life expectancy is associated with a greater or lesser proportion of the life course spent in poor health. This issue has obvious implications, in the context of aging populations, for future health care costs.

All of the examples just presented are important and interesting in their own right. In addition, and notwithstanding the diversity of their substantive domains, they share a common family of metrics – namely the amounts of time spent over the life course in various socio-economic states, or the average ages at or rates of transition between them. However, they are all examples of “stovepipe” indicators. Historically, these various indicators have all been estimated independently, with no obvious connections between them. They have not been constructed as elements or facets of a larger framework. The LifePaths vision is a conceptual and statistical framework that nests all of these indicators in a integrated and coherent manner.

Related Visions for Integrated Statistical Frameworks

Of course, LifePaths has not been developed in a vacuum. Other integrated and coherent socio-economic statistical frameworks have been proposed. The best developed and most widely used framework is the System of National Accounts (SNA). However, the SNA has been challenged as being too narrow, with its strong focus on the macro economy. In turn, a number of suggestions have been made to enlarge the SNA. These include social accounting matrices (e.g. Keunig, 1994) and Satellite Accounts (e.g. Vanoli, 1994), which are outlined in detail in the most recent revision of the SNA (UN, et. al., 1993, Chapters 20 and 21). The most clearly articulated and widely disseminated proposal for an independent (alternative) integrated system of <u>socio</u>-economic statistics is Stone’s SSDS (UN, 1975; Stone, 1973).

One important feature of both the SNA (including its SAM extensions) and the SSDS is their complexity. It is impossible to specify their full structure in a one-page diagram, or in a few paragraphs of text. LifePaths is similar in this regard, so in the next section we provide only a brief overview. Another feature of the SNA and SAMs, and of Stone's SSDS, is that their realization requires a network of carefully designed surveys and data collection vehicles. Neither could be constructed from a single data source. The same is true of LifePaths. It is in the nature of any integrated framework for socio-economic statistics that its realization requires both a carefully designed set of data feeder systems, and a set of methods for data integration. Concerns about the complexity of LifePaths, and the implied costs of its data feeder systems, should therefore be judged with the view that any alternative with similar objectives would have to be similarly complex and costly. Moreover, there has been a considerable increase in the number and breadth of longitudinal surveys in particular (certainly in North America) for a host of other reasons, so there is an increasingly fertile statistical base for LifePaths style development.

There is, however, one major difference between LifePaths and these other alternatives. This is its explicit microanalytic foundation. The SNA, SAMs, and Stone's SSDS all are constructed at the macro or meso level. This is understandable, given their history, and the fact that they predate the revolution in computing. However, it is a serious limitation, as noted decades ago by Ruggles and Ruggles (1973). Indeed, Stone (1973) was quite explicit that the SSDS would be better served by microanalytic foundations, if the necessary data were available:

> "Of course, if statistics are collected by means of a linked system of compatible records or, better still, by a continuously updated, comprehensive system of individual data, a discussion of sequence becomes largely irrelevant since the information in a vast, computerized data bank can be combined in any desired manner. But while these may be the methods of statistical collection in the future, they are not, with very limited exceptions, in operation at present, and so it makes sense to discuss the systematization of social statistics in terms of more familiar methods of collection." (p152)

In this sense, the future has arrived, albeit in two strands. First, many of the detailed longitudinal microdata sets about which Stone conjectured now exist; and second, modern microsimulation methods can in effect mimic Stone's ideal underlying data. As a result, Stone's matrix algebra, restrictive first order Markov assumptions, and "familiar methods of data collection" need no longer be constraining. Certainly in Canada and other advanced economies, richly multivariate and often longitudinal microdata sets are increasingly available – as are the powerful computing platforms and statistical methods needed to extract meaningful patterns and structure ("operating characteristics" in the sense of Orcutt (1957) and Orcutt et al (1976) from these data.

Overview of LifePaths Structure

LifePaths can be viewed in several ways. It is

- a conceptual framework,
- a representative microcosm of the Canadian population,
- a repository for a wide range of data, and
- a computer simulation model.

It is explicitly microanalytic, which means that the basic units of observation are individuals (as compared to groups or sectors in the SNA, SAMs, or the SSDS). It is also focused on micro-level dynamics – the way individuals flow among various socio-economic states over their life courses.

And finally, LifePaths is "meta-synthetic" – drawing upon multiple data sets, covering diverse subject matters, and using each in order to assemble the best possible overall estimate of the information of interest. (The term "meta-synthesis" is used in contrast to the epidemiological term "meta-analysis", which refers to the combination of results from a number of data sets, but where the data sets all pertain to the same question, such as a series of independent randomized clinical trials of a specific drug.) This is a characteristic LifePaths shares with the SNA (and the SSDS if it were implemented), since both have to draw on a very wide range of diverse data sets. However, a crucial difference is that the SNA and SAMs combine data at the meso or macro level, while LifePaths does so at the micro level. In turn, this means that the meta-synthesis underlying LifePaths is somewhat more complex statistically, and far more computerintensive. (The idea of synthetically matching data at the micro level is also decades old, though at that time, the focus was on cross-sectional data; see UN,1979.)

The basic unit of analysis in LifePaths is an individual life history, as shown in Figure 4. The "state space" of attributes or individual characteristics is shown along the vertical axis, with age and calendar time along the horizontal. The third axis indicates a representative sample of individuals in the population of interest. As Figure 4 shows, these are not all unrelated individuals; rather they are juxtaposed or sorted in a way showing that family structure is also included.

Given these micro level life histories as the basic building blocks, LifePaths then assembles representative samples of individuals (grouped into nuclear families) in a sequence of overlapping birth cohorts, as shown in Figure 5. Each "slab" in the diagram represents one birth cohort, while the sequence of slabs represents successive birth cohorts. Recalling Figure 1, each of those population pyramids corresponds to a vertical slice through the overlapping birth cohorts like that indicated in Figure 5 by the line for "today". On the other hand, the dashed lines in each of the three pyramids of Figure 1 correspond to a single birth cohort, the "slab" corresponding to the 1944 birth cohort. (Note that this diagram implies that time is discrete; in fact, LifePaths represents and models all events in continuous time.)

Figure 4 – State Space and Longitudinal Micro Data Sample Generated by a LifePaths Simulation

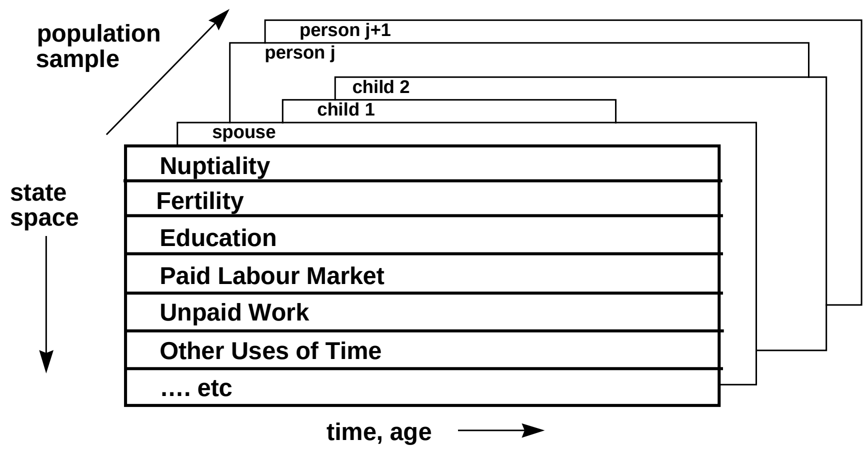
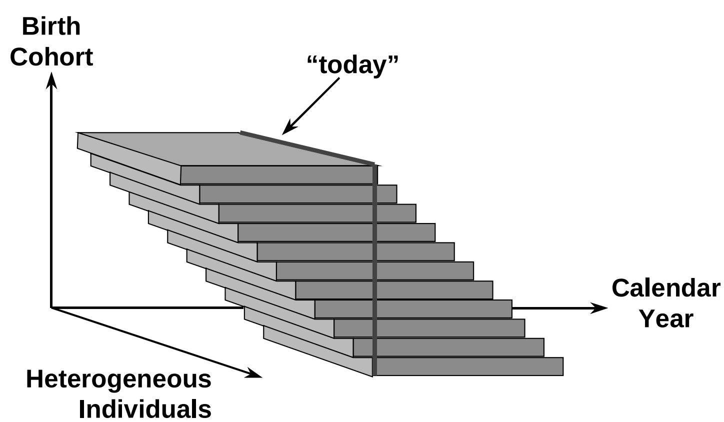


Figure 5 – Overlapping Birth Cohorts with Heterogeneous Members



LifePaths essentially estimates a set of individual life histories corresponding to decennial birth cohorts, in a way that is mutually consistent with a very wide range of data including population characteristics from censuses, mortality and fertility rates dating back to about the turn of the century, SNA figures on labour income and personal savings going back to the 1920s, longitudinal survey data on earnings dynamics in relation to age, sex, and education, and so on. Estimation proceeds by data synthesis using longitudinal microsimulation – each individual's life history is synthesized, starting at birth and then recursively generating all the events and characteristics indicated by the categories along the vertical axis of Figure 4 over time (i.e. along the horizontal axis) until death. Then another family of individuals is synthetically generated, and again, and again – until a very large sample (e.g. 1,000,000) is generated. The result is our "fitted" population microcosm. This is a longitudinal sample of individuals synthesized using computer simulation, that – by construction – reproduces a diversity of observed data, such as age- and sex-specific labour force participation rates, and similarly disaggregated average earnings.

As a final methodological note, LifePaths is readily "extensible". It is highly modular, so that as new data sets become available, with attendant new or revised sets of empirical relationships, or there are new characteristics to be added, this does not entail starting over again from scratch. Rather, old modules can be easily replaced and thereby updated, and new modules readily added, given the design of the software and modeling environment.

On Validating LifePaths TMH

Given the synthetic character of LifePaths results, a major concern is their validity. Earlier versions of LifePaths generated ahistorical *period* life table-type results, the same kinds of results shown in Tables 1 and 2 (working life and demography) and in Figures 2 and 3 (education and health). These period results are very widely used, not only because they generate intuitively accessible and useful indicators, but also in large part because they rely on data for only one calendar year or one point in time. As a result, data availability is good. However with period life table-type results, we face the fundamental problem that the underlying construct is an ahistorical hypothetical cohort, one that is born in the given year, say 1990, and every year thereafter is exposed to the transition probabilities observed in 1990. It is in the nature of this construct that it is inherently unverifiable, since it corresponds to a cohort that can never exist. The only way to "verify" an indicator like life expectancy in 1990 is to check the inputs, and then the calculations. There is no possibility of external validation.

