View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Research Papers in Economics

The Lengths of Psychiatric Hospital Stays and Community Stays

Fredrick Holt
Peat, Marwick

Elizabeth Merwin
University of Virginia

Steven Stern*†
University of Virginia

November 1998

Abstract

We use advanced survival analysis methods to estimate the parameters affecting the joint distribution of exit dates from psychiatric hospitals and return dates to those hospitals. Data comes from Virginia state psychiatric hospital administrative records. We find that sex, marital status, employment status, diagnosis, and age help explain durations. We also find that there is significant duration dependence and unobserved heterogeneity which suggest that earlier analyses in this field that used simpler estimation methods were flawed.

JEL codes: I12, I18, C41

*The corresponding author is Steven Stern, Department of Economics, University of Virginia, Charlottesville, VA 22903.

†The data and tabulations utilized in this paper were available through the Virginia DMHMRSAS. The data were originally collected by state mental health facilities. Neither the original source nor collectors of the data maintain any responsibility for the analyses or interpretations presented here. This project was supported by NIMH R29 MH48968-02, NIMH R01 MH53259-01A2, and Southeastern Rural Mental Health Research Center grant NIMH P50 MH49173.

1. Introduction

The public policy of deinstitutionalization has predominated mental health planning and decision-making in recent decades. The government and consumer groups have joined together to find ways to decrease the state mental hospital inpatient population. There is a consistent belief in the need to reduce the utilization of inpatient care that has resulted in a decline from 413,066 state mental hospital beds in 1970 to 93,058 in 1992 (Redick et al. 1996). However, there is ongoing concern about the utilization of inpatient care. Particular concern relate to the length of inpatient stays and the readmission to inpatient care following discharge. State mental hospitals have longer median lengths of stays for discharged clients than other types of psychiatric inpatient facilities (Rosenstein et. al. 1990). A study including data from eleven states on all of the state psychiatric hospitals clients for a four year time period showed that 25% of the clients were hospitalized for over four years (Leginski et. al. 1990). Of the clients with lengths of stay less than four years, 50% had one or more prior inpatient visits within four years. Fisher, et. al. (1992) empirically challenged the accepted belief that increasing community resources for the provision of outpatient and other types of community based care reduces the use of inpatient care, particularly through decreasing readmissions. They used a naturally occurring experiment where a set of counties had twice the community resources as other counties in the state. Although there was less utilization of inpatient care, it was due to less use by long term patients than by patients with stays of 90 or fewer days. Survival analysis was used to show that there was little difference in community tenure among the regions. They determined that in all but one region, there was a 50% chance that a patient discharged from a state hospital would not be readmitted in four years.

Due to the cost of inpatient care and its restriction on the freedom of clients, there is continual effort to find ways to reduce its utilization. This study explores in depth the characteristics of clients and communities that influence the length of inpatient stay and length of the stay in the community following discharge from inpatient care, termed community tenure, for clients treated in state hospitals of the Virginia Department of Mental Health, Mental Retardation, and Substance Abuse Services (DMHMRSAS). Its findings offer additional information on the utilization of inpatient care, particularly on factors that influence length of stay and subsequent community tenure. In order to reduce further the use of inpatient care, it is necessary to understand the relationship between length of stay and the pattern of care within the inpatient stay and subsequent community tenure.

This study considers the effect of inpatient length of stay and diagnosis on subsequent community tenure. It also incorporates information about a client's community as a way to consider the influence of community resources on utilization. The results can be used by census reduction programs and as a means to identify profiles of individuals at greater risk for recidivism. Section 2 describes the data. Section 3 describes the survival analysis techniques and details of the empirical specification used. Section 4 presents results.

2. Data

The main source of data is the master demographic file for the Patient/Resident Automated Information System (PRAIS) provided by DMHMRSAS. The file contains 134,236 records between 1978 and 1992, each of which details an episode for an individual in one of Virginia's eight public adult psychiatric hospitals. Each record includes a unique patient identifier; patient demographic characteristics; administrative information collected at the patient's admission and discharge, including beginning and ending dates for the episode; and psychiatric diagnosis codes.

This data contains patient stays which occurred both before and after the PRAIS system came on line. The first important step in the formation of our data set was to choose all episodes which began after the relevant hospital was using PRAIS.[1] This selection criterion reduced the number of observations from 134,236 to 7,256. Several variables were recoded into a more usable form. These variables include race, marital status, legal status, and employment status. The DSMIV diagnostic codes were also recoded into thirteen diagnostic categories in a two step process: a) they were grouped into 32 diagnostic codes based on a coding scheme used by NIMH with their Client Sample Surveys; b) then they were aggregated into the thirteen groups based on clinical similarities and cell sizes in each group.

Histories were then constructed for each individual in the data set. The beginning and ending dates of a hospital stay are given in the data. A constructed community tenure is the length of the span of time between hospital stays or, corresponding the last observed hospital stay, the length of the span of time after

[1] Each hospital converted to PRAIS at a different time. The first conversion was in April, 1991, and the last was in February, 1992. Only this data is used because it is richer than the data available prior to the implementation fo PRAIS.

that hospital stay until the data truncation point. The 5,847 individuals in the data set experienced 7,256 hospital stays and 6,316 community stays.

Several steps were taken to minimize the effect of missing variables. If we observed a county code at either admission or discharge but not both, we set the missing county code equal to the observed county code. Also, we assumed the race and sex of individuals did not change over episodes, and that the age of individuals changed in the expected increment over episodes. This allowed us to fill in missing race, sex, and age variables for individuals who had more than one episode.

Next, it was necessary to reject all observations for which race, marital status, age, county code, legal status, diagnosis, or employment status, was missing. A detailed missing variables analysis is presented in Table 1. After these rejections, the number of hospital stays was reduced to 5,662, and the number of community stays fell to 4,797. These observations make up the data set used in this study. Table 2 indicates what portion of these episodes were censored. Not surprisingly, a large portion (3,700) of the community stays are censored because of right censoring. A smaller number (765) of the hospital stays are censored. The average hospital length of stay was 41.7 days, and the average community tenure was 140.3 days.

