The Duration of Medicaid Spells: An Analysis Using Flow and Stock Samples*

by

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Abstract

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We use unique data from the Medicaid program of the Commonwealth of Kentucky to examine the duration of Medicaid spells. The data set consists of a one in ten sample of all Medicaid recipients in Kentucky on July 1, 1986, and a similar sample of all new spells between July 1, 1986, and June 30, 1987.

Because the beginning date of Medicaid recipiency is known for all spells, this mixed "stock" and "flow" sample allows us to identify the duration of Medicaid spells up to 20 years. This is in contrast to other studies using short panels of new spells. We find significant differences in hazard functions across program eligibility categories, suggesting that the cost of expanding Medicaid or the savings from contracting it would vary depending on the eligibility group affected by the change in policy.

I. Introduction

Between 1980 and 1991, Medicaid financed health expenditures grew at a compounded growth rate of 10.5 percent despite a modest 2.2 percent growth in the number of recipients (Pine, Clauser, and Baugh, 1993). During the same period, state tax collections increased at a rate of 7.0 percent and revenue from the federal government to state governments grew at only 6.7 percent (U.S. Bureau of the Census, 1994, Table 477). Thus, Medicaid is putting an increasing burden on state budgets. In response, states have looked at different types of reform to control the Medicaid costs, from market competition in Arizona, to selective provider contracting in California, and to rate setting based on the Medicare DRG system in Pennsylvania. Other states and the federal government have also been considering changes in the Medicaid program as part of overall health care reform.

Medicaid is a complicated program with many eligibility categories (Gurney, Baugh, and Davis, 1993). Some individuals, such as those receiving Aid to Families with Dependent Children (AFDC) or Supplemental Security Income (SSI), are “categorically eligible.” Their eligibility for AFDC or SSI automatically qualifies them for Medicaid. Mandatory Medicaid eligibility extends to infants, children under 6, and pregnant and postpartum women with incomes at or below 133 percent of the federal poverty level. In addition, states have the option of covering other groups under the Medicaid program. States may extend coverage to infants and pregnant women up to 185 percent of the federal poverty level and other “medically needy.” Many of the medically needy are “spend down” cases, older individuals whose medical expenses have exhausted their assets.

The medical expenditures that the different Medicaid eligibility groups generate vary widely. In 1991, the average expenditures for recipients over age 65 were $7,617 (Pine, Clauser, and Baugh, 1993). For the disabled, average expenditures per recipient were $7,005. On the other hand, those who on average were in better health or had less severe conditions had much lower expenditures. For example, low income adults had average expenditures per recipient of $1,555 and for children the average was $902. Thus, expenditures differ substantially by eligibility category.

Total expenditures depend not only on average expenditures per recipient, but also on the number of recipients. The number of recipients, in turn, depends on the flow of new recipients into the program and their length of stay in the Medicaid program. Durations of eligibility are likely be different for low-income adult recipients, many of whom return to the labor force after a brief duration, and other categories, some of whom remain in the program for long spells. In addition, expenditures may also vary by length of time in the program. In attempting to limit Medicaid expenditures, policymakers could choose to limit average expenditures, restrict the flow of new recipients into the program, or limit of duration stays in the program.

Unfortunately, the effects of policies to limit durations are uncertain because we know little about durations of Medicaid spells. While not formally modeling program durations, Short, Cantor, and Monheit (1988) examine transitions on and off Medicaid using 32 months of data from the 1984 Survey of Income and Program Participation (SIPP) data. Welch (1988) estimates Weibull survival functions using disenrollment rates for a particular Medicaid HMO in Puget Sound. Ellwood and Adams (1990) estimate logistic exit functions from Medicaid for AFDC and AFDC related recipients in Georgia and California. Much work has been done to estimate durations of AFDC recipiency, and AFDC recipients are eligible for Medicaid. Some of the studies that have estimated models of duration of AFDC recipiency include O'Neill, Bassi, and Wolf (1987), Blank (1989), Engberg, Gottschalk, and Wolf (1990), Fitzgerald (1991), Meyer (1993), and Hoynes and MaCurdy (1994). Moffitt (1992) provides a review of dynamic models of welfare participation. AFDC recipients, however, are only a portion of Medicaid recipients and an even smaller portion of total Medicaid expenditures. No previous work has focused on the durations of those who qualify for Medicaid in other ways, such as SSI recipients and "spend-down" recipients.

In order to estimate Medicaid duration models, researchers need panel data that contain information on Medicaid recipiency. One obvious candidate is the Survey of Income and Program Participation. Data sets such as the SIPP are handicapped in several ways in estimating Medicaid durations, especially for non-AFDC recipients. SIPP follows individuals for 28 or 32 months so that analysts see only relatively short spells. Besides this right-censoring problem, there is left-censoring as well. There is no way to know when the spells of Medicaid began, which in the AFDC spell literature requires researchers to restrict their analysis to spells that begin after the start of the panel. Finally, the SIPP sample does not include the institutionalized population. Yet, this group generates the largest Medicaid expenditures per recipient, for Kentucky nearly 15 times greater than the AFDC recipients.

We examine Medicaid durations using a unique data set. The data set is a one in ten sample of Medicaid recipients in the Commonwealth of Kentucky as of July 1, 1986, and new entrants to the program between July 1, 1986, and June 30, 1987. Our data follows these 35,000 individuals until June 30, 1991, or the end of their Medicaid eligibility spell, whichever comes first. These administrative data provide observations on all program participants, including the institutional population, unlike other data sets that survey only the non-institutional population such as SIPP. As the institutional Medicaid population comprises a significant portion of all Medicaid expenditures, this group is of particular interest. Because of its very nature, administrative data provides a complete census of all Medicaid spells. There is no possibility of an underreporting of brief spells. This may occur in survey data if respondents forget short spells or find discussing spells of program enrollment unpleasant to discuss because of a stigma associated with enrollment.

