Center for Policy Research

Maxwell School of Citizenship and Public Affairs

2008

Fitting Event-History Models to Uneventful Data

Douglas A. Wolf
Syracuse University. Center for Policy Research, dawolf@maxwell.syr.edu

Thomas M. Gill
Yale School of Medicine ; Dorothy Adler Geriatric Assessment Center, gill@ynhh.org

ISSN: 1525-3066

Center for Policy Research
Working Paper No. 101

FITTING EVENT-HISTORY MODELS TO UNEVENTFUL DATA

Douglas A. Wolf and Thomas M. Gill

Center for Policy Research
Maxwell School of Citizenship and Public Affairs
Syracuse University
426 Eggers Hall
Syracuse, New York 13244-1020
(315) 443-3114 | Fax (315) 443-1081
e-mail: ctrpol@syr.edu

December 2007

$5.00

CENTER FOR POLICY RESEARCH – Fall 2007

Timothy Smeeding, Director
Professor of Economics & Public Administration

Associate Directors

Margaret Austin
Associate Director
Budget and Administration

Douglas Wolf
Professor of Public Administration
Associate Director, Aging Studies Program

John Yinger
Professor of Economics and Public Administration
Associate Director, Metropolitan Studies Program

SENIOR RESEARCH ASSOCIATES

Badi Baltagi.. Economics
Kalena Cortes………………………………Education
William Duncombe .... Public Administration
Gary Engelhardt ....Economics
Deborah Freund ....Public Administration
Madonna Harrington Meyer ....Sociology
Christine Himes.......................................Sociology
William C. Horrace ....Economics
Duke Kao ....Economics
Eric Kingson ....Social Work
Thomas Kniesner ....Economics
Jeffrey Kubik ....Economics
Andrew London......................................Sociology
Len Lopoo ....Public Administration
Amy Lutz………………………………… Sociology
Jerry Miner ....Economics
Jan Ondrich...Economics
John Palmer ....Public Administration
Lori Ploutz-Snyder.......................Exercise Science
David Popp............................Public Administration
Christopher Rohlfs ....Economics
Stuart Rosenthal ....Economics
Ross Rubenstein....................Public Administration
Perry Singleton……………………………Economics
Margaret Usdansky ....Sociology
Michael Wasylenko ....Economics
Janet Wilmoth ....Sociology

GRADUATE ASSOCIATES

Amy Agulay……………………Public Administration
Javier Baez ....Economics
Sonali Ballal ....Public Administration
Jesse Bricker ....Economics
Maria Brown....................................Social Science
Il Hwan Chung…………………Public Administration
Mike Eriksen ....Economics
Qu Feng ....Economics
Katie Fitzpatrick.....................................Economics
Chantell Frazier…………………………........Sociology
Alexandre Genest ....Public Administration
Julie Anna Golebiewski..........................Economics
Nadia Greenhalgh-Stanley ....Economics
Tamara Hafner....................... Public Administration
Sung Hyo Hong...................................... Economics
Neelakshi Medhi .... Social Science
Larry Miller .... Public Administration
Phuong Nguyen .... Public Administration
Wendy Parker .... Sociology
Shawn Rohlin... Economics
Carrie Roseamelia .... Sociology
Cynthia Searcy....................... Public Administration
Jeff Thompson .... Economics
Coady Wing .... Public Administration
Ryan Yeung .... Public Administration
Can Zhou .... Economics

STAFF

Kelly Bogart.…....………….…Administrative Secretary
Martha Bonney……Publications/Events Coordinator
Karen Cimilluca..…………..Administrative Secretary
Roseann DiMarzo…Receptionist/Office Coordinator
Kitty Nasto……..………….…Administrative Secretary
Candi Patterson......................Computer Consultant
Mary Santy……..……………Administrative Secretary

Abstract

Data with which to study disability dynamics usually take the form of successive current-status measures of disability rather than a record of events or spell durations. One recent paper presented a semi-Markov model of disability dynamics in which spell durations were inferred from sequences of current-status measures taken at 12-month intervals. In that analysis, it was assumed that no unobserved disablement transitions occurred between annual interviews. We use data from a longitudinal survey in which participants' disability was measured at monthly intervals, and simulate the survival curves for remaining disabled that would be obtained with 1- and 12-month follow-up intervals. The median length of an episode of disability based on the 12-month interval data is over 22 months, while the "true" median, based on the 1-month interval data, is only one month.