As a final step, the data set was supplemented by information from the Area Resource File (ARF) provided by the Bureau of Health Professions. This file contains county and city aggregate data on variables such as patient care psychiatrists, nurses, a rural indicator, percent urban, percent black, median education, population in corrections facilities, and other variables. These variables were normalized by county population. The county level variables represented various years from 1980-1990; it would have been optimal to have all variables from one point in time, but generally the change in these variables is consistent over time. There is also some concern for this data that some "zeroes" in the data are really either missing or occur in rural counties due to sampling problems. Nevertheless, there is no better alternative data with similar information.

Table 3 provides names and definitions of the variables, and Table 4 provided the means and standard deviations for the explanatory variables from the ARF and the PRAIS file for both hospital stays and community stays. There is little difference between the means of the explanatory variables for hospital stays and community stays. An exception to this is that individuals entering a community stay live in counties with more long term psychiatric hospitals than those beginning a hospital stay. This documents the concern of communities regarding the migration of clients to areas near state hospitals. The "typical" individual in the data is a white, unmarried, unemployed male in his late thirties, although there is a disproportionately large number of blacks in the data relative to the population as a whole. The most commonly assigned diagnosis is schizophrenia followed by bipolar disorders and then alcohol and other depressive disorders.

Some smoothed Kaplan-Meier survival curves were generated from the data. We computed these curves for blacks and whites for both community stays and hospital stays. For example, Figure 1 shows that the probability of still remaining in the community after 100 days is approximately 54% for whites in the data and 57% for blacks in the data. At 200 days, these probabilities are approximately 27% and 32%. Figure 2 shows that the probability of still remaining in the hospital after 100 days is 11% for whites in the data and 15% for blacks in the data. At 200 days these probabilities are 3% and 5%. It is noteworthy that the curve for blacks is everywhere above the curve for whites for hospital stays. This is surprising because later results show that the marginal contribution of being black to the hazard rates for both types of spells is positive. This indicates that the higher survival curve for blacks in Figure 2 results from factors correlated with being black and not from the marginal effect of being black itself.

3. Empirical Specification

3.1. Basic Model

Let t_{ij}^h be the length of the jth psychiatric hospital stay for individual i, and let t_{ij}^c be the jth community stay for individual i. Assume i has n_i^h hospital stays and n_i^c community stays. Let $d_{ij}^h = 1$ if the jth hospital stay was censored, and let $d_{ij}^h = 0$ otherwise. Define d_{ij}^c analogously for community stays. Let X_{ij}^h be a set of explanatory variables for the jth hospital stay, and let X_{ij}^c be a set of explanatory variables for the jth community stay. Then the conditional hazard rate at time τ is modeled as

$$\lambda_{ij}^k \left(\tau \mid X_{ij}^k, \varepsilon_{ij}^k\right) = \exp\left\{X_{ij}^k \beta^k + g^k(\tau) + \varepsilon_{ij}^k\right\} \tag{3.1}$$

for $k = h$ or c. This is the standard proportional hazards model (Cox, 1972). The baseline hazard $g^k(\cdot)$ is modelled as a piecewise linear spline function (Meyer, 1990):

$$g^k(\tau) = \sum_{\ell=0}^{m-1} \overline{g}_l^k \left(\overline{\tau}_{\ell+1}^k - \overline{\tau}_\ell^k\right) + \overline{g}_m^k \left(\tau - \overline{\tau}_m^k\right) \tag{3.2}$$

for $\overline{\tau}_m^k \leq \tau \leq \overline{\tau}_{m+1}^k$. The $\overline{g}^k$ variables are the slopes, and the $\overline{\tau}^k$ variables are the nodes. We fix the nodes and estimate the slopes. The unobserved heterogeneity, ε_{ij}^k, takes different forms. In the simplest case, we assume there is no unobserved heterogeneity. In the next case, we assume ε_{ij}^k does not vary over j but is independent over k and i. In the most general case, we still assume ε_{ij}^k does not vary over j but allow ε_{ij}^h and $\varepsilon_{i\ell}^c$ to be correlated. In all cases, we use a 4-point Gaussian quadrature approximation to the normal distribution following Lillard (1993). We also tried using a generalization of the 2-point discrete distribution approximation described in Heckman and Singer (1984) allowing for unspecified correlation but found convergence properties of the optimization algorithm were not as nice.[2]

The likelihood of observing a set of spell lengths t_{ij}^h, $j = 1, 2, ..., n_i^h$ and t_{ij}^c, $j = 1, 2, ..., n_i^c$ is

$$L_i = \sum_{e^h} \sum_{e^c} \prod_{k=h}^{c} \prod_{j=1}^{n_i^k} b_k \left(t_{ij}^k, d_{ij}^k \mid X_{ij}^k, \varepsilon_{ij}^k \right) \Pr \left[\varepsilon_{ij}^h = e^h, \varepsilon_{ij}^c = e^c \right] \tag{3.3}$$

where e^k takes on values implied by the covariance matrix of $\left(\varepsilon^h, \varepsilon^c\right)$ and the 4-point Gaussian quadrature approximation and

$$b_k \left(t_{ij}^k, d_{ij}^k \mid X_{ij}^k, \varepsilon_{ij}^k \right) = \left[\lambda^k \left(t_{ij}^k \mid X_{ij}^k, e^k \right) \right]^{1-d_{ij}^k} \exp \left\{ - \int_0^{t_{ij}^k} \lambda^k \left(s \mid X_{ij}^k, e^k \right) ds \right\}$$

is the contribution to the likelihood, conditional on $(\varepsilon_c, \varepsilon_h)$, for $\left(t_{ij}^k, d_{ij}^k\right)$.The log likelihood function is

$$L = \sum_{i=1}^{N} \log L_i. \tag{3.4}$$

It is maximized over $\theta = \left(\beta^h, \beta^c, \overline{g}^h, \overline{g}^c, \Omega\right)$ where Ω is the covariance matrix of $\left(\varepsilon^h, \varepsilon^c\right)$.

For most of the analysis, the set of explanatory variables used will consist of those listed in Table 1. In addition, there are two spike variables. The first is equal to 1 for the three days before and the two days after one's committed days end for hospital stays. This allows for a high hazard rate when committed days

[2] The joint distribution of the unobserved heterogeneity variables is conditional on having a hospital stay and is therefore not the same as for the U.S. population. However, it is really this conditional distribution which is of most relevance for policy.

run out. The other is equal to 1 for the first seven days of a hospital stay for those admitted under a temporary detention order (TDO).