We use data that contain ongoing, or “stock-sampled” spells that are not left-censored, as well as new or “flow-sampled” spells. After adjusting the likelihood function for the inherent length-bias problem associated with stock-sampled spells, we are able to provide estimates of hazard function for a very long period of time. For example, we are able to identify the hazard function for Medicaid SSI type recipients for 20 years. At the same time the new spells allow us to identify the early portions of the hazard function. This combination offers the most complete picture of Medicaid durations that has been available in the literature up to this time.

II. Duration Models with Mixed Flow and Stock Samples

Increasingly in economics, researchers are using panel data sets to measure the duration of certain events such as spells of employment (e.g., Light and Ureta, 1992 and Farber, 1994), spells of unemployment (e.g., Moffitt, 1985, and Meyer, 1990), spells without health insurance (e.g., Swartz and McBride, 1990, Klerman, 1992, and Swartz, Marcotte, and McBride, 1993a, 1993b), spells of AFDC recipiency (e.g. O’Neill, Bassi, and Wolf, 1987, Blank, 1989, Engberg, Gottschalk, and Wolf, 1990, Fitzgerald, 1991, Meyer , 1993, and Hoynes and MaCurdy, 1994), and spells of Medicaid recipiency (Short, Cantor, and Monheit, 1988, Welch, 1988, and Ellwood and Adams, 1990). When using these panel data sets, researchers confront a decision on how to draw their sample. In Figure 1, we depict a typical distribution of spells that we may observe in a panel data set. The panel data set covers a period from calendar time 0 to calendar time c_e. Some spells are ongoing at the time the panel begins, and hence they begin before calendar time zero. Other spells are new spells in the sense that they begin after calendar time zero. If researchers use the sample of ongoing spells, following Lancaster (1990) we refer to this sample as a "stock sample." If researchers use the sample of the new spells, again following Lancaster we refer to this sample as a "flow sample." The choice confronting researchers is whether to use the stock sample, the flow sample, or a mixed sample that use both the stock and flow samples. If a spell ends after calendar time c_e, we say the spell is censored, and in Figure 1, we mark the spell with a "o." If the spell ends before calendar time c_e, we say the spell is uncensored, and in Figure 1, we mark the spell with an "x."

Because we generally want to recover the parameters associated with the distribution of new spells, it appears natural to use the flow sample. An advantage of this approach is that numerous statistical packages provide procedures to estimate hazard functions for data in this form, which simplifies estimation of such models. In fact, most of the studies in the AFDC duration literature have followed this approach (i.e. O'Neill, Bassi, and Wolf, 1987, Blank, 1989, Engberg, Gottschalk, and Wolf, 1990, Fitzgerald, 1991, Meyer , 1993, and Hoynes and MaCurdy, 1994). Figure 1, however, highlights an immediate disadvantage of that strategy: the approach limits the length of spells in the sample to the duration of the panel. While this constraint may not be too severe for panels with extremely long panels such as the PSID, this may be an undesirable limitation for relatively short panels such as the SIPP. In addition, Klerman (1992) argues that those duration estimates excluding individuals with an existing spell will be biased downward because they exclude some relatively long spells. Another potential problem with the approach of using a flow sample only is that there may be relatively few observations initiating new spells in short panels.

By using stock samples, researchers may avoid these problems. Because ongoing spells may include spells that have lasted a long time, this sample may prove to be informative about the hazard function well in excess of the c_e periods, which is the inherent limit of flow samples. This advantage is not, of course, without a cost. As Figure 1 indicates, researchers are not able to identify the hazard function for relatively short spells. Because stock samples must have survived from the time their spells began to calendar time zero to be in the sample, stock samples provide no information about spells shorter than the shortest duration of the stock sample at calendar time zero. In addition, as Swartz, Marcotte, and McBride (1993b) ague, without adjustments, estimates from ongoing spells suffer from length bias because relatively long spells are overrepresented.

While a mixed sample of flow- and stock- sampled observations allows the identification of the hazard function for both long and short spells, the use of a mixed sample requires us to adjust the likelihood function to reflect the presence of stock-sample observations. The problem is even more difficult if the starting date of the stock-sampled spells is unknown. Klerman (1992) and Swartz, Marcotte, and McBride (1993b) use mixed samples from the SIPP to estimate spells without health insurance when the date the spell began is unknown; see Lancaster (1991) for a discussion of the estimation of duration models when the date the spell begins is unknown. Fortunately, we know the beginning date of the stock-sampled spells in our data, which makes the problem more tractable. Wang, Brookmeyer, and Jewell (1993) provide a discussion of the problem and an application to the AIDS literature.

To see what the likelihood function looks like in the presence of both stock-sampled and flow-sampled observations, let us first consider the case of flow data with no censoring. In this exposition, we shall first consider the case of a parametric model with no unobserved heterogeneity. We wish to model the durations of a single spell, and we assume a homogeneous environment so that the length of the spell is uncorrelated with the calendar time in which the spell begins.

Let the density function of durations given by

(1) $$f(t, x, \beta)$$

where t is the duration of the spell, x is a vector of (time-invariant) covariates, and β is a vector of parameters. Importantly, we assume that $f(t, x, \beta)$ does not vary over time. If we have a sample of n observations, $\{t_1, t_2, \ldots, t_n\}$, the likelihood function of the sample is

(2) $$L(\beta) = \prod_{i=1}^{n} f(t_i, x_i, \beta).$$

Often times it is not possible to observe all spells until they end, and hence often spells are censored on the right-hand side. Let the set A be the set of all observations where the spells are completed and the set B be the set of all observations where the spells are right-hand censored. Clearly A and B are disjoint sets whose union is exactly the set of observation. For the set of censored observations, all we know is that the actual length of the spell is greater than t_j, the observed length of the spell. If we let F(t,x,β) denote the cumulative distribution function, the probability that a spell lasts longer than length t° is simply 1- F(t°,x,β). Define the survivor function S(t,x,β) ≡ 1 - F(t,x,β), and we may write the likelihood function as

(3) $$L(\beta) = \prod_{i \in A} f(t_i, x_i, \beta) \times \prod_{i \in B} S(t_i, x_i, \beta).$$

Define the hazard function h(t,x,β) ≡ f(t,x,β) / S(t,x,β), and applying the definition of the hazard function, we may rewrite the likelihood function as

(4) $$L(\beta) = \prod_{i \in A} h(t_i, x_i, \beta) \times \prod_{i \in A \cup B} S(t_i, x_i, \beta),$$

which is a standard likelihood function for a parametric duration model with right-hand censoring.