The situation is different with historical cohorts, as in the current version of LifePaths. From the viewpoint of data availability, the exercise is much more challenging – there is a paucity of data going back in time, and a need to project into the future until the end of life for the last of those cohorts still living. On the other hand, we can claim to be constructing a causal story. In addition, at least in principle, the results are externally verifiable. Of course, practically, the stock of socio-economic data inherited from the past is essentially fixed, so that to the extent that we use it in building LifePaths, we diminish our capacity for the strongest form of validation – external comparisons. Going into the future, the possibility of assessing predictive validity would seem to offer the strongest test of all. But there are a number of problems:

- having to wait until we reach the end of the projection period to see whether or not everything turned out as projected, though intermediate results clearly would not require as long a wait;
- the fact that the LifePaths projections are conditional, depending in turn on other projections such as those of the Chief Actuary for mortality and long run economic growth; and
- the possibility that projections will be self-destroying, for example as the prospects of adverse fiscal outcomes from population aging are acted upon by amending public pension structures.

As a result, the minimum requirement for valid results is to use a set of reasonable data gathering and meta-synthesis practices to assure the best possible quality for the inputs and processes of both forms of LifePaths results – period and cohort. The methods available for the external validation of historical cohort results have their limitations. However, they do have the major advantage of offering the possibility of falsifiability. Moreover, it is difficult to imagine other methods – both for understanding historical dynamics and for making projections in these areas of inquiry – that would have superior capacities for validation, while delivering the same level of detailed results.

On the Relationship of LifePaths TMH and the SNA

This Time/Money/Health (TMH) version of LifePaths complements the SNA and its possible extensions such as SAMs. The two overlap with regard to household sector incomes and expenditures, and government direct taxes and cash transfers collected from and paid to households. The SNA then provides complementary information on intermediate production, other categories of final demand, with commodity and industry detail. Meanwhile, LifePaths TMH provides coherently integrated and detailed data on demography, labour force participation, health status, time use, etc.

These strengths of LifePaths, by design, address some of the inadequacies of SNA – the absence of explicit microanalytic foundations, the dominance of money-metric measurement and the associated focus on activities relating to economic markets (quite properly, since that has been the purpose of the SNA, but) to the exclusion of other major aspects of socio-economic life.

Finally, the SNA and LifePaths share important similarities with regard to validation. GDP is a concept or construct – just like period life expectancy, and period LifePaths results more generally. Both are inherently and necessarily aggregations or constructions from many data sources. Fortunately, GDP can be built up in alternative ways. Hence, the key to the validation of the GDP concept (as well as some, but by no means all, of its components) is multiple independent estimates of the same concept, particularly income and expenditure (sources = uses). This in turn leads to "data confrontations" (Wilk, 1987) where two independent estimates of GDP must be reconciled. On the other hand, some elements of GDP (e.g. selected cells in input/output tables, or flow of funds tables) have no underlying data at all, let alone multiple data sources to generate data confrontations.

. LifePaths is similar in these regards. It has also been designed and constructed to build upon data confrontations (e.g. census data on educational attainment versus school and university administrative data on enrolments, household survey versus SNA data on household incomes). On the other hand, LifePaths is similar to the SNA in having a number of estimates where there are no directly underlying data. For example, LifePaths generates results on transition rates from [good health and working] to [good health and not working] by age and sex and leisure time – even though the data on which this is based include only various partial versions of this multivariate relationship. For example, data on the average transition rate leaving aside any breakdown by leisure time are available, as are data on leisure time in relation to work status. This is not unlike selected cells in the input/output tables which are estimated residually, or based on some form of pro-rating.

Working Results

"Active Sequence" – In this section, we present an initial series of estimates from LifePaths TMH. We start with the basic trichotomy of school, paid work, and other activities, shown in Figure 6a. This basic activity classification in fact corresponds to the first of a number of sub-accounts or "views" in Stone's SSDS, specifically his "active sequence". It is important to note a fundamental difference between these population pyramids, and those shown in Figure 1 above. The earlier population pyramids were cross-sectional or point-in-time slices through a series of overlapping birth cohorts, while those in Figure 6a are for actual historical cohorts.

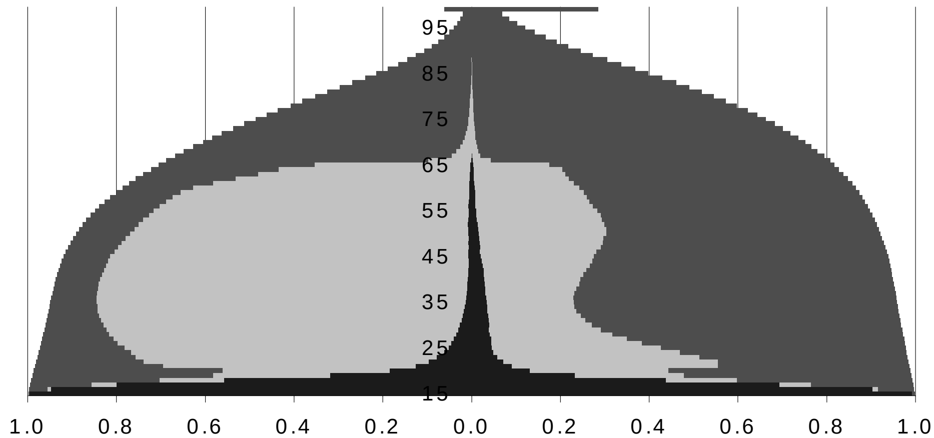
The "envelopes" for these population pyramids represent male (left) and female (right) survival curves (with age going up the middle vertical axis). They show not only falling mortality rates over time, but also the "rectangularization" of the survival curve. They also show a substantial increase in time spent in schooling, and a dramatic increase in female labour force participation.

However, these results are based on a very coarse classification of time use, basically using calendar years as the smallest unit. Since they draw on census data, the classification of being in "school" was based on reporting full time attendance at school for the nine months preceding census day (typically mid-summer). If the person was not in school, then they were classified as working if they indicated receipt of a non-zero amount of employment or self-employment income on their census form. Otherwise, they were classified to "other". However, it is obvious that during the course of a year, individuals may spend some of their time working, some in school, and certainly quite a bit in "other" activities. LifePaths has not only included the census-based annual classification of activity, but also much more detailed data drawn from a large household sample that collected time use data using daily diaries, with the smallest interval of time reporting being 15 minutes (Statistics Canada, 1997).

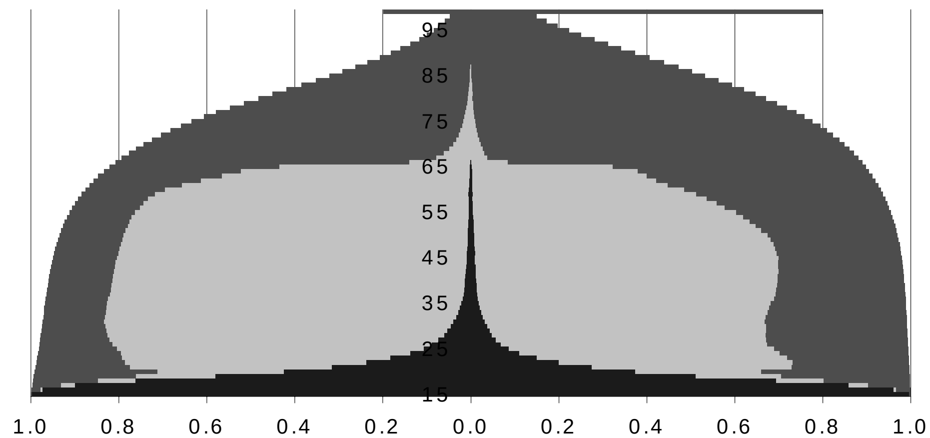
Figure 6a – "Active Sequence", Cohort Populations by Age, Sex, and Activity

(Leisure & Other, Paid Work, and School – from outside to inside bands)

1912 – 1921 Birth Cohort



1952 – 1961 Birth Cohort



1992 – 2001 Birth Cohort

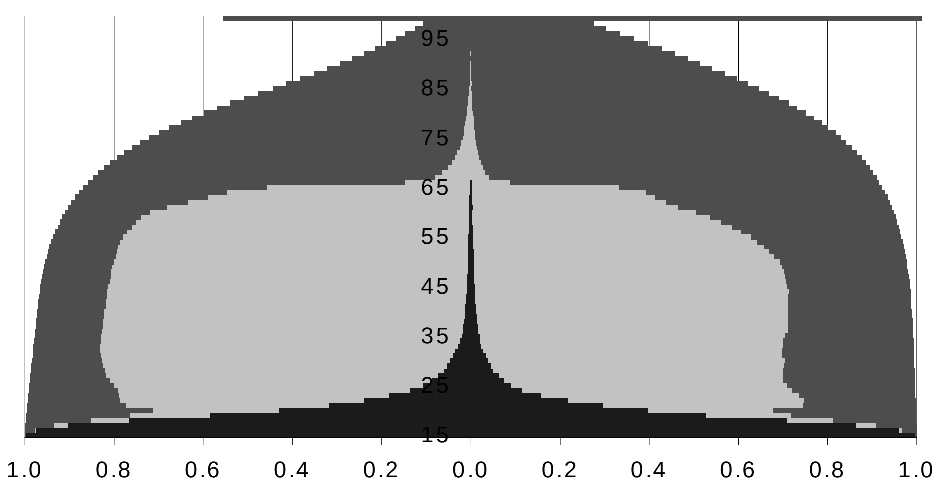
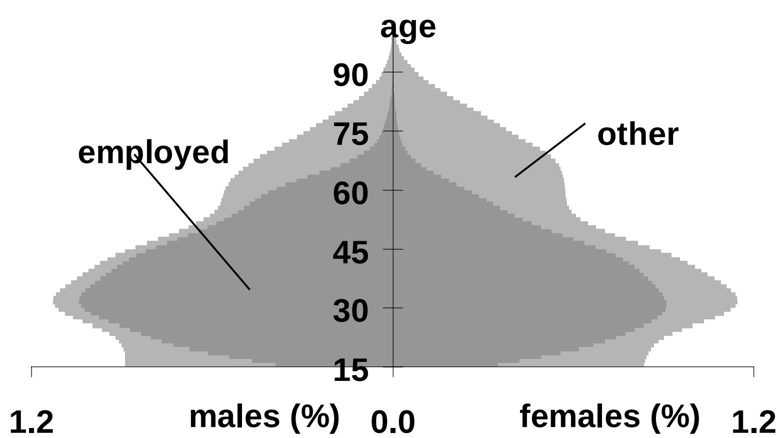


Figure 7 contrasts the impressions of the amount of time spent in work and school using these different "granularities" of time reporting. The population pyramid on the top is from Figure 1 for 1991, while that on the bottom integrates data from both the census and the time use survey. Essentially, the 1992 time use survey was post-stratified so that its sample weights matched the 1991 census population disaggregated first by the joint distribution of age and family size, and second by the joint distribution of labour force participation, age and sex. Perhaps the most dramatic difference in these images is in the amount of time spent in paid work. It is far smaller when time is (more accurately) classified hour by hour than by the year.