The nodes for the baseline hazard are 7 days, 15 days, 31 days, 50 days and 60 days. Thus we estimate six $\overline{g}^k$ slopes for each type of spell.

Some of the analysis is presented in terms of the probability of remaining (either in the hospital or in the community) at time t. This probability, called the survivor curve, is defined in terms of the hazard rate as

$$S_{ij}^k(t) = \int \exp\left\{-\int_0^t \lambda_{ij}^k\left(\tau \mid X_{ij}^k, \varepsilon_{ij}^k\right) d\tau\right\} \phi^k\left(\varepsilon_{ij}^k\right) d\varepsilon_{ij}^k \tag{3.5}$$

where ϕ^k is the density of ε_{ij}^k.

3.2. Controlling for Left Censoring

It is well known that discarding the first left-censored community stay leads to inconsistent parameter estimates when there is unobserved heterogeneity (Heckman and Singer, 1985 and Lancaster, 1990). This occurs because one is undersampling long community stays and long hospital stays relative to their distribution in the population. A number of reasons suggest ignoring this problem. First, we are not really interested in the population distribution of unobserved heterogeneity; rather we are interested only in the distribution for those people who enter a psychiatric hospital. Given our interest, if our sample consisted only of people whose first hospital stay was observed, there would be no consistency problem. We would be specifying the joint distribution of the subpopulation of interest. However, since many of the observations are missing the first hospital stay, we suffer the above mentioned problem even for our subpopulation of interest. Heckman and Singer (1985, p.86-87) suggest a correction to the likelihood function which is implemented to some degree in Gritz (1993). But most authors with similar data structures follow Heckman and Singer (1948b) who suggest ignoring the first left-censored episode[3] because the correction involves estimating a number of other parameters that are not much interest.

We do construct, however, an estimator that controls for the effect of left censoring so that we can determine the importance of left censoring. Let τ be the time of the first entry into the hospital since time 0, and let $\kappa\left(\tau \mid X_{ij}^c, \varepsilon_c\right)$ be the "intake rate" at time τ as defined in Heckman and Singer (1984). Note that

[3] See, for example, Ham and Rea (1987), Blank (1989), Butler, Anderson, and Burkhauser (1989), Gunderson and Melino (1990), Johnson and Ondrich (1990), and Meyer (1990).

$\kappa\left(\tau \mid X_{ij}^c, \varepsilon_c\right)$ depends upon X_{ij}^c and ε_c but not X_{ij}^c and ε_h; this is because we are conditioning on the person being in the community at time 0, and τ is the first time they enter the hospital (it is directly related to the community hazard rate. Then, generalizing Heckman and Singer (1984),

$$L_i = \frac{\sum_{e^h}\sum_{e^c} \kappa\left(\tau \mid X_{ij}^c, \varepsilon_c\right) \prod_{k=h}^{c} \prod_{j=1}^{n_i^k} b_k\left(t_{ij}^k, d_{ij}^k \mid X_{ij}^k, \varepsilon_{ij}^k\right) \Pr\left[\varepsilon_{ij}^h = e^h, \varepsilon_{ij}^c = e^c\right]}{\sum_{e^h}\sum_{e^c} \kappa\left(\tau \mid X_{ij}^c, \varepsilon_c\right) \Pr\left[\varepsilon_{ij}^h = e^h, \varepsilon_{ij}^c = e^c\right]} \tag{3.6}$$

It is assumed in equation (3.1) that $\lambda_{ij}^k\left(\tau \mid X_{ij}^k, \varepsilon_{ij}^k\right)$ depends upon X_{ij}^k and ε_{ij}^k only through an index

$$z_{ij}^k = X_{ij}^k \beta^k + \varepsilon_{ij}^k.$$

If we assume that $\kappa\left(\tau \mid X_{ij}^c, \varepsilon_c\right)$ depends upon X_{ij}^c and ε_c only through z_{ij}^c, then equation (3.6) becomes

$$L_i = \frac{\sum_{e^h}\sum_{e^c} \kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right) \prod_{k=h}^{c} \prod_{j=1}^{n_i^k} b_k\left(t_{ij}^k, d_{ij}^k \mid X_{ij}^k, \varepsilon_{ij}^k\right) \Pr\left[\varepsilon_{ij}^h = e^h, \varepsilon_{ij}^c = e^c\right]}{\sum_{e^h}\sum_{e^c} \kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right) \Pr\left[\varepsilon_{ij}^h = e^h, \varepsilon_{ij}^c = e^c\right]} \tag{3.7}$$

where $z_{ij}^c\left(\varepsilon_c\right)$ is explicitly denoted as a function of ε_c so that it is clear where dependence on realizations of unobserved heterogeneity occurs. Following Heckman and Singer (1984), we propose to model $\kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right)$ as a nonparametric function in two arguments, τ and $z_{ij}^c\left(\varepsilon_c\right)$.

One way to do this is to create a grid defined by $\{\overline{\tau}_k\}_{k=1}^{m_\tau}$ and $\{\overline{z}_k\}_{k=1}^{m_z}$, treat $\kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right)$ as an extra set of $m_\tau m_z$ parameters to estimate, and interpolate $\kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right)$ between grid points. Note that an interpolation scheme should be picked that allows for easy integration. Also note that any monotone transformation of $z_{ij}^c\left(\varepsilon_c\right)$ or $\kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right)$ that increases $\kappa^*\left(\tau \mid z_{ij}^c\left(\varepsilon_c\right)\right)$ proportionally at all points has no effect on equation (3.7). Let $\tau_{\max}$ be a value greater than the largest τ in the data. Let

$$\kappa^*\left(\tau \mid z^c\right) = \kappa^+\left(\widetilde{\tau}, \widetilde{z}^c\right) \tag{3.8}$$

where $\widetilde{\tau} = \frac{\tau}{\tau_{\max}}$ and

$$\widetilde{z}^c = \frac{z^c - z_{\min}^c}{z_{\max}^c - z_{\min}^c}; \tag{3.9}$$