To introduce stock sampling, let the set C be the set of observations that were in progress when data collection began. For these observations, we know that the spell has lasted for r periods before the panel begins so that the probability that the total spell length will be t, given that the spell has lasted until time r, is simply given by

(5) $$\frac{f(t, x, \beta)}{S(r, x, \beta)}.$$

Because we are sampling spells that are already in progress, these observations enter the sample only if the spells are at least of length r. We must adjust these observations by the conditional probability of the spell having length r. With the addition of these observations, we may write the likelihood function as

$$(6)\qquad L(\beta) = \prod_{i \in A} h(t_i, x_i, \beta) \times \prod_{i \in A \cup B} S(t_i, x_i, \beta) \times \prod_{i \in C} \frac{f(t_i, x_i, \beta)}{S(r_i, x_i, \beta)}.$$

If we convert the last term in equation (6) to a hazard function, the likelihood function becomes

$$(7)\qquad L(\beta) = \prod_{i \in A \cup C} h(t_i, x_i, \beta) \times \prod_{i \in A \cup B \cup C} S(t_i, x_i, \beta) \times \prod_{i \in C} \frac{1}{S(r_i, x_i, \beta)}.$$

The third term of the right-hand side of equation (7) reflects the adjustment necessary for our stock sample. Because stock-sampled observations, by definition, must have survived until time r, that they survived until time r provides no information. Their survival is an artifact of the sampling strategy.

Of course, some stock-sampled observations may be right-hand censored. Let the set D be the set of all stock-sampled observations that are also right-hand censored. A stock sampled observation that is right-hand censored at time t occurs with probability

$$(8)\qquad \frac{S(t, x, \beta)}{S(r, x, \beta)},$$

so that the likelihood function becomes

$$(9)\qquad L(\beta) = \prod_{i \in A \cup C} h(t_i, x_i, \beta) \times \prod_{i \in A \cup B \cup C \cup D} S(t_i, x_i, \beta) \times \prod_{i \in C \cup D} \frac{1}{S(r_i, x_i, \beta)}.$$

In equation (9), the censored, stock-sampled observations' contributions to the likelihood function are strictly from the last two terms; such observations simply provide information about the survivor function between (r,t).

Unlike the approach that Lancaster's derives, we estimate the underlying parameters of $f(t,x,\beta)$ while conditioning on r. To get a feel for what this approach entails, it is helpful to think of t as being discrete. In this case, $f(t,x,\beta)$ becomes a probability mass function (pmf) and the survivor function may be written as

(10) $$S(t,x,\beta) = \prod_{i=0}^{t-1}[1-h(i,x,\beta)] .$$

Applying the definition of a hazard function, we may then express the pmf $f(t,x,\beta)$ as

(11) $$f(t,x,\beta) = S(t,x,\beta)\,\frac{f(t,x,\beta)}{S(t,x,\beta)} = \left[\prod_{i=0}^{t-1}[1-h(i,x,\beta)]\right]h(t,x,\beta) .$$

Using this expression for the pmf, we may rewrite equation (5) as

(5') $$\frac{f(t,x,\beta)}{S(r,x,\beta)} = \left[\prod_{i=r}^{t-1}[1-h(i,x,\beta)\right]h(t,x,\beta) .$$

The only contributions that the observation makes to the likelihood function are for those periods between (r,t) when the agent is at risk of exiting the program. Because the stock sampling assures that the agent will be sampled only if t ≥ r. Similarly, we may rewrite equation (8) as

(8') $$\frac{S(t,x,\beta)}{S(r,x,\beta)} = \left[\prod_{i=r}^{t-1}[1-h(i,x,\beta)\right]$$

so that, again, the only contributions that this observation makes to the likelihood function are for those periods between time (r,t) when the agent is at risk of exiting the program.

III. Data and Background

The data set used to examine the duration of Medicaid spells is a one in ten sample of the administrative records of every individual receiving Medicaid in the Commonwealth of Kentucky as of July 1, 1986, or beginning a new spell of Medicaid recipiency between July 1, 1986, and June 30, 1987. We follow the recipients until they exit the Medicaid program or until June 30, 1991.[1] For those who were on the program as of July 1, 1986, the data include the date the spell of recipiency began, allowing use to correct for any left-censoring problems. In addition, these administrative data include limited demographic information on each recipient: date of birth, race, gender, and the last county of residence. We use these data to construct a series of variables to control for the age structure of the population, gender, race and location of residence. Unfortunately, we are not able to identify family members.

Kentucky divides its Medicaid recipients into five major groups: the Aged, Blind, and Disabled Categorically Needy (ABDCN), Aid to Families with Dependent Children categorically needy (AFDC), the Aged, Blind, and Disabled Medically Needy (ABDMN), Medical Assistance for families with Children (MAC), and "other needy recipients."[2] We use four of the five major Medicaid recipient groups in this study. We exclude the “other needy recipients” from the study because they make up a small share of total recipients (1.6 percent in fiscal 1991) and receive only Medicare services as part of the Medicare Catastrophic Care Act of 1988.

Of the four groups, AFDC recipients are the largest; they comprised 49.6 percent of Kentucky’s Medicaid recipients in fiscal year 1991. These are individuals in families that have received AFDC or are part of the AFDC unemployed parent (AFDC-UP) program. While numerous, AFDC recipients receive only 19.9 percent of all Medicaid benefits at an annual cost of about $1144 per recipient in fiscal year 1991. Recently, Medicaid rolls in Kentucky have increased dramatically as a result of the requirements of the Family Support

[1]We call a completed spell one in which there is more than a one month interruption in Medicaid eligibility. We treat cases in which the interruption is less than one month as a continuous spell. Many of these cases occur when the recipient is changing from one eligibility category to another and there is not a real interruption in eligibility.