Figure 7 – Period Population Age 15+ in 1991 by Age, Sex and Kind of Activity for Two Levels of "Granularity" for Time Accounting

a. Census (annual) Classification



b. Time Use Diary (hourly) Classification

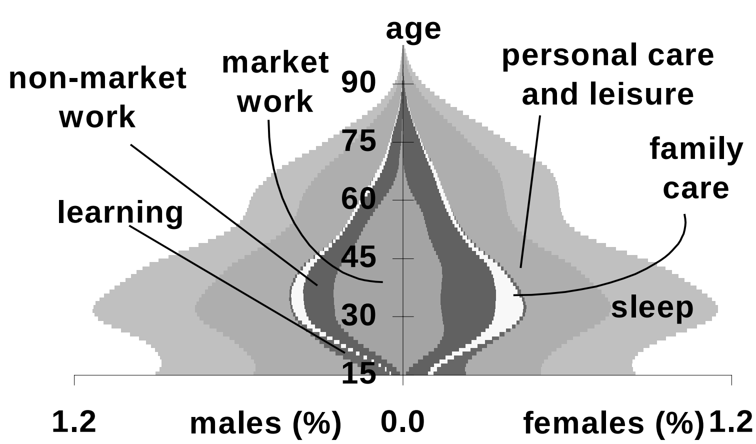


Figure 7, however, returns to a cross-sectional result. Using LifePaths, we have estimated the corresponding activity patterns for the same birth cohorts. They draw on time use patterns from the 1992 General Social Survey, the same as those underlying the bottom part of Figure 7, based on methods described in the Appendix. These historical and projected time use estimates necessarily involve rather heroic assumptions. However, this is more than sufficient for our purposes of illustration, and it provides a base for improvement as new time use surveys, such as the 1998 General Social Survey, become available, and historical time use surveys dating back to 1971 are subject to detailed re-analyses.

Table 3 shows the resulting comparisons between annual and hourly granularity of time accounting for the three LifePaths birth cohorts. It presents, in effect, two new set of estimates of the working life table results shown in Table 1 above. In addition, these earlier results have been significantly generalized – first to include women, second to use historical or generational birth cohorts rather than hypothetical period data, and third to use much more fine-grained data on time patterns of activity.

Table 3 – Average Sojourn Times (years) by Activity and "Granularity" of Time Accounting (age 15+)

	Annual Basis			Hourly Basis				Total = Life Expectancy	
Sex and Birth Cohort	School	Paid Work	Leisure + Other	School	Paid Work	Leisure	Other	At Age 15	At Birth*
Males									
1912-1921	4.7	34.0	18.2	2.2	9.0	14.6	31.1	56.9	71.9
1951-1962	6.3	34.4	21.9	2.7	9.1	16.3	34.2	62.3	77.3
1992-2001	6.4	34.5	25.7	2.7	9.3	17.7	36.9	66.6	81.6
Females									
1912-1921	4.6	12.9	45.9	2.0	3.9	15.7	41.8	63.4	78.4
1951-1962	5.8	28.0	35.7	2.5	6.8	16.9	43.2	69.5	84.5
1992-2001	6.0	29.0	39.2	2.5	7.0	18.3	46.2	74.0	89.0

* assuming 100% survival from birth to age 15

The left side of the table, the "annual basis", shows the numbers of years spent in each of three categories of activity defined exactly as in Figure 6a. The "hourly basis" data on the right side draw on the same data as in the bottom of Figure 7, and correspond to the cohort population pyramids shown in Figure 6b. In this case, "paid work" is defined as time spent in either employment or self-employment, "school" as time spent either attending formal elementary, secondary or post-secondary classes or adult classes, and leisure as time spent in socializing, in active pursuits like sports, in "serviced pursuits like attending movies, and reading or other passive activities. The residual "other" category includes sleep, personal care, volunteer activity, unpaid household work, caring for others, and shopping.

As in Figure 7, the most dramatic differences between the two sides of Table 3, and between Figures 6a and 6b, are for paid work. This drops by almost 75% when moving from the annual to the hourly basis for time accounting. But it should be noted that the 9.3 years of hourly basis paid work that the 1992-2001 male birth cohort can expect to do over its lifetime shown in Table 3 are "solid" years – 24 hours per day, 365 days per year, compared to the years on the left had side where a "year" of full-time, full-year work might amount to 2,000 hours of paid work. Still, for every hour of paid work, this cohort can expect over 2 hours of leisure.

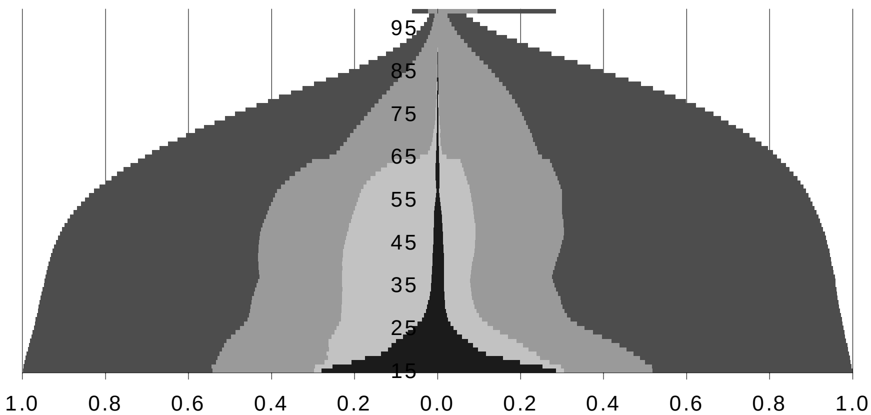
Looking to the trends over time, the increase in female working time is much more dramatic using the annual granularity, because no account is taken of part- versus full-time work. The increases in leisure time appear somewhat more modest for men than the increases in retirement in Table 1 above, though the results are not comparable conceptually. For women, the largest part of the increase in life expectancy for the first two cohorts is taken up by the increase paid work.

Recalling Stone's SSDS, Figures 1, 6a, 6b, and 7, and Table 3, are different versions of the first of the proposed accounts or views, his "active sequence" – though we have the contrasts of cross-sectional versus cohort (Figure 1 versus Figure 6a and 6b), and annual versus hourly granularity (Figure 7, Table 3, and Figure 6a versus 6b).

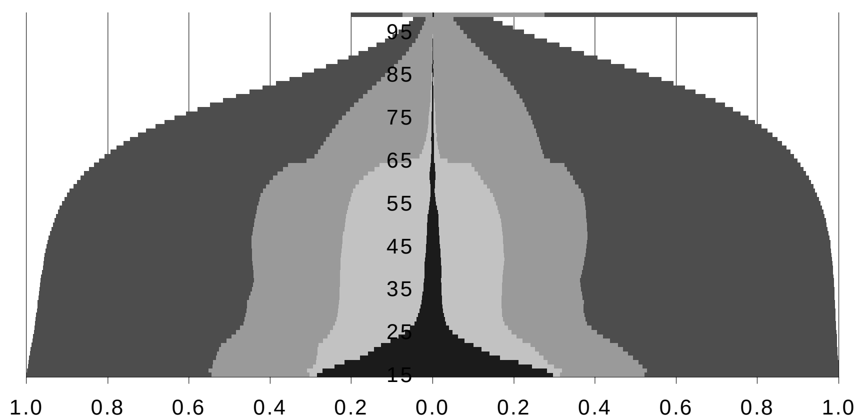
Figure 6b – “Active Sequence”, Cohort Populations by Age, Sex, and Main Activity

(Other, Leisure, Paid Work, and School – from outside to inside bands)

1912 – 1921 Birth Cohort



1952 – 1961 Birth Cohort



1992 – 2001 Birth Cohort

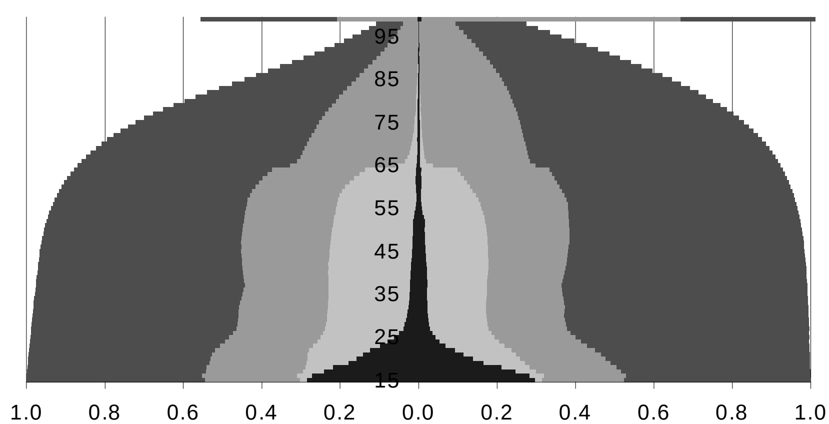
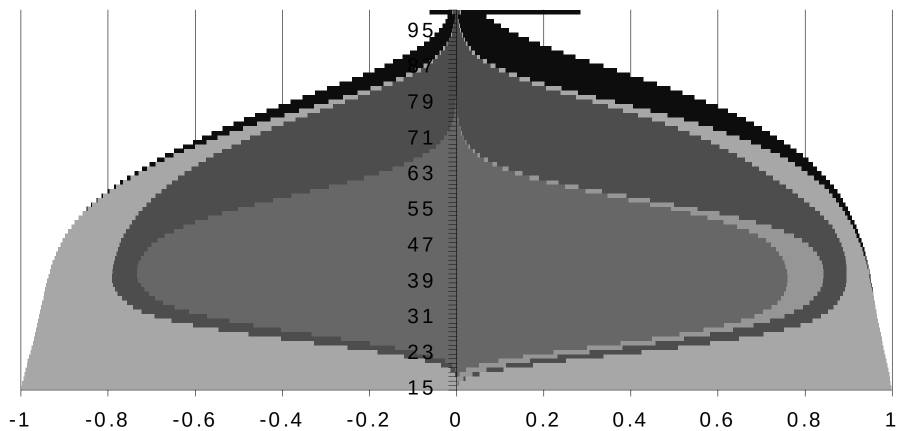


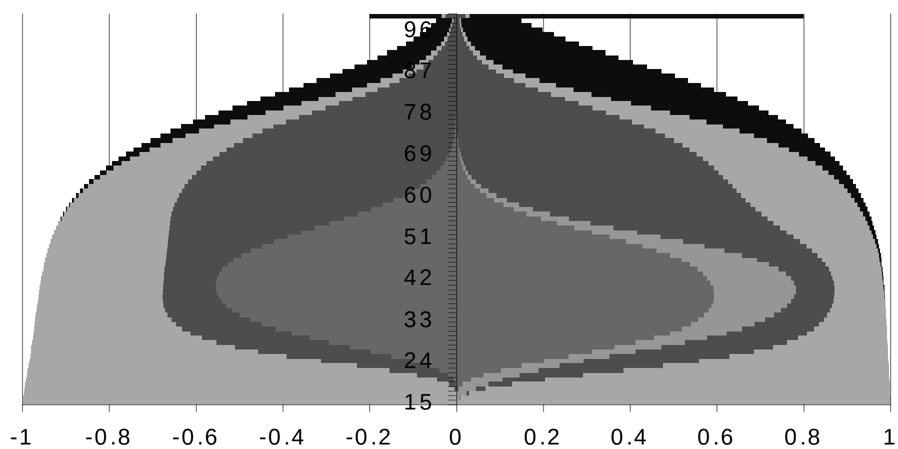
Figure 8 – "Passive Sequence", Demographic Circumstances