i.e., $\widetilde{\tau}$ and $\widetilde{z}^c$ are normalized to be between 0 and 1. For $\overline{\tau}_k \leq \widetilde{\tau} \leq \overline{\tau}_{k+1}$ and $\overline{z}_l \leq \widetilde{z}^c \leq \overline{z}_{l+1}$, define $\zeta_\tau(\overline{\tau}_k) = \overline{\tau}_{k+1}$, $\zeta_\tau(\overline{\tau}_{k+1}) = \overline{\tau}_k$, $\zeta_z(\overline{z}_l) = \overline{z}_{l+1}$, $\zeta_z(\overline{z}_{l+1}) = \overline{z}_l$, and

$$\kappa^+(\widetilde{\tau}, \widetilde{z}^c) = \frac{\sum_{\tau=\overline{\tau}_k}^{\overline{\tau}_{k+1}} \sum_{z^c=\overline{z}_l}^{\overline{z}_{l+1}} \omega(\widetilde{\tau} - \zeta_\tau(\tau), \widetilde{z}^c - \zeta_z(z^c)) \kappa^+(\tau, z^c)}{\sum_{\tau=\overline{\tau}_k}^{\overline{\tau}_{k+1}} \sum_{z^c=\overline{z}_l}^{\overline{z}_{l+1}} \omega(\widetilde{\tau} - \zeta_\tau(\tau), \widetilde{z}^c - \zeta_z(z^c))} \tag{3.10}$$

where $\kappa^+(\tau, z^c)$ are parameters to be estimated at the values where it is evaluated in equation (3.10) and $\omega(\widetilde{\tau} - \zeta_\tau(\tau), \widetilde{z}^c - \zeta_z(z^c))$ is the weighting function used in Brien, Lillard, and Stern (1998):

$$\omega(\widetilde{\tau} - \zeta_\tau(\tau), \widetilde{z}^c - \zeta_z(z^c)) = |\widetilde{\tau} - \zeta_\tau(\tau)|^r |\widetilde{z}^c - \zeta_z(z^c)|^r \tag{3.11}$$

for some power r. Note that,

a) when $\widetilde{\tau}$ is a grid point (let's say $\overline{\tau}_k$), then neither $\kappa^+(\overline{\tau}_{k-1}, z^c)$ nor $\kappa^+(\overline{\tau}_{k+1}, z^c)$ recieves any weight (this implies that $\kappa^+(\widetilde{\tau}, \widetilde{z}^c)$ is continuous at grid lines and grid points);

b) if $r \geq 1$, then $\kappa^+(\widetilde{\tau}, \widetilde{z}^c)$ is differentiable at grid lines and grid points; and

c) if $r < 2$, then $\kappa^+(\widetilde{\tau}, \widetilde{z}^c)$ has a derivative bounded from zero (almost always) in neighborhoods of grid lines and grid points.

Thus we pick $1 < r < 2$.[4]

4. Results

Table 5 presents coefficient estimates assuming there is no unobserved heterogeneity. The estimates measure how the predicted log hazard rate changes with the observed characteristic. For example, the log hazard for hospital stays is 0.251 higher for married people than single people; a married person leaves the

[4] Consider integration of $\kappa^+(\widetilde{\tau}, \widetilde{z}^c)$. Let $\overline{\tau}_k \leq \tau^* \leq \overline{\tau}_{k+1}$ and $\overline{z}_l \leq z^{c*} \leq \overline{z}_{l+1}$. Then

$$\int_{\overline{\tau}_k}^{\tau^*} \int_{\overline{z}_l}^{z_c^*} \kappa^+(\widetilde{\tau}, \widetilde{z}^c)\, d\widetilde{z}^c d\widetilde{\tau} =$$

$$\int_{\overline{\tau}_k}^{\tau^*} \int_{\overline{z}_l}^{z_c^*} \frac{\sum_{\tau=\overline{\tau}_k}^{\overline{\tau}_{k+1}} \sum_{z^c=\overline{z}_l}^{\overline{z}_{l+1}} \omega(\widetilde{\tau} - \zeta_\tau(\tau), \widetilde{z}^c - \zeta_z(z^c)) \kappa^+(\tau, z^c)}{\sum_{\tau=\overline{\tau}_k}^{\overline{\tau}_{k+1}} \sum_{z_c=\overline{z}_l}^{\overline{z}_{l+1}} \omega(\widetilde{\tau} - \zeta_\tau(\tau), \widetilde{z}^c - \zeta_z(z^c))} d\widetilde{z}^c d\widetilde{\tau}.$$

This is infeasible to evaluate analytically. Instead, we can compute $\kappa^+(\widetilde{\tau}, \widetilde{z}^c)$ over a very fine grid (and therefore $\int_{\overline{\tau}_k}^{\tau^*} \int_{\overline{z}_l}^{z_c^*} \kappa^+(\widetilde{\tau}, \widetilde{z}^c)\, d\widetilde{z}^c d\widetilde{\tau}$ numerically) prior to evaluating the likelihood function. This is a fixed cost that does not increase with the sample size.

hospital $exp\{0.251\}$ $(= 1.285)$ times faster than a single person with other similar characteristics.

For hospital stays, demographic variables have predicted and significant effects. In particular, being male, married, younger, or employed increases one's hazard rate. Demographic variables also affect community tenure in predicted ways. In particular, being single or not employed increases hazards of being readmitted into the psychiatric hospital, while being black has a positive but insignificant effect on the hazard.

Psychiatric diagnoses have predicted effects on hospital stay hazard rates. In particular, the ranking of psychiatric diagnoses, using DEMENTIA as a base, is what would be expected from clinical experience and from the literature. The diagnostic groups with the highest risk for long inpatient stays include dementia, schizo-affective, paranoid, schizophrenia, and organic diagnoses, with alcohol, substance abuse, and adjustment disorders being discharged the soonest. Although the diagnostic classification scheme differed somewhat, this is similar to findings of Leginski et. al. (1990). For state hospital patients, they showed that patients diagnosed with organic or schizophrenic disorders have the longest median and average length of stays while patients with alcohol, and with substance abuse disorders have the shortest. We also tried using the initial psychiatric diagnosis from the preceding hospital stay to help explain community stay hazards. The twelve coefficients were jointly significant but no single diagnosis coefficient had a t-statistic greater than 1 in absolute value.[5]

There are eight unreported hospital dummies for each hazard function. In both cases, they are significantly different from each other. They are not reported because we do not know the identity of any particular hospital.