[2]For more details on the Kentucky Medicaid System, see Kentucky Cabinet of Human Resources (1992). This is the source for the summary data on the Kentucky Medicaid System presented in this section.

Act of 1988. After several years of virtually no growth, the AFDC Medicaid rolls increased nearly 11 percent in fiscal year 1990 and 19 percent in fiscal year 1991.

The Medical Assistance for families with Children (MAC) group comprised 16.6 percent of recipients in fiscal 1991. With average expenditures of $2,661 per recipient, the MAC group accounted for 15.5 percent of Medicaid expenditures. This group is comprised mainly of children in families not eligible for AFDC (or SSI), but who qualify for Medicaid in Kentucky because of unemployment, death, absence or incapacity of a parent, or are low-income, pregnant women. Kentucky is one of many states to choose the option of providing Medicaid coverage to these low income groups. Together, the AFDC and MAC recipients in Kentucky correspond to the sum of the federal Medicaid categories of adults and children in low income families. In fiscal year 1991, the average expenditure per recipient for the combined AFDC-MAC group was $1,524, while the national average for adults and children in low income families was $1,271.

The other two major groups are made up of aged, blind, and disabled recipients. The Aged, Blind, and Disabled Categorically Needy (ABDCN) is comprised primarily of Supplemental Security Income (SSI) recipients, although Kentucky, as most states, allows recipients of state supplementation to receive Medicaid.[3] This group accounts for 28.0 of Medicaid recipients and 39.5 percent of Medicaid expenditures, with expenditures per recipient averaging $4,005 in fiscal year 1991. The Aged, Blind and Disabled Medically Needy (ABDMN) group is primarily made up of "spend-down" cases, i.e., aged who have exhausted their assets and have illnesses that require extended treatment that Medicare will not cover. This group comprised only 4.2 percent of recipients in fiscal 1991. Nevertheless, with average expenditures of $16,902 dollars per recipient in fiscal 1991, they account for 24.8 percent of Medicaid expenditures. Expenditures on nursing homes account for 71.6 percent of this group's expenditures. Even excluding nursing home expenditures, however, the average expenditure for a recipient is $4,795, which still makes them the most expensive group on a per capita basis. The expenditures per recipient in Kentucky in fiscal 1991 for the combined ABDCN and ABDMN groups were $5,677, while the U.S. average for the comparable combined aged and disabled recipient groups were $7,282.

[3]In 1990, 32 states allowed some individuals receiving state supplementation to receive Medicaid; see U.S. Health Care Financing Administration (1991) for details.

Overall, Kentucky's Medicaid program is similar to numerous states. It covers a large number of optional services and serves populations similar to the U.S. as a whole. Table 1 provides a comparison of the characteristics of the overall and Medicaid populations in Kentucky and the U.S. According to the U.S. Health Care Financing Administration (1991), in 1986 the age and gender compositions of the Medicaid population in Kentucky and the U.S. were roughly similar. The fraction of total expenditures going to the young was somewhat higher in Kentucky and the fraction going to the old was somewhat lower in Kentucky.[4] This is consistent with the result that average expenditures are higher in Kentucky than the U.S. for AFDC/MAC recipients who tend to be younger, and lower for ABDCN/ABDMN recipients who tend to be older. Perhaps the biggest difference between Kentucky's Medicaid program and the national average is the lower payments per recipient, due to lower rates of reimbursement to providers in Kentucky and a different mix of services provided to Kentucky recipients. The average payment per Medicaid recipient across all jurisdictions in the U.S. in 1986 was $1,822 compared to $1293 in Kentucky.[5] A similar difference existed in fiscal year 1991: an average payment per recipient of $2,752 for the U.S., and $2,284 for Kentucky (Silverman, 1993, Table 16.12).

Table 1 also shows that there are differences in the characteristics of the overall populations in Kentucky and the U.S. According to the 1990 Census of Population and Housing, the age and gender composition of the U.S. and Kentucky populations are quite similar. Kentucky, however, has a much lower fraction of its population that is black and is living in urban areas. Median family income in Kentucky is substantially below that for the U.S. and a higher percentage of its families are below the poverty line. The unemployment rate in Kentucky is higher than the U.S. average and the labor force participation rate is lower. Finally, the proportion of adults who have completed high school and college is below the national average.

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[4] This was also the case in fiscal year 1991 (Silverman, 1993, Table 16.12).

[5] U.S. Health Care Financing Administration (1991, Table 4.21). According to Table 4.16, Kentucky Medicaid recipients were less likely to use hospitals and nursing homes and more likely to use physician visits than the average U.S. Medicaid recipient. The Kentucky mix of services, with a greater emphasis on physician visits and less emphasis on hospital and nursing home days, helps in part explain the lower expenditures per recipient in Kentucky.

IV. The Duration of Medicaid Spells

A. Nonparametric Estimates

In Table 2, we present some descriptive statistics for each of our four subsamples: AFDC, MAC , ABDMN, and ABDCN. We provide statistics on the number of observations, the percentage of uncensored observations, and some percentiles of the empirical distribution function. (We provide percentile estimates at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles or until censoring does not allow us to obtain estimates.) The empirical distribution is the distribution of the length of spells since July 1, 1986 for the stock sample --what we term "net spell" because in this table we ignore the portion of the spells prior to July 1, 1986 -- and is the distribution of the total length of spells for the flow sample.