(Institutionalized, Single, Couple without Children, Lone Parent (females only), and Couple with Children – from outside to inside bands)

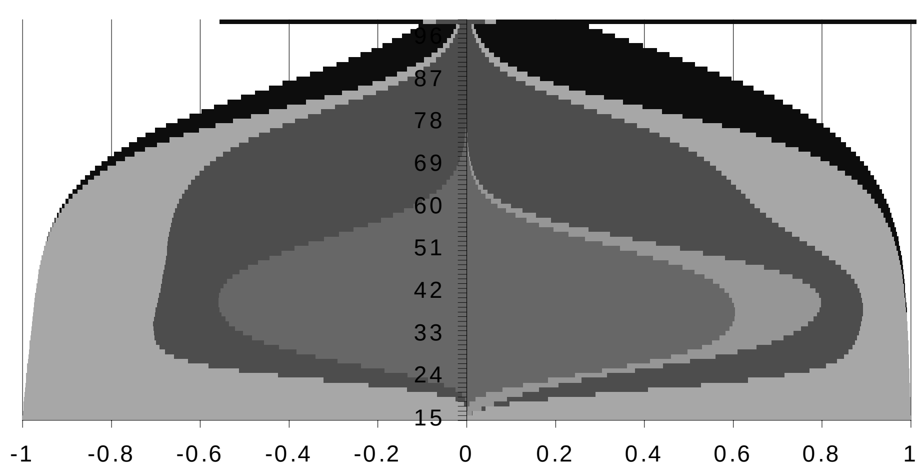
1912 – 1921 Birth Cohort



1952 – 1961 Birth Cohort



1992 – 2001 Birth Cohort



"Passive Sequence" – The second view or account in the SSDS was called the "passive sequence". It classified individuals according to their demographic circumstances over the life course. Figure 8 shows the LifePaths counterpart to Stone's passive sequence, while Table 4 shows corresponding summary sojourn times.

Table 4 – Average Sojourn Time (years) by Family or Demographic Status after Age 15

Sex and Birth Cohort	Couple without Kids	Couple with Kids	Lone Parent	Unmarried	Living in an Institution	Total = Life Expectancy at Age 15
Males						
1912-1921	14.2	22.5	0.0	18.2	2.0	56.9
1951-1962	20.3	15.0	0.0	24.0	3.1	62.3
1992-2001	22.7	15.5	0.0	23.8	4.5	66.6
Females						
1912-1921	16.8	24.2	3.2	13.3	5.8	63.4
1951-1962	21.0	15.9	5.3	19.2	8.1	69.5
1992-2001	22.3	16.4	5.6	18.4	11.3	74.0

The shrinking amount of time spent in a "couple with kids" family from the first to the second cohort reflects both the fall in fertility rates, and the increase in marriage breakdown. The increase in "lone parent" person-years is another consequence of increased marriage breakdown (note that for now, only mothers are given custody), while the increased time spent as a "couple without kids" also reflects increased survival in the "empty nest" phase of the life course. The increase in "institutional" time reflects increased life expectancies. (For the time being, the usual naïve assumption has been used – that rates of institutionalization will remain constant within age/sex groups, so the only factor that influences the expectation of time over the life course spent institutionalized is the increasing numbers of more aged elderly individuals.)

Of course, there is clearly more to life than work and school (the "active sequence") and family life (the "passive sequence"). Leisure or discretionary time is not of much value if the individual has no money with which to enjoy it, or is in poor health. As a result, we have also used LifePaths to estimate time spent with "adequate income", time spent in "adequate health", and time spent with a combination of all three – "good life time" or GLT, defined as those portions of the life course when individuals were fortunate enough to have adequate income, good health, and the leisure time to enjoy them. (In principle, other attributes of life such as a supportive social environment could also be included, but the attributes being considered pose sufficient challenges at this stage in the development of LifePaths.)

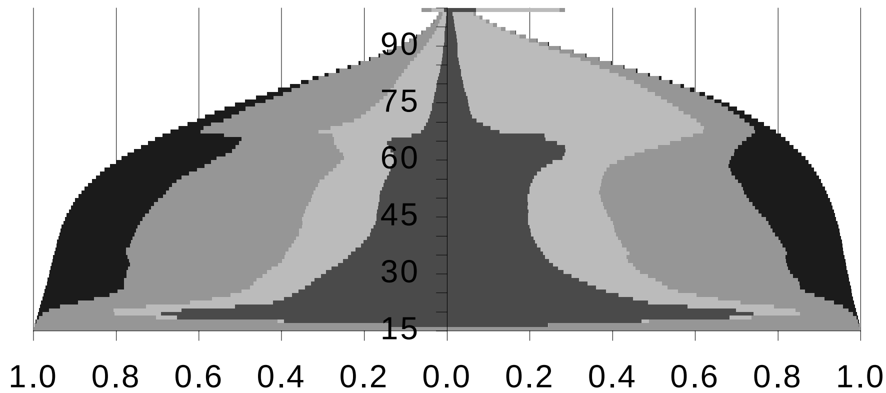
Income Sequence – As the next step beyond the active and passive sequences, Table 5 and Figure 9 show an "income sequence" view of the underlying LifePaths population microcosm. Both show, for each birth cohort, a coarse view of the distribution of income.

Note that these cohorts span about 200 years, and except for the 1990s, we do not have data on all contemporaneously living individuals. Thus, we have constructed an income cut-point designed to approximate a relative, family-size adjusted or equivalized median income. For each person-year in each cohort, the individual's after-tax income was first added to that of his or her spouse (if present), and then divided by an equivalence scale to adjust for family size (based on 40% for second and subsequent adults and the first child in a lone parent family, and 30% for children otherwise). This equivalized income was then classified into four groups – less than half, 50 to 100%, 100 to 200%, and over twice the "cut-point".

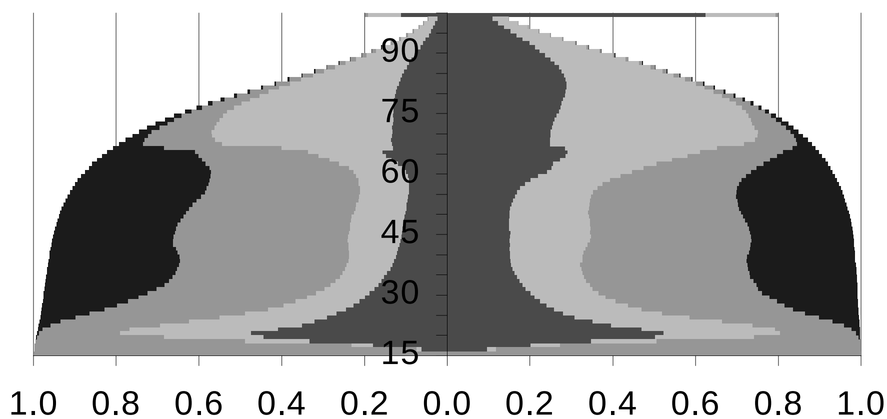
Figure 9 – Income Sequence

(Over 200%, 100 – 200%, 50 – 100% and Less than 50% of "Cut Point" – from outside to inside bands)

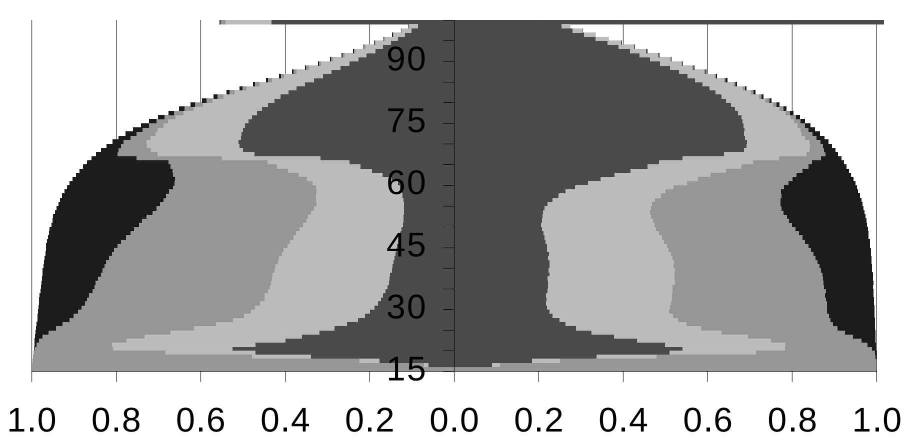
1912-1921 Birth Cohort



1952-1961 Birth Cohort



1992-2001 Birth Cohort



This cut-point in turn was set at $13,750 in 1996 dollars for a single individual (i.e. $27,500 for a family of two adults plus two children). The cut-point was inflated or deflated for other calendar years by the change in the average wage. This cut-point, by construction, divides all the person-years in all birth cohorts from 1900 to 2100 (as simulated) roughly in half. It is therefore something like the median equivalized family income, but not in the usual sense. It is not a year-by-year median adjusted family income, because we do not have data in LifePaths on all families, say, in 1930 or 2030. Rather we have only those families associated with the birth cohorts LifePaths is following, namely those born in the twentieth century (including those born in other decades than the three that have been the focus of the graphs and tables). While this is not a conventional income cut-point, in the context of this LifePaths analysis it is a useful cut-point. It allows us to make comparisons not only amongst individuals within a birth cohort, but also between cohorts.

The most dramatic result in Figure 9 is the projected ballooning of “low income” (i.e. incomes below half the “cut-point”) amongst the future elderly. At the same time, virtually none of today’s elderly women (those born in the 1912-1921 cohort) have incomes *above* the cut-point, while the baby boom (1952-1961) cohort and the current (1992-2001) birth cohort can both expect to have considerable numbers in the highest income range (i.e. over twice the cut-point). In other words, these results signal a “disappearing middle” among the future elderly, a polarization between a majority who depend principally on public pensions and those who pass a minimal threshold of private saving. (While these results are based on a moderately rich portfolio model of household savings that tracks the historical SNA figures for the personal sector, there have not been any household surveys of net worth in Canada since 1984. Thus, Statistics Canada’s forthcoming Asset and Debt survey will provide a very important benchmark for this part of the LifePaths data synthetic effort.)