Douglas A. Wolf; Center for Policy Research, Syracuse University, Syracuse, New York 13244, USA. E-mail: dawolf@maxwell.syr.edu
Thomas M. Gill; Yale University School of Medicine; Dorothy Adler Geriatric Assessment Center, New Haven, CT 06504, USA. E-mail: gill@ynhh.org

JEL codes: C41, C81, I19
Keywords: Disability; semi-Markov process; duration analysis.

Fitting Event-History Models to Uneventful Data

An Event-History Analysis of Disability Dynamics

Cai et al. (2006) propose an algorithm for estimating the parameters of a semi-Markov event-history process using data in which backwards recurrence times—elapsed times since the most recent event—for initial spells are unknown. Because many prospective studies collect such data, Cai et al.'s "SMP-EM" approach appears to be quite useful. They illustrate their approach using disability data from the Medicare Current Beneficiary Survey (MCBS). The MCBS is a panel study of older people, in which subjects are periodically asked a series of questions about their functional capacities and their ability to carry out daily tasks. In the MCBS, these disability assessments are taken at 12-month intervals. As Cai et al. acknowledge, use of an event-history model with data of this sort necessitates assuming that at most, one disability transition can occur between adjacent annual observations.

Cai et al. find positive duration dependence in three of four of the transitions studied. Because virtually all past research on active life expectancy assumes that disability dynamics follow a first-order Markov process, Cai et al. conclude that their calculations based on the semi-Markov model are superior. Cai et al. note that it would be worthwhile to relax the implied assumption that there are no undetected events; our goal is to assess the consequences of the assumption, using data from a study in which disability assessments occurred at one-month intervals.

Measurement Problems Associated with Panel Current-Status Data

Panel data on disability of the sort collected in the MCBS are widely used for studies on disability dynamics, where they are used to calculate probabilities or rates of transitioning between various statuses. For example, both the Longitudinal Survey of Aging (Crimmins et al.

(1994)) and the Health and Retirement Survey (Reynolds et al. (2005)) collect current disability status at two-year intervals. Data with assessment intervals of four (Hidajat et al. 2007) and five (Lynch et al. 2003) years have also been used for this purpose. In nearly all studies of disability dynamics that employ such data, researchers treat the data as though they were generated by a discrete-state event-history process, and assume—as in Cai et al.—that there are no unobserved disability events. When interview times are one or more years apart, this assumption may be incorrect. For example, Hardy and Gill's (2004) analysis of data from the Precipitating Events Project (PEP), which assessed disability at one-month intervals, indicates that 65 percent of new disability episodes ended after only 1 or 2 months. Thus there might be numerous undetected disability spells when assessments are taken only at 1- or 2-year intervals.

The panel-data sources mentioned above collect data on current disability ***status*** but not on disability ***events***. The problems associated with an annual-monitoring design are illustrated in Figure 1. The figure displays nine hypothetical disability histories that occur over a three-year period. In the figure, a bold **D** indicates a month in which disability is detected by the annual-monitoring design. An italicized *D* indicates additional months of disability that are detected only by the monthly-monitoring design. Empty cells correspond to months without disability. A **U** indicates that a subject has been lost to follow-up at one of the annual follow-up times.

There are two types of error produced by the annual-monitoring design. The first is a variation on the familiar phenomenon of length-biased sampling (Zelen (2004)). Disability histories 1-3 include short disability spells that begin and end between months 1 and 11, and are therefore not detected by the annual-monitoring design. Because the undetected spells are short, on average, while spells in progress on month 12 can last arbitrarily long, the length-biased sample overstates the duration of disability spells.