A quick glance at Table 2 provides several interesting observations. First, any attempt to pool our four groups appears totally inappropriate; each group has very different empirical distribution functions. In addition, the data do not support the hypothesis that the distribution of spells is exponential. If the distribution of spells was exponential, the distribution function of the net spells of the stock sample and the distribution of spells of the flow sample should be the same; see Heckman and Singer (1984) for a proof. While some of the lower percentiles of the stock and flow samples are quite similar, a quick comparison of the medians of the flow and stock samples for each of samples indicates that the stock sample has much larger median of net spells than the median of the flow samples. Table 2 also demonstrates that the AFDC and MAC populations provide a majority of the new cases, 38.3% and 40.3% respectively. In contrast, ABDMN comprises only about 8.6% of the new cases, and the ABDCN comprise only 12.9% of the cases. Among the MAC sample, there is very little problem with censoring, with only 1% of the stock sample being censored.

Somewhat hidden in Table 2, however, is the fact that the data for all four samples exhibited extreme spikes at the end of months. For instance, for the AFDC population there was only 1 spell of length 178 days, 1 of length 179, 48 of length 180, 21 of length 181, 58 of length 182, 81 of length 183, 1 of length 184, and none of length 185. Clearly, the data are not from a continuous distribution. As a result, we estimate the hazard functions as discrete (monthly) functions. We use the first 15 days as month zero, the first month is from day 16 to day 45, the second month is from day 46 to day 76, *et cetera*.[6] We estimate a monthly hazard function for month t as

$$\hat{h}_t = \frac{d_t}{n_t} \tag{12}$$

where d_t is the number of spells that end in month t and n_t is number of individuals at risk during month t. We define an individual at risk if the month falls between July 1986, and June 1991, in calendar time.

For instance, consider individuals in the stock sample who begin their spell on January 1986. For the first 181 days of their spell they are not at risk. Because they are members of the stock sample, we know with probability one they could not exit between January 1986 and June 1986. Any time before they exit the program between July 1986 and the next 60 months, the individuals are at risk. At month 67 of their spells, they are no longer at risk and hence are not members of n for those months. This estimate is the discrete time Kaplan-Meier estimates of the hazard function; see Kalbfleisch and Prentice (1980) for a more detailed discussion.

In Figures 2 through 6, we provide a graphical depiction of the hazard functions for 10 years for the ABDMN group, for 20 years ABDCN group, and 15 years for the group, and for 9 years of data for the MAC group. The ABDMN group exhibits a very high hazard rate in the first three months, then it falls sharply. As this group is aged, the high hazard rate probably reflects high mortality rates of this population. Interestingly, after the first 12 months, the hazard rate becomes reasonably constant for this ten-year period. This group is quite expensive to treat, and our analysis suggests that after surviving the first 12 months, the expected duration of program participation for such a patient is reasonably long. The median falls in the 7th month for this group, but over 10% of the sample survive at least 5 years. Toward the end of our ninth

[6] We actually center our estimates of each month around 365.25/12=30.44 days to correspond to the exact length of the year. By centering our estimates about multiples of 30.44 days, we can estimate monthly hazard rates without being too concerned about the precise length of the month.

year of data, the number of exits becomes rather small and hence the estimate of the hazard function somewhat volatile, but there are 160 or more at risk for any monthly observation.[7]

The second most expensive group, the ABDCN group, has a much lower hazard function. It too, however, is relatively high in the first few months of program participation, averaging over 4.5% in the first 8 months of enrollment. After about two years, however, the hazard function falls and remains more or less constant at a very low rate. Unlike the hazard function for the ABDMN group, which appears declining over time, the ABDCN hazard function appears much more volatile in the first two years of program participation. The median occurs in the 19th month for this group, but nearly 12% of the population survive 10 years. Using the mixed flow and stock samples provides us with a very large data set: the sample size of those at risk never falls below 290 even at the end of the 20 year period.

The AFDC population has a very high hazard rate in the first eight months, averaging over 9.5% during this period. Indeed, after one year, fewer than 36% of participants remain on the program, and the median spell length occurs in the 7th month. The sharp spike in the first few months suggests that few people remain on AFDC for extended periods of time in Kentucky. Indeed, less than 10% of participants are on the program for 4 years. After about 5 years, however, monthly hazard rates fall to about 3% to 2% a month range, with some evidence of the hazard rate drifting down. Again, the mixed stock and flow sample results in very large data set: the number at risk never falls below 350 in our data.

If we compare our survival function estimates for the AFDC group to those that Blank (1989) reports, we find that the exit rates from Kentucky's Medicaid system are considerably higher than those in the SIME/DIME experiments that Blank analyzes. For instance, in her Table 5, Blank reports that for Seattle program participants the chances of the spell lasting longer than 6 months was at least 65% and was at least 30% for lasting longer than two years. In contrast, we have only a 56% chance of a spell lasting longer than 6 months and 20% chance of a spell lasting two years. Similarly, Meyer (1993) reports that

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[7] The variance of the estimate of the hazard, $Var(h_t)$ is

$$Var(h_t) = \frac{h_t\,(1-h_t)}{n_t},$$

where n_t is the number of recipients at risk in month t.

33% of Wisconsin AFDC recipient have a spell that lasts at least two years. Using data from the NLS Young Women cohort, O'Neill, Bassi and Wolf (1987) report that the probability of a spell lasting two years is over 38%. Kentucky has some of the lowest AFDC payments of any state. This low level of support may explain some of the differences in the exit rates. Another possibility is that in data sets that rely on self-reporting of program participation, program participants fail to report short spells of program participation, perhaps because of a stigma associated with program participation or perhaps they simply forget short spells.

The MAC group also has a very high initial hazard, but exhibits another spike about month 14, probably signaling the end of pregnancy and postpartum eligibility. As a result of these two spikes, participants exit the program very quickly. The median occurs in the 6th month. Only about 6% of participants are in spells that last longer than two years, and only about 0.67% remain for the full five year period we present compared with the next lowest five year survival rate of 6.7% for the AFDC group.[8]

The data from each group seems to exhibit a common feature of a relatively sharp spike in the first few months of program participation. Blank (1989) and McDonald and Butler (1990) found a similar spike in their analysis of AFDC spells. We find, however, spikes in all four recipiency groups. Because we are using administrative data that capture all spells, we know that we are not missing short spells and that the spikes in the hazard functions are real features of the data. One reason that the spikes may occur is that eligibility for the Medicaid program is very complex in all eligibility categories. Some individuals may be initially eligible, for example through meeting "spend-down" criteria, but then become ineligible after a short period of time, perhaps because of income considerations.