Characteristics of the county of residence of the individual are not as helpful in explaining hazard rates. This may occur because of measurement error in the county variables. Only percent of county urban (CNTY-URB) and a rural dummy (CNTY-RUR) are significant in explaining hospital stay hazards, and only per capita patient care psychiatrists (CNTY-PCPSY) is significant in explaining community stay hazards. CNTY-PCPSY has an unexpected positive sign. This may suggest that communities with relatively more psychiatrists may be receiving more mental health care resulting in greater identification of need for inpatient care. This could result in either an improvement in the quality of mental health care with appropriate referral to inpatient care or in the over-utilization of in-

[5] They were also jointly significant after being grouped into five (instead of thirteen) diagnoses but were still each statistically insignificant.

patient care. This would be consistent with the hypothesis posed for further investigation by Fisher, et. al. (1992) who suggested that "comprehensive community service systems, where most patients have case managers and many live in some form of residential program, identify patients in need of hospitalization more quickly and more often than do those in which patients are less carefully followed." (pg. 390).

The other person-specific variables control for previous experience. The length of the last previous hospital stay decreases the hazard in the present hospital stay and increases the subsequent community stay hazard. The number of previous hospital stays has similar effects on the hospital stay and community stay hazards. These two coefficients may be estimating true structural effects (e.g., spending more time in a psychiatric hospital makes one dependent upon the care one receives in a hospital). However, they may also be measuring the effect of unobserved heterogeneity (e.g., severity of illness) on the hazards. We have left them in the specification of the hazard function because a) they may truly have a structural component to them and b) they are usually available in similar data sets and can be used for prediction even if they represent only the effect of unobserved heterogeneity.

LGST and JAIL measure the effect of one's source of admission on the hazards. In particular, LGST=1 if one enters the psychiatric hospital involuntarily, and LGST=0 otherwise. Entering involuntarily increases the hazard rate out of the hospital but has an insignificant effect on the subsequent community tenure. JAIL=1 if one enters the hospital from jail, and JAIL=0 otherwise. Entering the hospital from JAIL has a small, positive, statistically significant effect on both hazard rates.

The last set of parameters in Table 5 measure the effect of duration dependence on the hazard rates. These are the SLOPE coefficients and the SPIKE coefficients. The SLOPE coefficients, defined as the $\overline{g}$ coefficients in equation (3.2) with nodes specified in note (3) of Table 5, measure how the slope of the hazard rate changes over time. For example, for hospital stays, the log hazard rate increases by 0.115 per day during the first week, decreases by 0.027 per day in the second week, increases by 0.012 per day in the 3rd and 4th week, and then slowly declines thereafter.[6] For community tenure, the hazard rate declines steadily at a decreasing rate except for a statistically insignificant positive slope for days 32 through 50.

[6] All episodes are truncated by the time frame of the data. Thus, we can make no statements about the hazard rate beyond two years.

The SPIKE variables allow for discrete jumps in the hazard rate at particular times due to the nature of the hospital stay. The CD-SPIKE variable measures the increase in the log hazard rate at the time when one's committed days end. The estimate, 5.799. is very large and statistically significant. This suggests that committed patients are frequently kept in the hospital until their committed days end and then they are discharged. The TDO-SPIKE measures the increase in the log hazard during the first week in the hospital for patients entered under a temporary detention order. The temporary detention order is usually only for three days. But the TDO-SPIKE variable lasts for a week to cover TDO patients who remain a few extra days. This coefficient, 1.194, is also large and statistically significant.

Table 6 measures the same hazard rates but allows for uncorrelated, unobserved heterogeneity. In particular, each patient is assumed to have two unobserved errors, one for all hospital stays and one for all community stays, that affect each hazard rate as specified in equation (3.1). Adding unobserved heterogeneity does not change the results qualitatively but does change some of the quantitative results. Both unobserved heterogeneity standard deviation estimates (SIGMA) are significant and relatively large. The addition of each standard deviation improves the likelihood function significantly. We also estimated a correlation between the two unobserved heterogeneity errors, and found it to be significant at -0.46. This is consistent with unobserved heterogeneity capturing the effects of unobserved severity. The other parameter estimates changed but not significantly.

Tables 7 and 8 provide estimates associated with allowing for correlated unobserved heterogeneity. The first column of Table 7 provides estimates when there is no control for left censoring, and the second column controls for left censoring as described earlier. Table 8 provides estimates of the κ^+ function using a 3x3 grid system.[7] In both cases, the estimate of the correlation between the two unobserved heterogeneity errors is negative (-0.464 and -0.485 respectively). This suggests that unobserved heterogeneity is capturing, among other things, illness severity. A severely ill person will have a large value of unobserved heterogeneity for community stays (implying short community stays) and a small value of unobserved heterogeneity for hospital stays (implying long hospital stays). The other parameter estimates change to some degree relative to each other and relative to allowing only uncorrelated unobserved heterogeneity (Table 6). But no signifi-

[7] We also experimented with a 5x5 grid and found little difference in the parameter estimates of interest along with κ^+ estimates measured with no precision at all.

cant estimates change signs, and most do not change magnitude. One sees in Table 8 that the estimates of the κ^+ function are estimated very imprecisely and do not seem to follow any recognizable pattern. Comparison of the two columns in Table 7 suggests that left censoring is not a serious issue in the sense of causing asymptotic bias of the parameter estimates of interest.

The standard methods used in the psychiatric episode literature have been regression,[8] Kaplan-Meier estimation,[9] and Cox (1972) regression.[10] The existence of censoring and duration dependence makes linear regression inappropriate. Kaplan-Meier estimation is misleading in that a) variation caused by observed covariates is missed, and b) effects of duration dependence and unobserved heterogeneity are confounded. Cox regression usually ignores unobserved heterogeneity and is thus inappropriate at least in the way it is practiced.

It was of some concern to us that the TDO-SPIKE effect might vary across people with different demographic characteristics. We tested for this by estimating a logit model using TDO patients where the dependent variable was equal to 1 if the patient did not exit after 7 days and 0 otherwise. Table 7 shows that TDO release effects do vary significantly by sex and employment status. However, for parsimony's sake, we continue to use only a single TDO-SPIKE coefficient.