The second type of error associated with the annual-monitoring design concerns measurement error among those spells that it does detect. Disability histories 4-9 in Figure 1 include disability spells that are in progress in month 12 and are therefore detected by the annual-monitoring design. Under the actuarial assumptions employed in the construction of ordinary life tables, events are assumed to be uniformly distributed over discrete time intervals. Thus, in the annual-monitoring design subjects coded as nondisabled in month m, disabled in month m + 12, and once again nondisabled in month m + 24, are considered to have experienced disability spells that lasted an average of 12 months. Disability histories 3 and 4 are of this type. The actuarial assumption also implies that censored disability spells in progress when observed in month m + 12 have an average elapsed duration of 6 months when censored. Disability history 5 in Figure 1 illustrates this situation; because this individual's history is unobserved in month m + 24, it must be considered censored at month m + 12. If the observation interval is large relative to the average duration of spells, as it turns out to be in the case of disability, then the actuarial assumption, in combination with the use of a time-aggregated duration measure, causes the length of spells to be overestimated.

Cai et al.'s attempt to measure the ***duration*** of disability spells exacerbates the measurement problems associated with the annual-monitoring design. Disability histories 7 and 8 in Figure 1 are observationally equivalent under the annual-monitoring design: using the annual measurements, both have completed durations of 24 months. However, it is apparent that history 8 consists of two shorter spells that happen to be in progress at months 12 and 24, respectively. Histories 6 and 9 depict the analogous problems for right-censored histories; in both cases, the spells in-progress in month 12 must be coded as censored at month 24, and in both cases will be treated as representing 18 months of exposure to risk.

Analysis with PEP Data

The suitability of "uneventful data" for fitting event-history models is a relatively unstudied issue. We address the question using data from the PEP study. Using PEP's monthly disability histories to represent the true underlying process, we simulate the disability indicators that would be obtained from an annual-interview design such as that used in the MCBS. We restrict our analysis to spells of disability with observed onset. We compare life-table estimates of the duration of disability episodes obtained from the annual and the monthly data.

The PEP study, which began in 1998, includes information collected from 754 members of a New Haven, Connecticut, health plan. All subjects were initially nondisabled, community-dwelling, and 70 or more years old; further details of the study design can be found in Gill et al. (2001) or Hardy and Gill (2004). In the present analysis, we used up to 85 months of data for a subsample of 752 "complete" cases, i.e. subjects for whom there is an uninterrupted series of two or more sequential disability assessments, ending in either (a) a month in which the disability indicator is missing, due to a missed or incomplete interview, or to participant drop-out, (b) right-censoring by the end of the observation period, or (c) death. At each interview, subjects are considered disabled if "at the present time" they either need help from someone else, or are unable to do, one or more of the following tasks: bathing themselves, walking around indoors, dressing themselves, or getting in or out of a chair.

In order to simulate annual-monitoring data of the sort used by Cai et al., we used PEP data to define a series of one-year disability-onset cohorts. Thus, any subject observed to be nondisabled at baseline (i.e., month 0), but disabled in month 12, was coded as beginning a spell of disability in the first year of the study. Subjects in that group who were also reported to be disabled in months 24, 36, and 48 were coded as remaining disabled for 2, 3, and 4 years, respectively. We adopted analogous procedures to create a cohort of subjects with onset in year two (i.e., nondisabled in month 12 but disabled in month 24), three, four, and so on, for a total of 6 onset cohorts. The annual–monitoring design produces a total of 228 disability spells with observed beginnings.

Figure 2 presents discrete-time survival curves based on life-table calculations, for three observation plans. The uppermost curve is produced by data from the annual-monitoring design with annual measurements, which corresponds to the MCBS data used by Cai et al. In this case failure times are coded 12, 24, 36, or 48 months, as described above. Linear interpolation indicates that the median survival time using this approach is about 22.2 months. The second curve uses the same 228 disability spells, but uses the exact duration, in months, of those spells at either failure or censoring times. The difference between the two survival curves results from the measurement error associated with the actuarial assumption. The bias due to the actuarial assumption is evident; when we use the actual monthly values for duration, the median survival time falls to 6 months.