Table 5 – Average Sojourn Time (years) by Adjusted Family Disposable Income after Age 15

Sex and Birth Cohort	Income Groups as Proportions of the Median				Total = Life Expectancy at Age 15
	Below 50%	50 to 100%	100 to 200%	Above 200%	
Males					
1912-1921	13.1	10.5	23.8	9.4	56.9
1951-1962	11.8	15.6	22.8	12.2	62.3
1992-2001	21.5	16.7	20.9	7.5	66.6
Females					
1912-1921	16.3	20.2	19.6	7.3	63.4
1951-1962	19.5	19.9	20.4	9.8	69.5
1992-2001	33.8	16.2	17.9	6.1	74.0

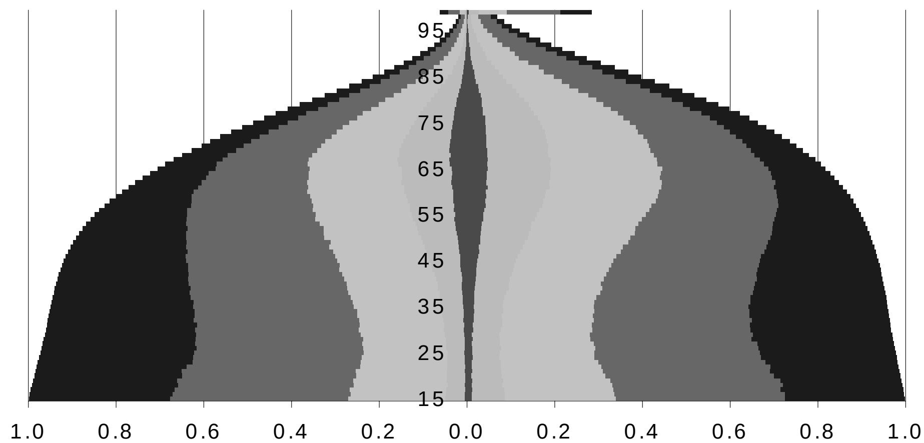
Table 5 is based on exactly the same data as Figure 9, but gives a somewhat different view. It too shows a growing proportion of time spent (i.e. person-years lived) with incomes below half the “cut-point”. But in this case, years at any point in the life course (after age 15) are considered.

Health Sequence – The last component of “good life time” for purposes of this analysis is health status. This has been estimated from the 1994-95 National Population Health Survey (Statistics Canada, 1995). Figure 10, analogously to the active, passive and income sequences shown in Figures 6a and 6b, 8, and 9 above, shows a “health sequence” for each of the three cohorts being examined. In each case, the shading of the population pyramids shows the distribution of self-reported health status (classified as excellent, very good, good, fair, or poor – n.b. the monochrome shading appears to have combined good + fair). At younger ages, 70 to 80% of Canadians report themselves as in excellent or very good health. However, not surprisingly, the proportions in fair or poor health rise with age.

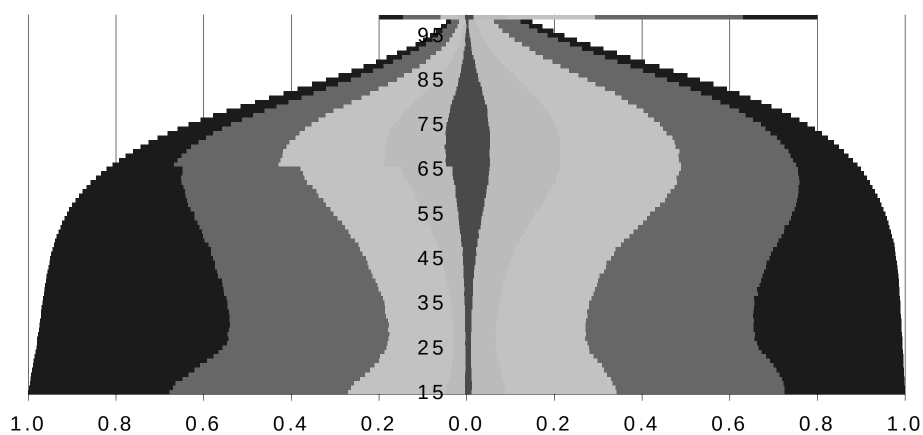
Figure 10 – Health Sequence

(Excellent, Very Good, Good, Fair and Poor – from outside to inside bands)

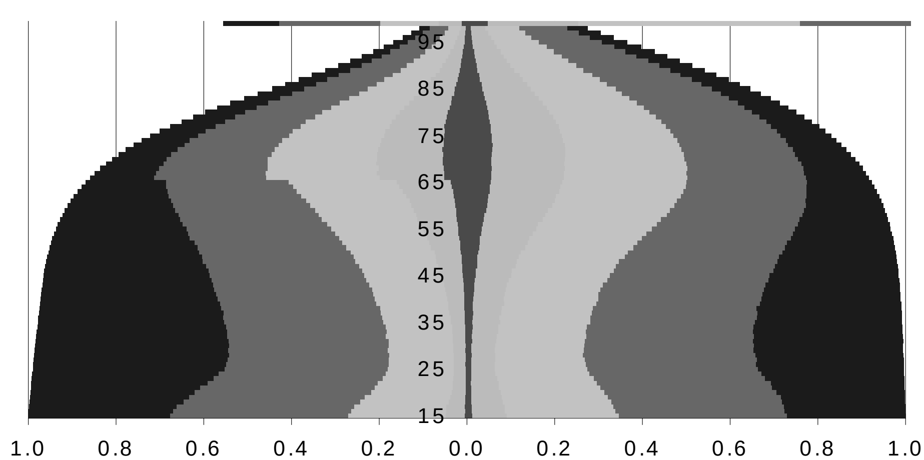
1912-1921 Birth Cohort



1952-1961 Birth Cohort



1992-2001 Birth Cohort



Unfortunately, there are very limited historical data on health status in Canada, so LifePaths has used a rather naïve method, summarized in the Appendix, for imputing health status both for earlier and later years than 1994. In future development work, we will draw on the occasional earlier surveys and subsequent waves of the NPHS (which is longitudinal, so that it will provide data not only on trends over time, but also patterns of micro-level dynamics) in order to improve the results. Note, however, that the mortality data being used are of high quality, and based on a long historical series, as well as official projections (OSFI, 1995). Moreover, we have used special analyses of the Alameda County survey (Berkman and Breslow, 1983), a U.S. longitudinal study dating from the mid 1960s, in order to differentiate mortality rates not only by age and sex, but also by educational attainment and health status.

Table 6 – Average Sojourn Time (years) by Self-Reported Health Status after Age 15

Sex and Birth Cohort	Excellent	Very Good	Good	Fair	Poor	Total = Life Expectancy at Age 15
Males						
1912-1921	16.0	20.6	13.7	5.2	1.4	56.9
1951-1962	20.2	22.1	13.4	5.1	1.5	62.3
1992-2001	21.1	23.5	14.6	5.8	1.7	66.6
Females						
1912-1921	15.5	22.1	16.4	7.3	2.1	63.4
1951-1962	16.9	24.5	17.9	8.0	2.3	69.5
1992-2001	17.6	26.2	19.1	8.6	2.4	74.0

Table 6 suggests that the projected increase in life expectancy will largely be years of “good” or better health. However, the reader is cautioned again that the underlying projections are based on rather naïve assumptions.

Combination Sequences – The “bottom line” in this analysis is a set of estimates of “good life time”, defined as periods over the life course characterized by the combination of adequate income, health, and leisure time. For each of these three attributes, we have arbitrarily defined two levels, adequate and inadequate. The thresholds are:

- for equivalized family income: the “cut-point” (which has been defined as roughly the inter-temporal median of equivalized wage-indexed family income over the two centuries spanned by the birth cohorts),
- for health status: self-reported “excellent” or “very good”, and
- for leisure time: an overall annual average of at least 6 hours per day.

It turns out that, on more detailed investigation, the extent of leisure time seemed rather low. So we have also defined “extended” leisure which is the sum of leisure, as originally defined on the time use survey, plus sleep in excess of 9 hours per day plus personal care in excess of 2 hours per day plus shopping in excess of one hour per day. The implicit assumption is that sleep, personal care and shopping in excess of these amounts might better be considered a form of leisure.

Figures 11 and 12 show the resulting estimates of the age profiles of “adequate” time (i.e. leisure), extended time (i.e. leisure plus “excess” sleep, personal care and shopping), money and health, as well as the intersection of these presumably desirable states – namely “Good Life Time” and “Extended Good Life Time”. The vertical axis shows the number of individuals assuming an initial cohort size of 1,000. The upper-most curve, “Life (excl…)”, is the overall survival curve with two major exclusions – years lived prior to immigrating to Canada, and years while still in school full-time (i.e. continuously since childhood). The reader should also bear in mind the rather arbitrary definitions of “adequacy” being used, and that the data on time use patterns and health status, while accurate for the 1990s, are based on rather naïve historical imputations and projections for future years.