The most intuitive way to measure the effects of different characteristics on hospital and community stays is to graph survivor curves corresponding to equation (3.5) for Table 6 estimates. Figure 3 displays a base case survivor curve for a community stay. The individual is a white, single , nonworking, 36-year-old male from the average county with a schizophrenic diagnosis, and four previous hospital stays, the last of which was 41.5 days. For example, it shows that the probability of still remaining in the community after 100 days is about 85% and after 200 days is about 78%. For a black person with otherwise similar characteristics, the 100 and 200 day survivor probabilities are about 83% and 75% respectively. On the other hand, starting from our base case, if the number of patient care psychiatrists is doubled, the 100 and 200 day survivor probabilities decline to about 84% and 76% respectively. Using either the hazard rate or the survivor function estimates, one could also compute expected length of a community stay. However, given the episode truncation rule implied by our data,

[8] See, for example, Fontana and Dowds (1975), Caton (1982), Schumacher, et. al. (1986), Horn, et. al. (1989), and Stoskopf and Horn (1991).

[9] See, for example, Caton, et. al. (1985), Greenhouse, et. al. (1989), Stevens and Hollis (1989), Burke, et. al. (1990), and Fisher, et. al. (1992).

[10] See, for example, Smeraldi, et. al, (1983), Leckman, et. al. (1984), Klerman, et. al. (1985), Merikangas, et. al. (1985), Siegal, et. al. (1986), and Leon, et. al. (1990).

our survivor functions beyond 610 days are basically based on an assumption of functional form. Since the survivor probabilities are still relatively high at this truncation point, expected episode length calculations are not very meaningful.

Figure 4 graphs survivor curves for hospital stays. Using the same base case described above, we observe 50, 100, and 200 day survivor probabilities 45%, 30%, and 6% respectively. A black, otherwise similar person has survivor probabilities very similar to the base individual. A rural, white, otherwise similar person has survivor probabilities of 55%, 40%, and 28% respectively.

Rural counties have different other county characteristics than nonrural counties. Figure 5 compares the survivor probabilities for an individual with the same personal characteristics as the base case described above living in the average rural county to the same individual living in the average nonrural county. In fact, other differences in county characteristics move the two survivor curves closer together. It should be noted though that this exercise is not very precise because it relies upon a set of estimates which were not precisely estimated.

5. Conclusions

This paper has demonstrated the value of including observed covariates, duration dependence, and unobserved heterogeneity in a survival model of psychiatric hospital and community stays. In particular regression analysis would have been inappropriate because a) there is censoring, and b) there is nontrivial duration dependence. Kaplan-Meier estimation is deficient because of significant covariates and unobserved heterogeneity. Cox regression would be hard to implement because of unobserved heterogeneity.

We find that sex, marital status, employment status, diagnosis, age, committed days, and urban/rural codes help explain hospital stay lengths, and that marital status, employment status, and some county medical resources measures help explain community tenure. Previous history helps explain both stay lengths. There is significant evidence of interesting duration dependence and of unobserved heterogeneity.

References

[1] Blank, R. (1989). "Analyzing the Length of Welfare Spells." Journal of Public Economics. 39: 245-2273.

[2] Brien, M., L. Lillard, and S. Stern (1998). "Cohabitation, Marriage, and Divorce in a Model of Match Quality." Unpublished manuscript.

[3] Burke, K., J. Burke, D. Regier and D. Rae (1990). "Age at Onset of Selected Mental Disorders in Five Community Populations." Archives of General Psychiatry. 47: 511-518.

[4] Butler, J., K. Anderson, and R. Burkhauser (1989). "Work and Health After Retirement: A Competing Risks Model with Semiparametric Unobserved Heterogeneity." Review of Economics and Statistics. ?: 46-53.

[5] Caton, C. (1982). "Effect of Length of Inpatient Treatment for Chronic Schizophrenia." American Journal of Psychiatry. 139: 856-861.

[6] Caton, C., S. Koh, J. Fleiss, S. Barrow, and J. Goldstein (1985). "Rehospitalization in Chronic Schizophrenia." The Journal of Nervous and Mental Disorders. 173(3): 139-148.

[7] Fisher, W. H., J. L. Geller, F. Altaffer, and M. B. Bennett (1992). "The Relationship Between Community Resources and State Hospital Recidivism." American Journal of Psychiatry. 149(3): 385-390.

[8] Fontana, A. and B. Dowds (1975). "Assessing Treatment Outcome." Journal of Nervous and Mental Disease. ?: 231-238.

[9] Greenhouse, J., D. Stangl, and J. Bromberg (1989). "An Introduction to Survival Analysis: Statistical Methods for Analysis of Clinical Trial Data." Journal of Consulting and Clinical Psychology. 57(4): 536-544.

[10] Gritz, R. (1993). "The Impact of Training on the Frequency and Duration of Employment." Journal of Econometrics. 57: 21-51.

[11] Gunderson, M. and A. Melino (1990). "The Effects of Public Policy on Strike Duration." Journal of Labor Economics. 8(3): 295-316.

[12] Ham, J. and S. Rea (1987). "Unemployment Insurance and Male Unemployment Duration in Canada." Journal of Labor Economics. 5(3): 325-353.

[13] Heckman, J. and B. Singer (1984a). "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." Econometrica. 52(2): 271-320.

[14] Heckman, J. and B. Singer (1985). "Social Science Duration Analysis." in Longitudinal Analysis of Labor Market Data. (eds.) J. Heckman and B. Singer. Cambridge: Cambridge University Press.

[15] Horn, S., A. Chambers, P. Sharkey, and R. Horn (1989). "Psychiatric Severity of Illness." Medical Care. 27(1): 69-83.

[16] Johnson W. and J. Ondrich (1990). "The Duration of Post-Injury Absences From Work." Review of Economics and Statistics. ?: 578-586.

[17] Lancaster, T. (1990). The Econometric Analysis of Transition Data. Cambridge: Cambridge University Press.

[18] Klerman, C., P. Lavori, J. Rice, T. Reich, J. Endicott, N. Andreasen, M. Keller, and R. Hirschfield (1985). "Birth-Cohort Trends in Rates of Major Depression Disorder Among Relatives of Patients with Affective Disorder." Archives of General Psychiatry. 42: 689-693.