The bottom curve in Figure 2 depicts survival in the complete sample of 1050 spells detected by PEP's monthly-monitoring design. Thus, the annual measurement scheme, which detects a total of 228 disability spells, misses almost 80 percent of the disability spells recorded in the PEP sample. Some of these additional spells result from recoding the apparently lengthy spells detected by the annual-monitoring design as two or more shorter spells (i.e., the situations depicted as histories number 8 and 9 in Figure 1). Others result from the inclusion of short spells overlooked by the annual-monitoring design (i.e., the situations depicted in histories 1-3 of Figure 1). In the monthly-monitoring sample, the median duration of a disability spell is 1 month. This agrees with results based on PEP data previously reported by Hardy and Gill (2004), which used data from the first 51 months of the PEP study. Although error bars are not shown in Figure 2, the "annual-monitoring design, annual measure" and "monthly-monitoring design, monthly measure" survival curves are significantly different at all relevant points of comparison. For example, for the former, S(12+) = 0.604 ± 0.066, while for the latter S(12+) = 0.076 ± 0.01. The biases produced by the annual disability measures would be considered unacceptably large by any reasonable standard.

Conclusion

As noted above, most applied research on disability dynamics and active life expectancy assumes that disability dynamics are Markovian. Cai et al. claim that their less-restrictive assumption that disability dynamics are semi-Markovian provides a more accurate representation of the underlying process. We suspect that most researchers whose work adopts the Markov assumption would readily admit that disability dynamics are non-Markovian, but that the assumption represents the best that can be done in view of the deficiencies of data available for studying disability. Land et al. (1994) fitted the parameters of a embedded Markov Renewal Process to disability histories taken at 12-month intervals, while Laditka and Wolf (1998) adopted a discrete-time approach, fitting an embedded Markov chain, defined on a one-month time scale, to disability data collected at 24-month intervals. In both cases, the methods relax the assumption that there are no missed events between assessments, but at the cost of imposing a strong Markov assumption. The discrete-time approach has since been applied in a number of additional studies of active life expectancy (e.g., Jagger et al. (2003), Kaneda et al. (2005), Pérès et al. (2005)). The results presented here cast strong doubt on analyses that use current-status measures collected at intervals of 12 or more months, yet fail to account for the possibility of unrecorded events. Researchers should carefully consider the measurement properties of their data, and take care to weigh the sometimes competing demands of realism and accuracy.

References

Cai, L., Schenker, N. and Lubitz, J. (2006) Analysis of functional status transitions by using a semi-Markov process model in the presence of left-censored spells. *J. R. Statist. Soc.* C, **55**, 477-491.

Crimmins, E.M., Hayward, M.D. and Saito, Y. (1994) Changing mortality and morbidity rates and the health status and life expectancy of the older population. *Demography*, **31**, 159-175.

Gill, T.M., Desai, M.M., Gahbauer, E.A., Holford, T.R. and Williams, C.S. (2001) Restricted activity among community-dwelling older persons: Incidence, precipitants, and health care utilization. *Ann. Internal Med.*, **135**, 313-321.

Hardy, S. and Gill, T. M. (2004) Recovery from disability among community-dwelling older persons. *JAMA*, **291**, 1596-1602.

Hidajat, M.M., Hayward, M.D. and Saito, Y. (2007) Indonesia's social capital for population health: the educational gap in active life expectancy. *Pop. Res. Policy Rev.*, **26**, 219-234.

Jagger, C., Goyder, E., Clarke, M., Brouard, N and Arthur, A. (2003) Active life expectancy in people with and without diabetes. *J. Pub. Hlth. Med.*, **25**, 42-46.

Kaneda, T., Zimmer, Z. and Tang, Z. (2005) Socioeconomic status differentials in life and active life expectancy among older adults in Beijing. *Disab. & Rehab.*, **27**, 241-251.

Laditka, S.B. and Wolf, D.A. (1998) New methods for analyzing active life expectancy. *J Aging Health*, **10**, 214-241.

Land, K.C., Guralnik, J.M. and Blazer, D.G. (1994) Estimating increment-decrement life tables with multiple covariates from panel data: The case of active life expectancy. *Demography*, **31**, 297-319.