Figure 11 -- GLT, "Extended" GLT, and Their Components

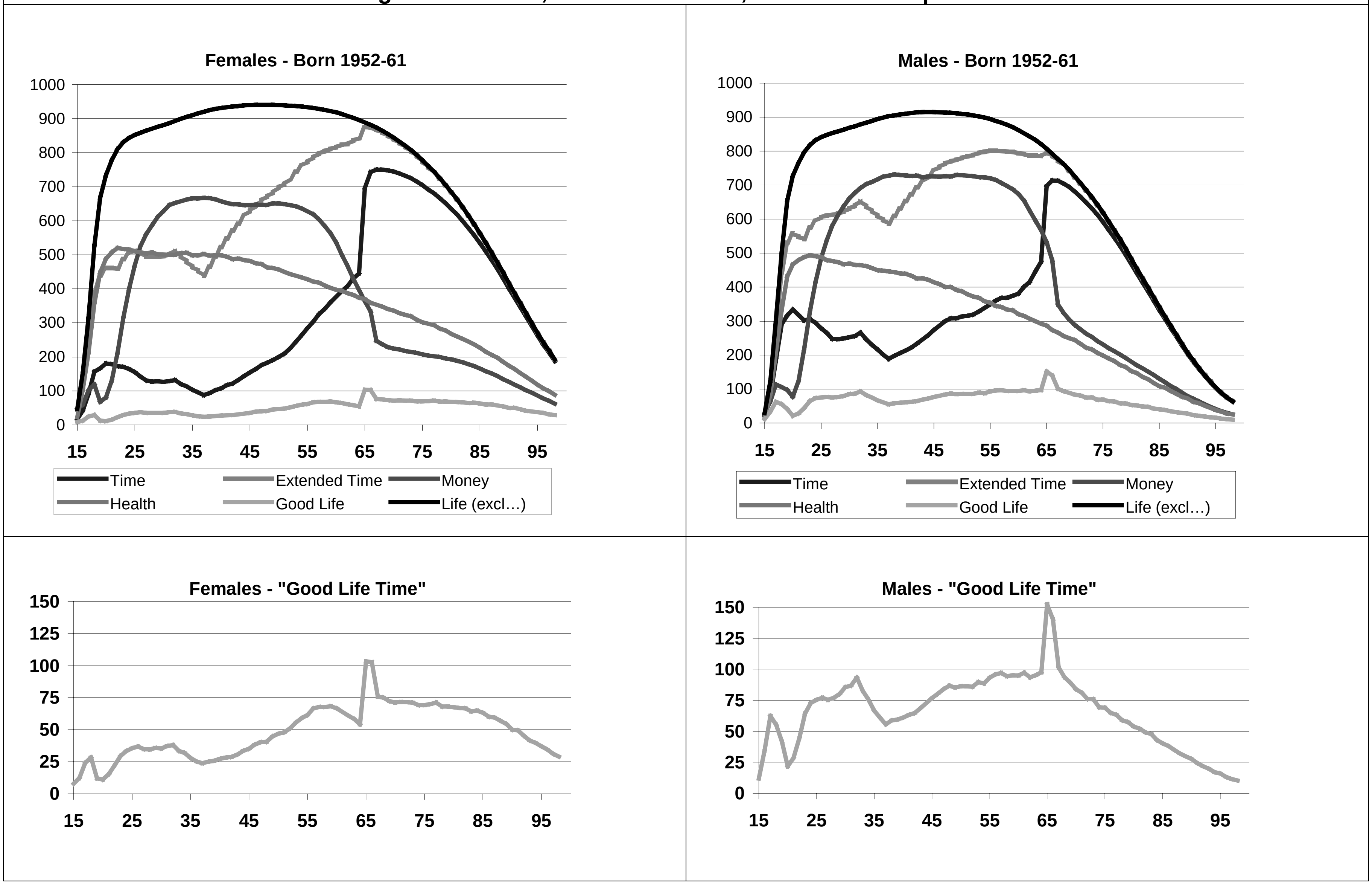


Figure 12 -- GLT and "Extended" GLT by Cohort

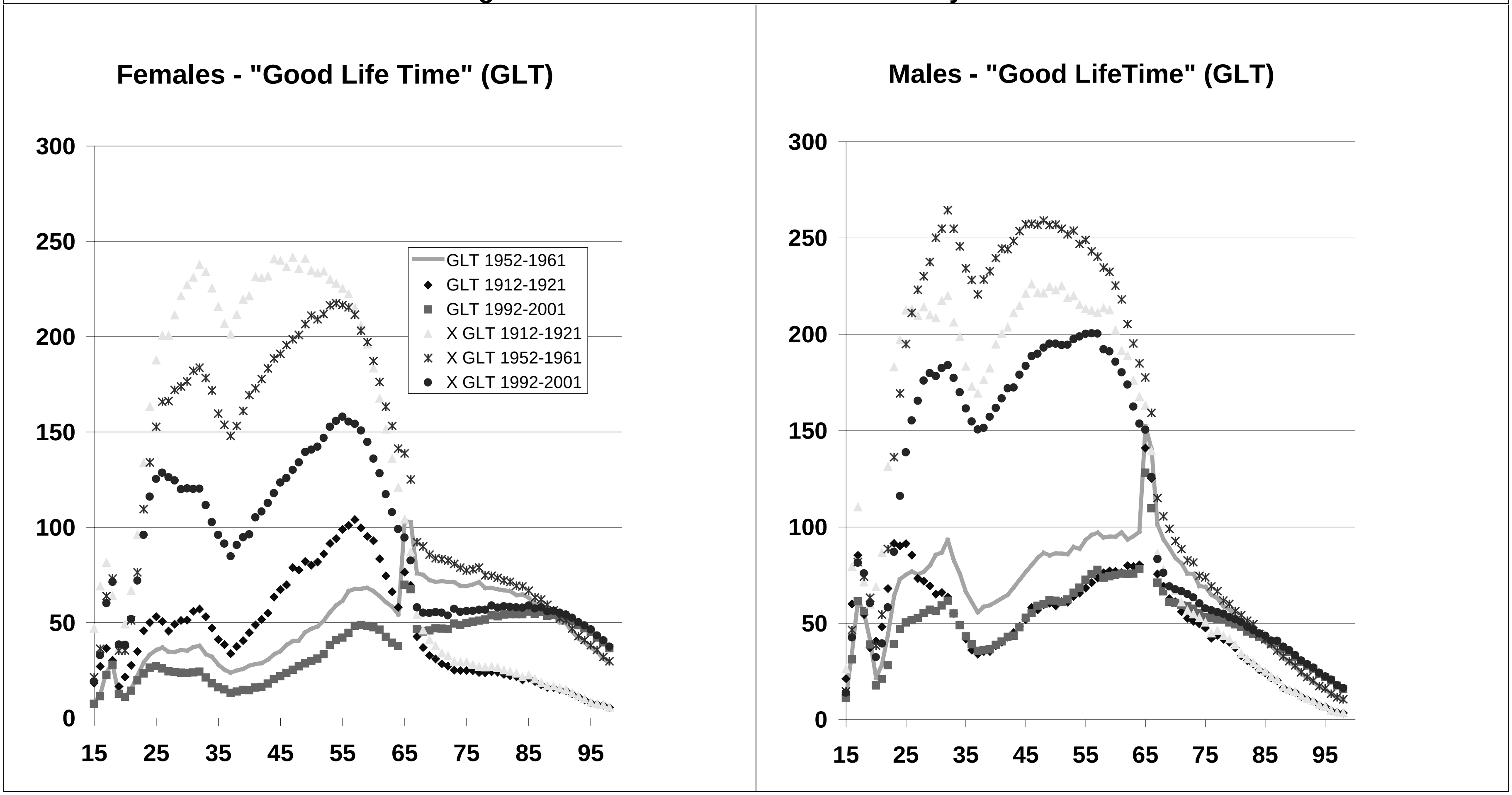


Figure 11 shows some expected as well as several interesting results. Not surprisingly, the curve for adequate income shows a typical life-cycle pattern, and is somewhat higher for men than for women. (Recall that in both cases, it is the joint spousal income that is used.) Adequate health shows similar patterns for men and women, and declines gradually with age (after rising initially with the overall cohort population as it either completes school or immigrates). Leisure time is rather low at the beginning of working years, rising gradually toward retirement age, then sharply at age 65. Extended leisure is considerably higher.

The intersection of these three states, the age profiles of “Good Life Time” or GLT is shown both in the top pair of graphs, at the same time as the other profiles, and then by itself in the bottom pair of graphs. It is generally higher for men than women, but generally amounts to less than 10% of the person years at each age.

All the data in Figure 11 are for the baby boom birth cohort. Figure 12 shows only the GLT profiles, but this time for all three of the cohorts, and for “extended” GLT as well as GLT. For both measures of GLT, the situation appears to be deteriorating during working ages, particularly for women. This is related to their increased participation in the paid labour force. After age 70 though, particularly for women, increases in longevity are associated with increased GLT.

More generally, the strongest factor militating against more “good life time” over the life course is the negative association between adequate income and adequate time – not the pariwise relationships between time and health, or money and health. Thus, one way to increase the extent of “good life time” is for individuals to spread their incomes over a wider range of the life course.

Of course, many individuals feel most satisfied when engaged in socially productive work – by definition then at the cost of leisure time. This in turn raises basic questions about just how good the “good life time” measure we have developed really is. At least a partial answer will be forthcoming in Statistics Canada’s 1998 Time Use Survey which is gathering data not only on time use patterns, but also indicators of the satisfaction derived from various ways of spending one’s time.

Concluding Comments

This paper has described a work in progress – initial estimates of “good life time” based on the LifePaths system for socio-economic statistics. It is being developed as a framework for data integration, which in turn is designed to support the production of a range of coherent socio-economic indicators. Moreover, because it is based on computer simulation, LifePaths can also support research and policy analysis with its capacity to answer “what if” questions.

Similarly to the other major integrative statistical framework in wide use, like the System of National Accounts, LifePaths relies on an extensive network of data feeder systems. And like the SNA at its inception, LifePaths faces major problems of data availability. The challenge is that LifePaths builds on richly multivariate longitudinal data on individuals and their socio-economic circumstances. While these kinds of data are relatively new, there is also a growing consensus that these data are of high priority for a variety of analytical and public policy purposes. Thus, LifePaths not only fits in well with the developing appreciation of the needs for data on the micro-level dynamics of individual behaviours, it also provides a major rationale and integrating framework for such data. Indeed, it can act as the conceptual framework for the design of networks of surveys and other data collection vehicles and, analogously to the role played by the SNA in national statistical offices, give the impetus for the common concepts and definitions that are fundamental to maintaining coherence and consistency in the statistical system. As such, it represents a development and “post computer revolution” extension of the UN’s (1975) proposed System of Social and Demographic Statistics.

In terms of the working results presented, LifePaths highlights the value of a more integrated while multi-faceted view of individuals in society. A full life-course perspective is essential, as (for example) childhood progression through the education system influences subsequent labour market experience, and this in turn affects expected incomes during retirement. It is also important to bridge information on domains that up to now have been disparate. For example, it is obvious to the general public that having a good income is not of much benefit if one has neither the time or the health to enjoy it.

But when we take this kind of integrated view, we see that there are serious “mismatches” in the availability of time, money and health both over individuals’ lifetimes, and between individuals. This general point lies at the core of such differing policy suggestions as mandating shorter work weeks, shifting health care from hospital to outpatient and home care, raising the age of entitlement to public pensions, and forcing or encouraging employers to adopt more “family friendly” policies especially to accommodate the needs of children in families where both parents are working. In the private sector, consumption of new products is often constrained more by lack of time than by lack of money (Linder, 1970). LifePaths provides a statistical framework within which to analyze these kinds of policy options and social changes. It also helps in understanding concerns increasingly expressed by the general public, for example being squeezed into caring both for their children and frail elderly parents, and experiencing “time crunch” more generally.

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APPENDIX -- Microsimulation of Patterns of Health and Time Use

This appendix provides further detail on the methods by which health status data from the 1994-95 National Population Health Survey (NPHS, Statistics Canada, 1995) and the time use data collected in the 1992 General Social Survey (GSS, Statistics Canada, 199X) were estimated for / imputed to the individual histories simulated by LifePaths.

Health Status – The NPHS provides data on subjectively rated health states and their contemporaneous SES correlates for a cross-section of about 17,000 Canadians in 1994. Our objective in using these data was, however, to specify a plausible model for variations in health over the life course and to link these variations to differential mortality risks.