The spikes in the hazard functions make it extremely difficult to fit a parametric hazard function to the data. We regressed the estimated Kaplan-Meier hazard functions against a quartic of time for each of the groups, weighted by the number of recipients at risk in each month.[9] Across every group, the largest residuals from such a regression were associated with observations from the spikes. Given that a quartic is

[8] The number at risk never falls below 185 in our sample.

[9] For the AFDC and ABDCN population, we limited our data to the first 10 years.

a reasonably flexible functional form, this suggests that attempts to fit a standard parametric model to the data are likely to be unsuccessful. Fortunately, as Meyer (1990) emphasizes, semiparametric models allow for very flexible specifications of the hazard functions.

B. Semiparametric Estimates

The nonparametric estimates of the hazard function are consistent only if the underlying population is homogenous. One may expect, however, that the characteristics of the recipients may well affect the length of their spell. Importantly, not controlling for characteristics that affect the hazard rate biases the estimates of the hazard function downward; see Heckman's and Singer's (1984) Proposition 1 for a formal proof. Thus, the spikes that we found in the first few months of the spells may be underestimated.

To model the impact of covariates on the hazard function, we could assume an explicit form of the density function and use maximum likelihood methods to get estimates of the parameters. Unfortunately, theory provides little guidance about the distribution of Medicaid spells. If the data were continuous, we could use the Cox (1972) approach. Cox suggests that we assume the hazard function is of the form

$$h(t, x, \beta) = \lambda_0(t)\, e^{x\beta}, \tag{13}$$

where x is a vector of (time invariant) covariates, β is the corresponding vector of parameters, and $\lambda_0(t)$ is the baseline hazard function.[10] In essence, $\lambda_0(t)$ is an infinite dimensional nuisance parameter that we wish to avoid estimating. Using a marginal likelihood function, it is possible to obtain estimates of β without estimating the baseline hazard function, $\lambda_0(t)$. Once we obtain estimates of β, the baseline hazard function may be recovered; see Kalbfleisch and Prentice (1980) for details.

When data are discrete, we may use the approach of Kalbfleisch and Prentice (1973) and Prentice and Gloeckler (1978) to estimate the coefficients using maximum likelihood methods. See Meyer (1988) for an extended discussion, McCall (1990) for an application to occupational choice, and Meyer (1990) for an application to the duration of unemployment. For this approach, the hazard function is

[10]The method of estimation can also use time varying covariates; see Meyer (1988, 1990) or Kalbfleisch and Gloeckler (1978).

(14) $$h(t,x,\beta) = 1-(1-h_t)^{\exp(x\beta)}$$

where h_t is a parameter that we must estimated, x is a vector of covariates, and β is the corresponding vector of parameters. If we set β = 0, notice that the hazard function in equation (14) is equivalent to the Kaplan-Meier estimate of equation (12).

Cox (1972) and Moffitt (1985) propose alternative specification of the hazard function. Cox proposes

(15) $$\frac{h(t,x,\beta)}{1-h(t,x,\beta)} = \frac{h_t}{1-h_t} e^{x\beta},$$

which is closely related to the logit model. Moffitt estimates

(16) $$h(t,x,\beta) = h_t\, e^{x\beta}.$$

As Kalbfleisch and Prentice (1980) suggest, we use Kaplan-Meier estimates of the monthly hazard functions to derive starting values for the vector h. For starting values of the β vector we use a vector of zeros as well as estimates from a Cox model based on a subsample of new spells.

In discrete time, these hazard functions have a simple interpretation. To see why, we collect the contribution of each observation to the likelihood function for time t, which is

(17) $$L_t(\beta) = \prod_{i\in\alpha} h_t(x_i,\beta) \prod_{i\in a} (1-h_t(x_i,\beta))$$

where α is the set of recipients who exit the program at time t and *a* is the set of recipients who are at risk at time t but do not exit the program. The hazard function is the conditional probability that a spell will end in period t given that it has survived for (t-1) periods. An estimate of that probability would be to estimate a logit model for each period to calculate that probability. Such an approach, however, would involve a very large number of parameters because the β parameters would be estimated for each period. The approach of Cox is in essence to estimate a logit model for each period, but to constrain the β parameters to be the same each period. The approach of Kalbfleisch and Prentice (1973) and Moffitt (1985) simply represent different ways of estimating the probabilities.[11] In principle, one could choose any specification, assuming that the estimated probabilities stayed between zero and one.

We limit our analysis only to the ABDMN group.[12] We present the results in Table 3.[13] The age profile reaches a peak between 35 and 40, and then declines. It turns up again at age 85.[14] Those elderly that enter the program around age 85 appear to have the longest spells among the elderly, and their spells are considerably longer than those who enter into the program in their thirties and forties. Similarly, female recipients have substantially longer spells. Interestingly, when we evaluated at the means of all covariates, the plots of the implied hazard functions were all very similar to the Kaplan-Meier hazards. Perhaps most surprisingly, however, is the similarity in the parameter estimates: all three models provide extremely similar parameter estimates for the covariates.

A disadvantage of the semi-parametric approach with discrete data is the large number of nuisance parameters that we need to estimate, 61 in our case. One approach to reducing the number of parameter in the model is to aggregate the sample into fewer periods. Sometimes in small data sets there are relatively

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[11] Meyer (1990) notes that in using the Moffitt's model, researchers cannot be assured that the estimated probability will be between (0,1). In our application, however, the estimated probabilities were always between zero and one. To avoid this problem in the Kalbfleisch and Prentice estimator, Kalbfleisch and Prentice (1980) recommend the following transformation: $\gamma_i \equiv \ln(-\ln(1-h_i))$.

[12] Other data sets such as SIPP will contain recipients from the other three groups and will have more detailed controls. SIPP does not contain, however, a sample of the institutional population and hence will miss most ABDMN recipients.