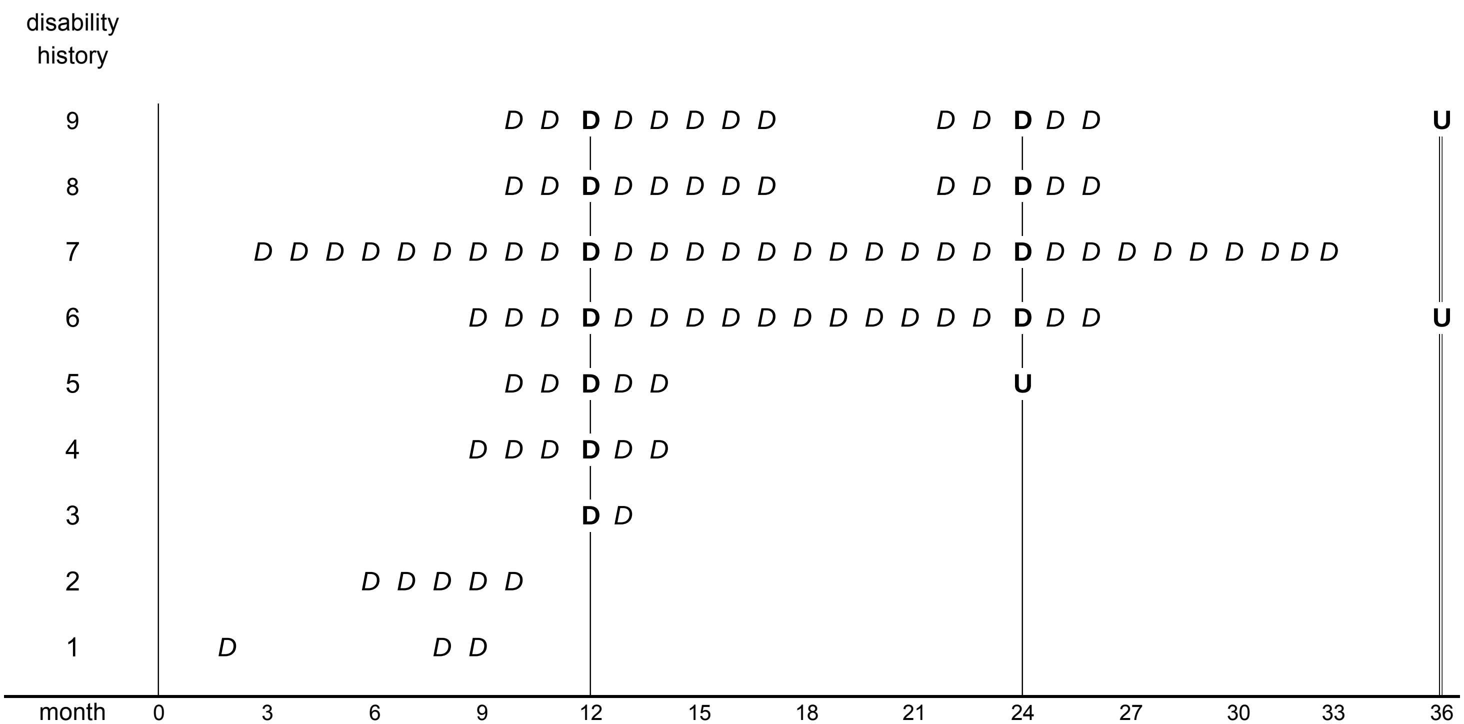
Lynch, S.M., Brown, J.S. and Harmsen, K.G. (2003) The effect of altering ADL thresholds on active live expectancy estimates for older persons. *J. Geron. Soc. Sci.*, **58**, S171-178.

Pérès, K., Jagger, C., Lièvre, A. and Barberger-Gateau, P. (2005) Disability-free life expectancy of older French people: Gender and education differentials from the PAQUID cohort. *Eur. J. Aging*, **2**, 225-233.

Reynolds, S.L., Saito, Y. and Crimmins, E.M. (2005) The impact of obesity on active life expectancy in older American men and women. *Gerontologist*, **45**, 438-444.