The NPHS variables employed in constructing this model were limited to:

Health States:	Excellent, Very Good, Good, Fair, Poor
Education Level:	Less than Secondary School, Secondary School Only
	Greater than Secondary School
Labour Force Stage:	Student, Working Age, Retired
Recent Work Experience:	Working, Worked within the last year,
	Worked more than 12 months ago
Age:	single years
Sex:	Male, Female

In order to model variations in health, we have used a linearization technique based on the cumulative proportions in ordered categories. Specifically, we assigned scores (e.g., Z(health | age, sex)) to health, education and recent work experience states. These scores corresponded to the standard normal value having the same cumulative probability as the state. That is, given the cumulative probability from 'poor' to 'very good' health at a given age and sex (i.e., F(health | age, sex)), then the score Z(health | age, sex) is the standard normal value that satisfies F(Z) = F(health | age, sex). In order to estimate F(health | age, sex) by single year of age, a moving average was used to draw on responses from adjacent ages. Hence, the scores are smoothed – with inevitable (good or bad) endpoint effects at the youngest and oldest ages.

Having transformed discrete observations to normal scores, the associations among variables are simply expressed as product moment correlations (i.e. linear associations). These correlations were approximated from rank correlations (i.e., τ - Kendall's tau) estimated from smoothed bivariate tables. For normally distributed variables, τ is directly related to the correlation parameter ρ (i.e., $\rho = \sin(\pi * \tau / 2)$).

At its core, our model expresses health as a combination of time-varying and time-invariant factors. The time invariant factor is represented by a random element determined once and for all at birth (i.e., Z_I for simulated person I) which has a fixed correlation (r_A) with Z(health | age at T, sex, I). The correlation ($r_A \approx 0.5$) was estimated from Alameda County data on the correlation between health scores of young respondents over a thirty year time lag. The time varying factors are represented by the correlation with contemporaneous work experience (if at the appropriate labour force stage) and by a purely random element drawn once each year of life (i.e., $Z_{I,T}$). Note that model represents health as a function of work experience and neglects the dependence of work experience on health.

Health Equations by Labour Force Stage

1. Student or Age < 15

$$Z(\text{ health} \mid \text{age at T, sex, I }) = r_A * Z_I + \sqrt{}(1- r_A^2)\, Z_{I,T}$$

2. Working Age

$$Z(\text{ health} \mid \text{age at T, sex, I }) = r(\text{age, sex, education}) * Z(\text{ recent work} \mid \text{age at T, sex, I })$$

$$+ \sqrt{}(1- r(\text{age, sex, education})^2)\ (\ r_A * Z_I + \sqrt{}(1- r_A^2)\, Z_{I,T})$$

3. Retired

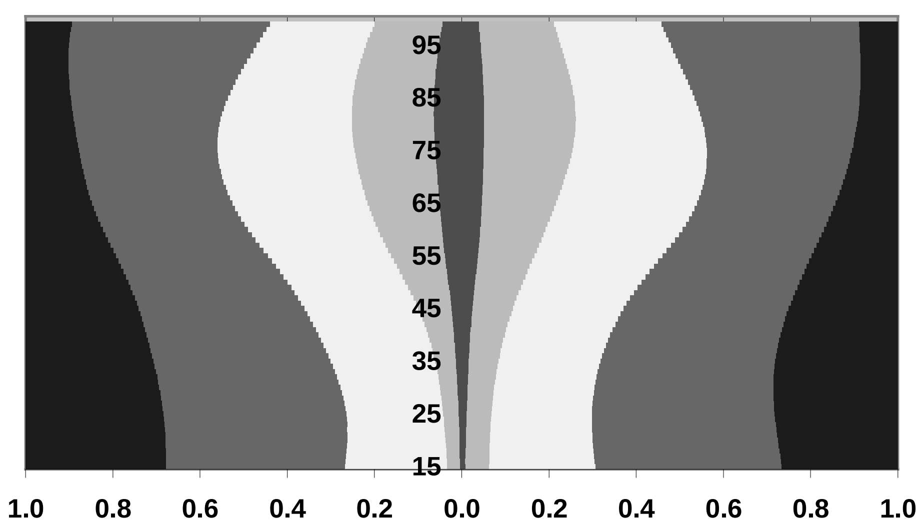
$$Z(\text{ health} \mid \text{age at T, sex, I }) = r(\text{age, sex, education}) * Z(\text{ recent work at retirement of I })$$

$$+ \sqrt{}(1- r(\text{age, sex, education})^2)\ (\ r_A * Z_I + \sqrt{}(1- r_A^2)\, Z_{I,T})$$

For any randomly generated health score, the corresponding health state (i.e., excellent, …, poor) can be obtained by locating the corresponding NPHS interval - Z(health=poor | age, sex), …, Z(health=excellent | age, sex). Thus, the (smoothed) NPHS distributions could be recovered – compare Figures 10 and A1.

Figure A1 - Simulated Distributions of Self-Reported Health Status

(Excellent, Very Good, Good, Fair, Poor – from outside to centre of graph)



In order to represent selective mortality based on health and SES, a log-linear model of the relative risk of death was estimated from Alameda County data. Education and health covariates were constructed in the same manner as above (i.e., Z(health | cohort, sex) and Z(years of education | cohort, sex)). The model included contemporaneous education, health and interaction effects, as well as a ten year lagged health term. The model was subsequently calibrated to reflect Canadian experience using cohort specific adjustment factors to ensure that the average simulated relative risk for each sex-cohort group was 1.0.

Detailed Time Use Patterns – The GSS data by their nature provide a cross-section of the time use patterns of Canadians in 1992, and cannot directly provide a view of time use over the life course. LifePaths simulations therefore require an imputation of time use patterns over the life times of synthetic individuals.

For these purposes, GSS time uses were partitioned into 17 mutually exclusive activity types:

employment	self employment	commuting
family care	domestic work	volunteer work
adult education	formal education	sleep/nap
shopping	personal care	social leisure
active leisure	serviced leisure (movies etc.)	passive leisure (tv etc.)
reading	other	

Given this classification of activities, the GSS data set can be thought of as an array of 8815 rows (each row corresponding to a respondent with a complete set of responses) and 17 columns. About 60% of all the cells of this array indicate zero reported time use. However, these zeros should not necessarily be interpreted as representing a complete absence of time engaged in a given activity, for two reasons:

- reported time use activities are "main" activities that partition the day into mutually exclusive periods; joint time use such as reading for leisure while traveling to work on the bus is precluded; and

- there is evidence of substantial rounding in the responses. For example, 32% of reported durations of sleep are even multiples of an hour, while 16% are even multiples of half an hour .

Moreover, it is important to distinguish between two types of zero in this overall array:

- Response Zeros -- zeros that represent activities that are engaged in with small probability, for short intervals, or that are unlikely to be a main activity. The expected values of such zeros in the observed GSS data should be represented as small positive quantities.

- Structural Zeros -- zero time spent in an activity that is likely to be a main activity, where such a zero is reasonable in relation to the stage in the life cycle. For example, retirement usually implies no paid work. Such zeros should be modeled as zeros – they are essentially impossible events.

Zero time spent in an activity was operationally identified as a structural zero for:

- employment or self-employment -- if the main activity in the previous 7 days was either retirement, long term illness, maternity/paternity leave, or other non-work if no work was reported in the previous year

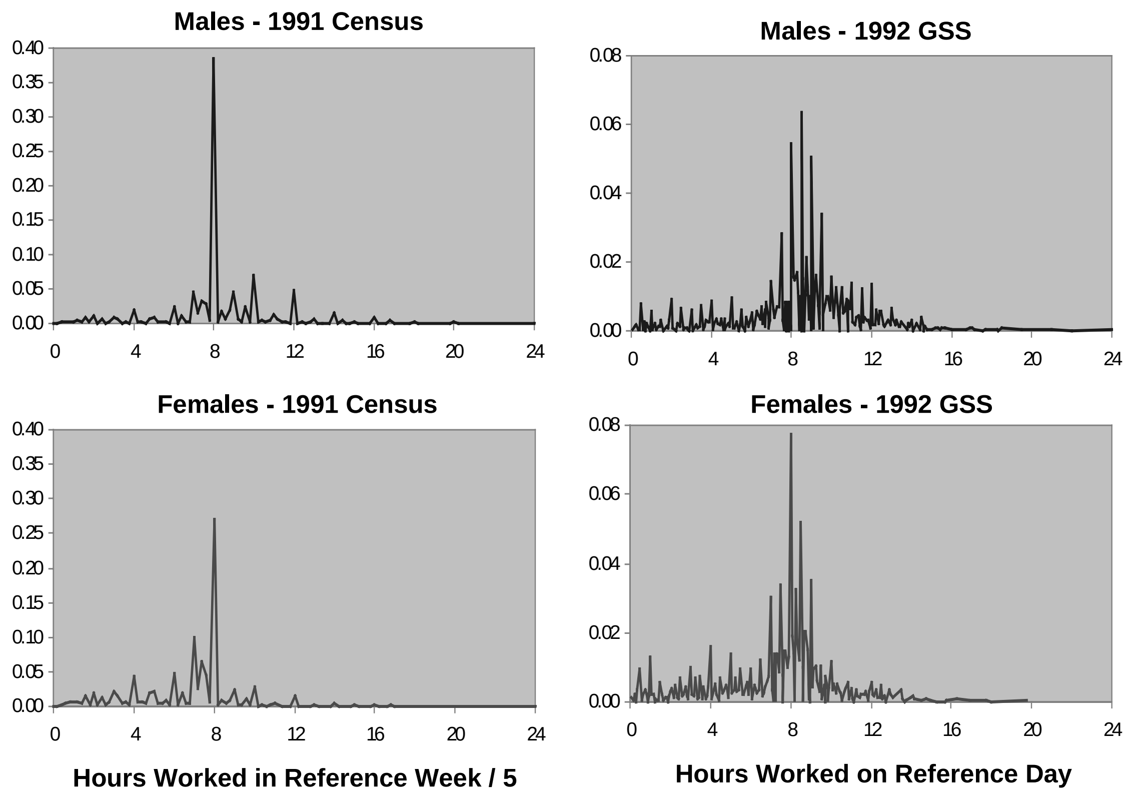
- commuting -- where both employment and self-employment are structural zeros.

- formal education -- if employment and/or self-employment are non-zero.

- family care -- if no spouse or child were present in the household.

About 12,000 structural zeros were identified by these definitions, representing about 13% of the zeros in the data array.

By way of further background, the GSS time use data are characterized by a higher degree of heterogeneity than is typically observed from other data sources. For example, Figure A2 compares 1992 GSS data on hours of work in the reference day to 1991 Census data on hours of work (employed and self-employed) in the reference week (the latter number of hours divided by 5 for comparability).



Appendix Figure A2 – Distributions of Hours of Work, 1991 Census and 1992 GSS

In common with similar survey data on hours worked in a week, the Census data exhibit a marked spike corresponding to exactly 40 hours (nearly 40% of responses for males and about 25% for females). In contrast, the GSS reveals no more than about 8% of exactly 8 hour day responses. As such, the GSS data are putatively the more accurate representation of the heterogeneity in individual time use patterns, and indicate significant rounding bias in the reported census data.