[13] For the Cox model, we used zero as starting values of all coefficients. For the other two models, we used the Kaplan-Meier estimates for the baseline hazard parameters and zero for the coefficients for the covariates for the starting values. To conserve on the number of nuisance parameters, we limited our analysis to the first five years (60 months) of data.

[14] While most of the recipients in the program are elderly, there are a few younger recipients. For instance, 1.3% of the recipients are younger than 20, 1.9% are between 20 and 29, 2.9% are between 30 and 39, 2.7% are between 40 and 49, and 6.7% are between 50 and 59. In contrast, 21.4% are older than 85.

few or no observed failures in a period so that aggregation may improve the accuracy of the estimate of the base line hazard. Such aggregation, however, is not without a cost. To see why, suppose that we aggregate all the monthly hazard rates within year one and two. We would then be discarding information about the rankings of individuals within the year two.

To get a feel for how such aggregation would affect the parameter estimates, in Table 4 we present estimates where we have aggregated our data into 16 categories: one each for months 0 through 6, one for each of the next two quarters, and one for each half-year until the end of the 5th year. This represents a great deal of aggregation; the number of coefficients for the baseline hazard is reduced from 61 to 16. Yet, a comparison of Tables 3 and 4 indicates that the parameter estimates are relatively unchanged by our aggregation. Interestingly, there is less agreement on the parameter estimates among the three models after aggregation than before we aggregated the data.

C. Unobserved Heterogeneity

If our admittedly limited demographic controls exclude some important heterogeneity in our samples, the estimates will be biased. To guard against this possibility, following Meyer (1990) we re-estimate the model assuming that the distribution of heterogeneity is gamma with the normalization that the mean equals one. The log-likelihood function in such a model is

$$(17) \qquad \Lambda(\beta,\gamma) = \sum_{i=1}^{n} \ln\left(\{[1+\sigma^2 \sum_{j\in R_i-1} \exp(\gamma_j + x_i\beta)\}^{-\sigma^{-2}} - \delta_i \{1+\sigma^2 \sum_{j\in R_i} \exp(\gamma_j + x_i\beta)\}^{-\sigma^{-2}} \} \right),$$

where δ_i is an indicator variable that is equal to one when i is an element of $A \cup C$, which is the set of all recipients who exit the program rather than being censored.

We estimated equation (17). At Bruce Meyer's suggestion, we demeaned the data and used the implied Kaplan-Meier estimates for the baseline hazard parameters (γ_i's) and zero for the β_i's. The estimated β_i's are

$$(18)\quad x_i\,\beta = \underset{(4.01)}{0.201}\,age - \underset{(4.42)}{0.352}\,(age^2/100) + \underset{(4.10)}{0.018}\,(age^3/10{,}000) + \underset{(1.73)}{0.257}\,black - \underset{(3.41)}{0.328}\,female - \underset{(0.73)}{0.065}\,urban$$

The largest change in coefficients is drop in the coefficient on age cubed. The resulting age profile still peaks between ages 30 and 40 but no longer turns up about age 85. Similarly, the coefficient on blacks increased substantially and becomes significant at the 10% level. The implied hazards are similar, with some drifting apart in the later years. The presence of unobserved heterogeneity cannot be rejected. What could this unobserved heterogeneity be? One unobservable in administrative data is health status. One might expect that those in poorer health are more likely to remain on Medicaid. While we cannot measure health status directly, we can observe expenditures, which are presumably related to health status.[15]

V. Medicaid Expenditures and Program Duration

In this section, we examine the relationship between Medicaid expenditures and amount of time on the program. In each of the four groups (ABDCN, ABDMN, AFDC, MAC) we regress log of Medicaid expenditures during fiscal year 1987 (July 1, 1986 through June 30, 1987) on demographics (female, black, urban, and a quartic of age), the fraction of fiscal 1987 that the recipient was eligible for the program (a quadratic in the fraction of year on program and dummy indicating whether the eligibility spell ends in fiscal year 1987), and a quartic measuring length of time the individual has been on the program. In Figure 7 we graph expenditures against time in the program.

In Figure 7, we plot the log differences in expenditures among those with various lengths of eligibility and expenditures of those entering the program. Among ABDMN recipients, after an initial dip, expenditures rise up to 10 years of eligibility. For ABDCN recipients, an early, steep rise is followed by relatively constant expenditures. AFDC and MAC expenditures fall over the early years of eligiblity and then turn up slightly. Thus not only do expenditures per recipient differ dramatically across program eligibility categories, but expenditures appear to vary with program duration. We can combine the results

[15] We do not include expenditures as a proxy for health status in our duration models because we are unable to observe them prior to fiscal year 1987. Thus, we would not have any previous expenditure data for anyone in our stock sample.

shown in Figure 7 with our earlier estimates of program duration to discuss the likely effects of policy changes on Medicaid expenditures.

One policy change that has been discussed recently has been to limit AFDC eligibility to two years. If this also applied to Medicaid eligibility, there would be some reduction in expenditures, but it would likely be less than expected for several reasons. First, as we saw in the duration analysis, AFDC eligibles have much shorter spells than other recipient groups so a lower percentage of them will reach the limit. Second, AFDC recipients have lower expenditures per recipient than other eligibility groups. Finally, the results in this section suggest that expenditures decline with length of spell. Therefore, even within the AFDC group, it would be the below-average expenditure recipients whose eligibility spells would be limited, reducing the potential savings.[16]

VI. Conclusions

We examine the duration of Medicaid spells using a unique data set from the Commonwealth of Kentucky. We estimate hazard models for a one in ten sample of all Medicaid recipients in Kentucky on July 1, 1986, and new recipients who entered the program between July 1,1986, and June 30,1987. Because the beginning date of ongoing spells is available for ongoing spells, the combination of "old" and "new" spells in our data allow us to identify very long hazards, in some cases up to 20 years. This is in contrast to other studies that use only new spells over relatively short periods of time. For example, the SIPP is limited to 28 or 32 months of new spells. Of course, the use of administrative data does not come without some cost. There are a limited number of available covariates, especially when compared with panel data sets such as SIPP.