[19] Leckman, J., M. Weissman, B. Prusoff, K. Caruso, K. Merikangas, D. Pauls, and K. Kidd (1984). "Subtypes of Depression." Archives of General Psychiatry. 41: 833-838.

[20] Leginski, W.A., R. W. Mandersheid, and P.R. Henderson (1990). "Patients Served in State Mental Hospitals: Results from a Longitudinal Data Base," in NIMH, Mental Health, United States 1990. R. W. Manderscheid, and M. A. Sonnenschein, eds., DHHS Pub. No. (ADM)90-1708. Washington, D.C.: Supt. of Documents, U.S. Government Printing Office.

[21] Leon, A., R. Friedman, J. Sweeney, R. Brown, and J. Mann (1990). "Statistical Issues in the Identification of Risk Factors for Suicidal Behavior: The Application of Survival Analysis." Psychiatry Research. 31: 99-108.

[22] Lillard, L. (1993). "Simultaneous Equations for Hazards: Marriage Duration and Fertility Timing." Journal of Econometrics. 56: 189-217.

[23] Merikangas, K., M. Weissman and D. Pauls (1985). "Genetic Factors in the Sex Ratio of Major Depression." Psychological Medicine. 15: 63-69.

[24] Meyer, B. (1990). "Unemployment Insurance and Unemployment Spells." Econometrica. 58(4): 757-782.

[25] Redick, Richard W., Michael J. Witkin, Joanne E. Atay, and Ronald W. Manderscheid (1996). "Highlights of Organized Mental Health Services in 1992 and Major National and State Trends." in Mental Health, United States, 1996, R. W. Manderscheid and M. A. Sonnenschein, Center for Mental Health Services, DHHS, Pub. No. (SMA)96-3098, Washington, D.C.: Supt. of Documents., U.S. Govt. Printing Office.

[26] Rosenstein, M. J., L. J. Milazzo-Sayre, and R. W. Manderscheid (1990). "Characteristics of Persons Using Specialty Inpatient, Outpatient, and Partial Care Programs in 1986," in NIMH, Mental Health, United States 1990. R. W. Manderscheid, and M.A. Sonnenschein, eds., DHHS Pub. No. (ADM)90-1708. Washington, D.C.: Supt. of Documents, U.S. Government Printing Office.

[27] Schumacher, D., M. Namerow, B. Parker, P. Fox, and V. Kofie (1986). "Prospective Payment for Psychiatry - Feasibility and Impact." New England Journal of Medicine. 315(21): 1331-1336.

[28] Siegel, C., M. Alexander, S. Lin, and E. Laska (1986). "An Alternative to DRGs." Medical Care. 24(5): 407-417.

[29] Smeraldi, E., M. Gasperini, F. Macciardi, C. Bussoleni, and A. Morabito (1983). "Factors Affecting the Distribution of Age at Onset in Patients with Affective Disorders." Journal of Psychiatric Research. 17(3): 309-317.

[30] Stevens, V. and J. Hollis (1989). "Preventing Smoking Relapse, Using an Individually Tailored Skills-Training Technique." Journal of Consulting and Clinical Psychology. 57(3): 420-424.

[31] Stoskopf, C. and S. Horn (1991). "The Computerized Psychiatric Severity Index as a Predictor of Inpatient Length of stay for Psychoses." Medical Care. 29(3): 179-195.

Table 1
Missing Variable Analysis

Cause	Hospital # Obs Lost	Stays Cumulative	Community # Obs Lost	Stays Cumulative
Race	107	107	95	95
Marital Status	207	314	176	271
County Code	2	316	680	951
Legal Status	3	319	3	954
Diagnosis	750	1069	137	1091
Employment Status	525	1594	428	1519

Table 2

Dependent Variable Sample Sizes

	Hospital Stays	Community Stays
Without Censoring	4897	1097
Right Censored	765	3700
Total	5662	4797
Mean Episode Length (days)	41.7	140.3

Table 3
Variable Name Definitions

BLACK	Individual is black
FEMALE	Individual is female
MARRY	Individual is married
AGE	Individual's age
EMPLOY	Individual is employed
DEMENTIA	Individual diagnosis is dementia
SUBSTABU	Individual diagnosis is substance abuse
ALCOHOL	Individual diagnosis is alcohol abuse
ORGANIC	Individual diagnosis is organic
SCHIZ	Individual diagnosis is schizophrenia
SCHIZAFF	Individual diagnosis is schizophrenia affect
PARANOID	Individual diagnosis is paranoid
OTH-PSYTIC	Individual diagnosis is other psychotic
BIPOLAR	Individual diagnosis is bipolar
DEPRESS	Individual diagnosis isdepression
PERSNLTY	Individual diagnosis is personality
ADJUST	Individual diagnosis is adjustment
OTHER	Individual diagnosis is other
COMMDYS	The number of committed days
LNPSP	Individual's longest previous hospital stay
NHSPS	Individual's number of previous hospital stays
LGST	Individual entered the hospital involuntarily
CNTY-MD	Per-capita medical doctors in county/city
CNTY-PCPSY	Per-capita patient care psychiatrists in county/city
CNTY-RN	Per-capita rn's in county/city
CNTY-LPN	Per-capita lpn's in county/city
CNTY-LTPH	Per-capita long term psychiatric hospitals in county/city
CNTY-GH	General hospitals in county/city
CNTY-AEDU	Median education in county/city
CNTY-PCI	Per-capita income in county/city
CNTY-URB	Percent of county/city which is urban
CNTY-RUR	County/city rural
CNTY-BLK	Percent of county/city which is black
CNTY-JAIL	Percent of county/city in jail