Figure A3 displays selected patterns of time use in the form of triangular scatter plots. These plots represent a three-way partitioning of the hours in a day by the perpendicular distances from each edge of the triangle. Each dot in a triangle represents a single GSS response, with the area of the dot being proportionate to the survey weight associated with the response. The distances from the edges of the triangles represent, respectively, (i) hours spent in work of all types (market, domestic (including family care) & volunteer), (ii) hours spent in leisure and (iii) hours of personal care and sleep.

The scatter of observations displayed in Figure A3 reinforces the impression that the GSS data exhibit a high degree of heterogeneity, even in respect of a simple three-way partition of activity types. Differences between the employed and not-employed are characterized as much by increased dispersion as by inevitable differences in the location of the scatter of observations.

In summary, the GSS time use data comprise both highly varied observations of time use and a preponderance of zeros reflecting patterns of activity choice and intensity. As a result, these data cannot be summarized parsimoniously, so a more involved imputation method has been developed.

A sequence of three equations was used to impute daily time use patterns to the individual trajectories simulated by LifePaths. In all cases, k indexes the 17 activities, and i the individual respondents to the GSS. These equations were estimated from the GSS 8815 by 17 array.

The first logistic equation describes the patterns of occurrence of structural zeros.

(1) $E(\ ZERO_{ik}\ ) \approx (\ 1 + \exp[\ - X^*_{ij}\ \beta^*_{jk}\ ]\ )^{-1}$

The second set of 17 log-linear equations provide estimates patterns of time use conditional on the structural zeros estimated in the first equation.

(2) $E(\ GSS_{ik} \mid ZERO_{ik} = 0) \approx \exp[\ X_{ij}\ \beta_{jk} + \beta_i\ ]$

where GSS_{ik} = the proportion of daily time spent by individual i in activity k. A special feature of this second set of equations is the term β_i representing a constant term for every respondent in the sample. These individual level constants represent a constraint on each individual's predicted time use pattern (i.e., it must sum to 100% of 24 hours). The individual level constants may also be interpreted as reflecting random factors at the individual level that can be further modeled.

The third set of equations then captures patterns in individual variability of time spent in each activity. Residual variances are defined in terms of differences in square root proportions, rather than the more usual log differences, to avoid problems with response and structural zeros (since the log residual ($\ln(0) - \ln(\mu)$) is undefined). As well as being defined for zeros, the vector distance measure expressed in terms of differences in square roots is a true distance (i.e., satisfying $d(x,y) \geq 0$, $d(x,y) = d(y,x)$ and $d(x,y) + d(y,z) \geq d(x,z)$) and is unique in that respect among common distance measures on the unit simplex.

(3) $SD_i = \sqrt{(\ \Sigma\ (\ \sqrt{GSS_{ik}} - \sqrt{\exp[\ X_{ij}\ \beta_{jk} + \beta_i\ ]}\ )^2\ )}$

$\approx \exp[\ X_{ij}\ \theta_{jk} + \sigma\varepsilon_i\ ]$, where $\varepsilon \sim \text{Normal}(\ 0, \sigma^2\ )$

In other words, it is being assumed that the standard deviations (SD_i) of time use proportions are log normal, though with means depending on X_{ij}.

Estimation for equations (1) and (2) was carried-out by iterative proportionate adjustment, while equation (3) was estimated by least squares.

The choice of predictor variables in each of the equations was constrained by what was available both on the GSS and in the LifePaths model. The following variables were used:

Predictor Variables	Definitions
reference day	Sunday, ... , Saturday
sex	Male, Female
age group	15-17, 18-19, 20-24, 25-29, ... ,65-69, 70+
marital situation	married or CLU (spouse not working last week), married or CLU (spouse worked last week), never married, widowed, divorced or separated
children	no children at home, all children at home aged 5+, one or more children at home aged <5
education attainment	less than secondary school, secondary school only, at least some post-secondary
respondent's work	mainly a full time student last week, working last week, not working and not mainly a full time student last week
response rounding	0 responses in multiples of 1/2 hour, 1 response in a multiple of 1/2 hour, 2 responses in multiples of 1/2 hour, 3+ responses in multiples of 1/2 hour

An evaluation of the fit of these equations is difficult both because of the zeros in the data, and because the statistical properties of entries in time use diaries are difficult to specify. The following evaluation measures were calculated by analogy to statistical models of count data and should be taken as merely suggestive of the explanatory power of each variable.

Reduction in Deviance due to addition of independent variables	Structural Zero Model (Equation 1)		Time Use Model (Equation 2)	
Variable	Deviance	# Fitted Parameters	Deviance	# Fitted Parameters
reference day	17.1 ns	42	4645 **	119
sex	875.0 **	12	923.1 **	34
age group	4611.8 **	78	1241 **	221
marital situation	29.1 ns	24	198.5 **	68
children	230.5 **	18	1325 **	51
education attainment	327.9 **	18	389.7 **	51
work	--	--	4355 **	51
rounding	--	--	48.55 ns	68

Note: ** denotes significance at 5%; ns denotes not significant at 5%

Finally, given the estimated set of equations, imputation of the 17 element time-use activity vectors was based on an algorithm that started with annual features, and then successively expanded to the imputation to weekly and ultimately daily features. For each individual life cycle history simulated by LifePaths, and for each year, the following procedure was implemented:

Starting at the annual level,

- choose ZERO day - based on a uniform random number ranging from 1 to 365. Note that the interval between successive ZERO days will range from 1 to 729 days.

- on ZERO day, it is decided whether not a structural zero will be imputed to market work, commuting, formal learning and/or care for family members for the next "year" (actually until the next ZERO day), based on probabilities determined from the logistic regression equation (1) estimated from GSS data.

Given these annual level imputations, the process next focuses on a week:

- choose a random REF day - based on a uniform random number ranging from 1 to 7. Note that the interval between successive REF days will range from 1 to 13 days.

- on REF day each week, one of the actual 8815 empirical residual vectors RESID is chosen at random. The residual vectors are in standardized form:

  RESID = [(sqrt (GSS) - sqrt (fitted from equation 2)] / SD.

- also on REF day, a random heterogeneity term ($\sigma\varepsilon$) is generated from the log-normal distribution represented by equation (3).

Finally, the imputation algorithm determines a set of daily activity patterns for all 365 days of the year (actually, all the days until the next ZERO day):

- each day, the appropriate average time use vector (AVG) is determined -- corresponding to the day of week, sex, age, marital situation, presence of children, employment/schooling and education attainment – by applying equation (2) to the LifePaths variables pertaining to that day. A corresponding calculation, based on equation (3), provides the heterogeneity term (SD) appropriate to the day of the week, etc. and to $\sigma\varepsilon$.

- subsequently, the average, residual and heterogeneity terms are combined:

  sqrt (AVG) + RESID*SD

  The added variability due to the RESID and SD terms preserve correlations among time use activities and account for inter-individual variation. By varying RESID and SD only on a weekly basis, some (possibly spurious) correlation is induced between days of a given week.

- impossible time uses are set to zero -- for example:

age < 6:	pre-school: domestic work, formal learning & reading;
age < 12:	family care;
age < 15:	market work, commuting & adult education;
institutional:	market work, commuting, family care, domestic work, & volunteer work

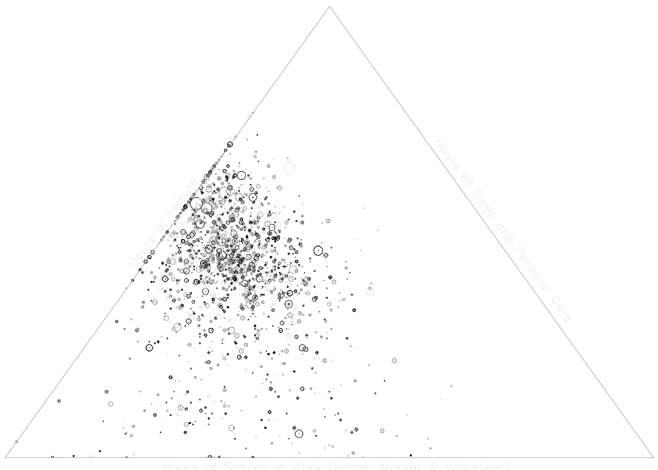
  Likewise, structural zeros as prescribed above are set if necessary conditions are still met:

  - employment time use = 0, if no work simulated for the previous 12 months
  - self-employment time use = 0, if no work simulated for the previous 12 months
  - commuting time use = 0, if no work simulated for the previous 12 months
  - formal learning time use = 0, if currently employed
  - family care time use = 0, if no spouse & no children are present at home

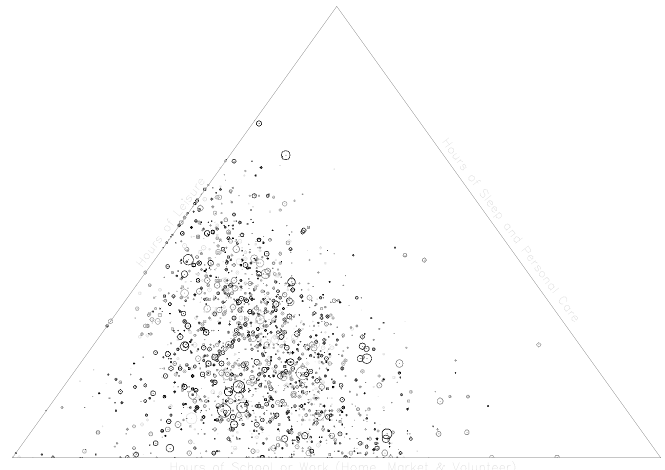
  - finally, negative [sqrt (AVG) + RESID*SD] combinations are set to zero, with the remaining values transformed and scaled to sum to 1.0.

The algorithm therefore provides simulated time use proportions that approximately reproduce time use averages, variances and covariances as observed in the GSS data.

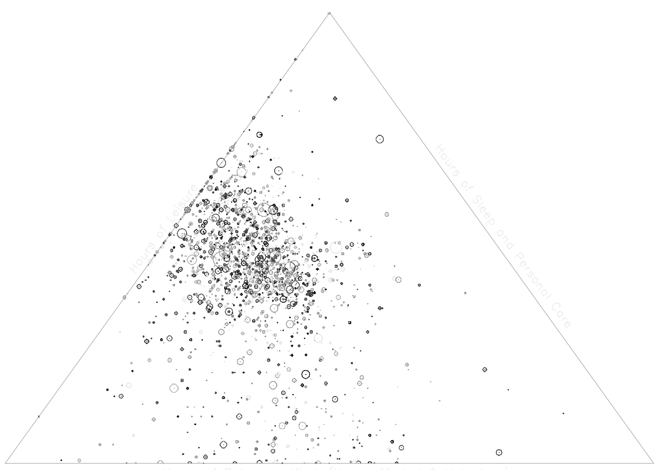
Women Employed
Time Use on Weekdays



Women Not Employed
Time Use on Weekdays



Men Employed
Time Use on Weekdays



Men Not Employed
Time Use on Weekdays