In addition, we provide the first estimates of hazard models of Medicaid recipients outside the AFDC population. Recipients in these groups generate the highest Medicaid expenditures. Changes in the durations of this group would produce the largest increases or decrease in Medicaid expenditures. Limiting the duration of AFDC and thus Medicaid recipiency, as has been recently proposed in Congress, would produce much smaller savings in Medicaid than would limiting the duration of other groups.

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[16] Of course, another reason reductions in expenditures would not be as great as anticipated is that recipients would be likely to increase their medical expenditures as their period of eligibility approaches an end by taking care of problems they may have been putting off, by filling prescriptions early, etc.

In all recipiency groups we find a spike in the hazard function in the first two or three months. Non-administrative data may miss these short spells. Also, these spikes make it difficult for parametric models to track the data very well. After the spikes, the hazards decline in all recipiency groups. Because the hazard is not constant over time, the longer average spells from the sample of ongoing spells do not look the same as the shorter average spells from the sample of new spells. Thus, correcting for length bias turns out to be important in these data. Similarly, using just the sample of new spells would not allow us to identify long hazards as we are able to do by including the sample of ongoing spells.

Of course, we would have preferred to combine extensive data on the demographics of recipients with the long spells available using administrative data. The data sets that have extensive demographic data, however, such as the SIPP have the problem that the potential spell lengths are very short and do not cover the entire Medicaid population. Perhaps longer panels with a broader set of demographic information will become available in the future. Until then, studies such as ours offer important insights into the Medicaid durations of different eligibility groups and thus into the dynamics of total Medicaid expenditures.

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Table 1: Comparison of Kentucky and U.S. Populations and Medicaid Populations

Medicaid Population, 1986[a]	**Kentucky**	**U.S.**
Percent of Population Receiving Medicaid	11.1	9.3
Percent Age 0-20	51.2	50.3
Percent Age 21-64	34.1	33.5
Percent Age 65 and Over	14.7	16.2
Percent Female	62.7	64.0
Distribution of Payments:		
Percent Age 0-20	25.3	19.6
Percent Age 21-64	44.6	41.1
Percent Age 65 and Over	30.1	39.3

Population, 1990[b]	**Kentucky**	**U.S.**
Percent Age 0-19	29.2	28.7
Percent Age 20-64	58.1	58.7
Percent Age 65 and Over	12.7	12.6
Percent Black	7.1	12.3
Percent Female	51.6	51.3
Percent Urban	51.8	75.2
Median Family Income	$27,028	$35,225
Percent of Families Below Poverty Level	16.0	10.0
Labor Force Participation Rate	60.5	65.3
Unemployment Rate	7.4	6.3
Percent of Individuals Age 25 and Over Who Have Completed High School	64.6	75.2
Percent of Individuals Age 25 and Over Who Have Completed College	13.6	20.3

[a] Source: Health Care Financing Program Statistics, *Medicare and Medicaid Data Book, 1990*
[b] Source: 1990 Census of Population and Housing

Table 2: A Comparison of the Stock and Flow Samples

AFDC	Flow Sample	Stock Sample
Observations	2,124	14,862
Uncensored	84.1%	80.2%
Percentiles	Spell Length (days)	Net Spell Length (days)
5th	60	61
10th	86	91
25th	120	214
50th	213	608
75th	654	1,460

MAC	Flow Sample	Stock Sample
Observations	2,232	5,483
Uncensored	99.96%	99.0%
Percentiles	Spell Length (days)	Net Spell Length (days)
5th	29	30
10th	56	30
25th	87	91
50th	152	214
75th	303	487
90th	487	1,095
95th	792	1,552

ABDMN	Flow Sample	Stock Sample
Observations	476	1,174
Uncensored	83.6%	78.9%
Percentiles	Spell Length (days)	Net Spell Length (days)
5th	19	61
10th	30	122
25th	70	303
50th	211	792
75th	790.5	1,583

ABDCN	Flow Sample	Stock Sample
Observations	714	10,256
Uncensored	59.8%	55.2%
Percentiles	Spell Length (days)	Net Spell Length (days)
5th	58	122
10th	89	214
25th	183	1,460
50th	776.5	---

Table 3: Comparison of Cox, Moffitt, and Kalbfleisch-Prentice Models Coefficients

Covariates	Cox Model	Moffitt Model	Kalbfleisch-Prentice Model
recipient's age	0.146 (3.28)	0.147 (3.40)	0.147 (3.34)
age squared /100	-0.260 (3.47)	-0.258 (3.58)	-0.259 (3.53)
age cubed /10000	0.134 (3.38)	0.132 (3.48)	0.133 (3.43)
recipient is black	0.028 (0.21)	0.027 (0.22)	0.028 (0.22)
recipient is a female	-0.385 (4.92)	-0.349 (4.81)	-0.368 (4.87)
recipient is an urban resident	-0.020 (0.28)	-0.023 (0.34)	-0.021 (0.30)
Log Likelihood values	-3388.70	-3385.96	-3387.38

Table 4: Comparison of Cox, Moffitt, and Kalbfleisch-Prentice Models Coefficients, Aggregated Sample

Covariates	Cox Model	Moffitt Model	Kalbfleisch-Prentice Model
recipient's age	0.166 (3.57)	0.141 (3.41)	0.153 (3.49)
age squared /100	-0.295 (3.76)	-0.247 (3.60)	-0.270 (3.68)
age cubed /10000	0.152 (3.66)	0.127 (3.50)	0.139 (3.58)
recipient is black	0.027 (0.19)	0.013 (0.11)	0.019 (0.15)
recipient is a female	-0.401 (4.92)	-0.333 (4.81)	-0.366 (4.86)
recipient is an urban resident	-0.022 (0.30)	-0.015 (0.22)	-0.018 (0.30)
Log Likelihood values	-2511.03	-2512.23	-2511.64