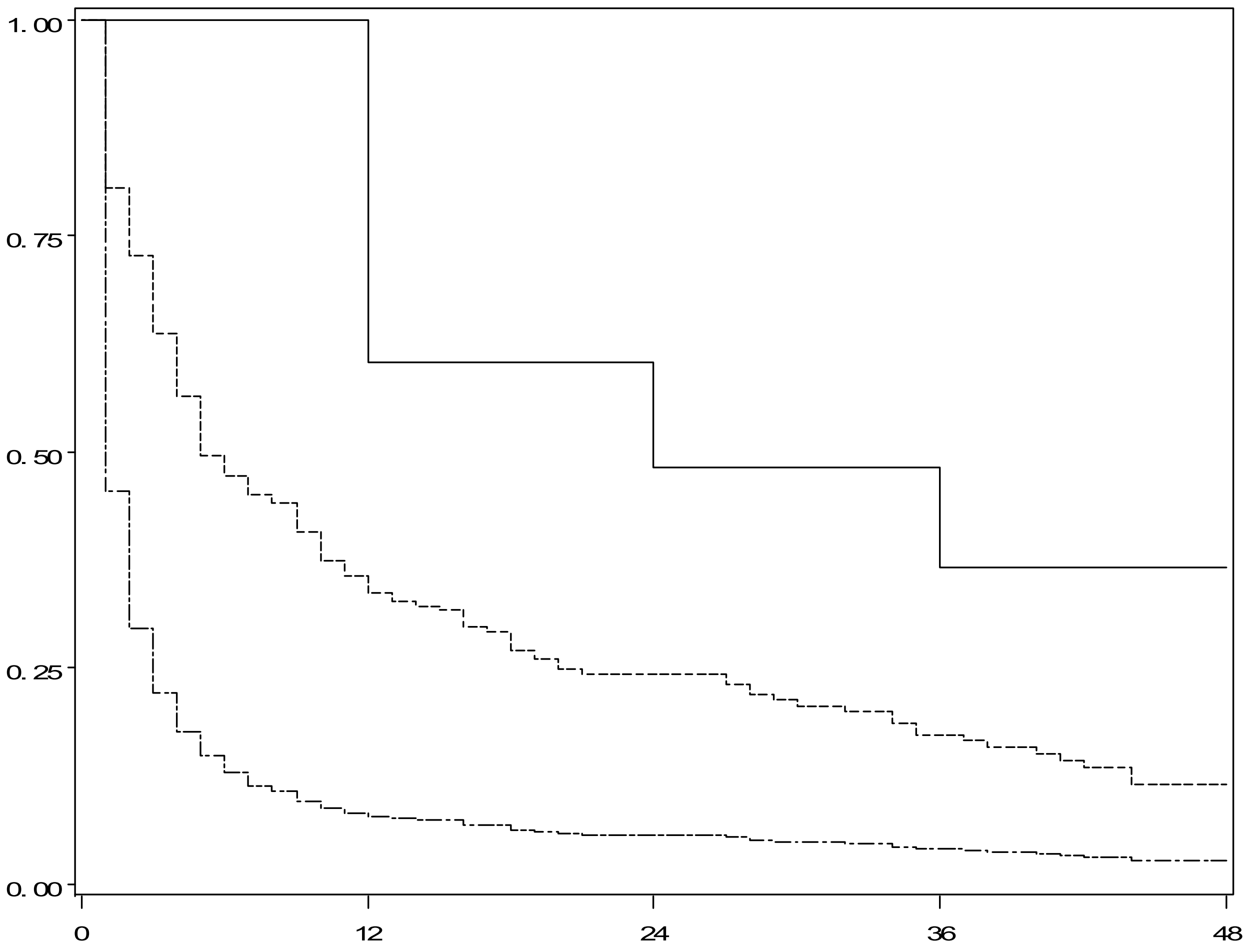
Zelen, M. (2004) Forward and backward recurrence times and length biased sampling: Age specific models. *Lifetime Data Analysis*, **20**, 325-334.

Fig. 1. Annual and monthly monitoring designs for detecting disability spells and measuring spell length



D: disability is present at annual follow-up
D: disability is present at monthly follow-up
U: disability is unknown at annual follow-up

Fig. 2. Survival curves for disability spells produced by three monitoring and measurement designs



Note: —— annual monitoring design, annual measure of duration
– – – annual monitoring design, monthly measure of duration
·–·–· monthly monitoring design, monthly measure of duration