Table 4
Explanatory Variables

Variable	Hospital Mean	Stays Std Dev	Community Mean	Stays Std Dev
BLACK	0.37	0.48	0.38	0.48
FEMALE	0.36	0.48	0.34	0.47
MARRY	0.17	0.37	0.18	0.38
AGE	37.45	13.95	36.10	12.54
EMPLOY	0.13	0.34	0.14	0.35
DEMENTIA	0.03	0.17	0.02	0.13
SUBSTABU	0.05	0.21	0.09	0.28
ALCOHOL	0.11	0.32	0.15	0.35
ORGANIC	0.05	0.22	0.05	0.22
SCHIZ	0.19	0.39	0.15	0.36
SCHIZAFF	0.07	0.26	0.10	0.30
PARANOID	0.01	0.07	0.01	0.08
OTH-PSYTIC	0.07	0.26	0.04	0.21
BIPOLAR	0.12	0.32	0.12	0.33
DEPRESS	0.10	0.31	0.08	0.27
PERSNLTY	0.02	0.15	0.02	0.14
ADJUST	0.08	0.28	0.14	0.35
OTHER	0.10	0.30	0.04	0.20
LNPSP			33.61	46.15
NHSPS	3.82	5.31	3.79	5.66
LGST	0.80	0.40	0.79	0.40
CNTY-MD	0.17	0.16	0.18	0.16
CNTY-PCPSY	0.01	0.01	0.01	0.01

Table 4 (continued)

Variable	Hospital Mean	Stays Std Dev	Community Mean	Stays Std Dev
CNTY-RN	0.41	0.22	0.40	0.22
CNTY-LPN	0.19	0.09	0.19	0.10
CNTY-LTPH	0.14	0.35	0.20	0.40
CNTY-GH	1.97	2.73	1.97	2.84
CNTY-AEDU	1.19	0.12	1.19	0.12
CNTY-PCI	17.04	4.86	16.88	4.60
CNTY-URB	0.54	0.39	0.54	0.38
CNTY-RUR	0.35	0.48	0.34	0.47
CNTY-BLK	0.21	0.16	0.23	0.17
CNTY-JAIL	0.07	0.19	0.08	0.20

Table 5
Estimation Results with No Unobserved Heterogeneity

Variable	Hosp Stay	Comm Stay	Variable	Hosp Stay	Comm Stay
BLACK	0.026	0.091	CNTY-MD	-0.222	-1.159
	(0.031)	(0.065)		(0.359)	(0.850)
FEMALE	-0.119**	0.042	CNTY-PCPSY	5.481	21.533**
	(0.029)	(0.067)		(3.790)	(8.516)
MARRY	0.251**	-0.228**	CNTY-RN	0.049	0.629*
	(0.038)	(0.090)		(0.125)	(0.350)
AGE/100	-1.500**	-0.380	CNTY-LPN	0.220	0.582**
	(0.079)	(0.248)		(0.229)	(0.546)
EMPLOY	0.332**	-0.252**	CNTY-LTPH	-0.071	0.143
	(0.041)	(0.098)		(0.070)	(0.147)
DEMENTIA	0.000		CNTY-GH	-0.011	0.002
				(0.011)	(0.023)
SCHIZAFF	0.635**		CNTY-AEDU	-0.454*	0.528
	(0.183)			(0.206)	(0.446)
PARANOID	0.642*		CNTY-PCI	0.004	0.002
	(0.291)			(0.004)	(0.012)
SCHIZ	0.660**		CNTY-URB	-0.359**	0.180
	(0.176)			(0.985)	(0.232)
ORGANIC	0.664**		CNTY-RUR	-0.254**	0.074
	(0.182)			(0.051)	(0.138)
OTH-PSYTIC	0.834**		CNTY-BLK	0.095	-0.258
	(0.179)			(0.117)	(0.265)
BIPOLAR	0.840**		CNTY-JAIL	-0.093	0.152
	(0.177)			(0.079)	(0.202)
PERSNLTY	0.984**		JAIL	0.046**	0.018**
	(0.190)			(0.036)	(0.006)
DEPRESS	1.015**		SLOPE-1	0.115**	-0.114**
	(0.178)			(0.013)	(0.027)

Table 5 (continued)

SUBSTABU	1.259**		SLOPE-2	-0.037**	-0.020
	(0.182)			(0.008)	(0.022)
ADJUST	1.349**		SLOPE-3	0.012**	-0.031**
	(0.178)			(0.004)	(0.011)
ALCOHOL	1.648**		SLOPE-4	-0.021**	-0.002
	(0.173)			(0.005)	(0.010)
OTHER	1.170**		SLOPE-5	-0.028**	-0.016
	(0.176)			(0.008)	(0.015)
LNPSP/100		0.076**	SLOPE-6	-0.004**	-0.005**
		(0.030)		(0.000)	(0.000)
NHSPS	-0.111**	0.065**	CD-SPIKE	5.799**	
	(0.043)	(0.005)		(0.353)	
COMMDYS/100	-0.807**		TDO-SPIKE	1.194**	
	(0.292)			(0.059)	
LGST	0.293**	0.117	Log Likhd	-21904.0	-7812.0
	(0.045)	(0.194)			

Notes:

1) Items in parentheses are standard errors. Single starred items are significant at the 10% level, and double starred items are significant at the 5% level.

2) There are 5662 psychiatric hospital stays and 4797 community stays. See Table 1 for the distribution of censored episodes.

3) Slopes: (1 for first 7 days; 2 for days 8-15; 3 for days 16-31; 4 for days 32-50; 5 for days 51-60; 6 for days after 60).

4) There are 8 hospital dummies for each equation whose coefficients are not reported to save space. In general, they are not significantly different from each other in either equation.

5) DEMENTIA is set equal to 0.0, and the coefficients on other diagnoses in the hospital equation should be interpreted as the effect of that diagnosis relative to dementia.

6) Diagnosis variables are jointly significant (at the 5% level) in the community tenure equation. But no single diagnosis coefficient has a t-statistic greater than 1 in absolute value.

Table 6
Estimation Results with Uncorrelated Unobserved Heterogeneity

Variable	Hosp Stay	Comm Stay	Variable	Hosp Stay	Comm Stay
BLACK	0.025	0.120	CNTY-MD	-0.234	-0.903
	(0.042)	(0.079)		(0.469)	(0.984)
FEMALE	-0.125**	0.002	CNTY-PCPSY	6.356	18.370**
	(0.039)	(0.079)		(4.978)	(9.914)
MARRY	0.297**	-0.302**	CNTY-RN	0.042	0.638*
	(0.515)	(0.105)		(0.169)	(0.402)
AGE/100	-1.890**	0.006	CNTY-LPN	0.331	0.593
	(0.130)	(0.300)		(0.298)	(0.617)
EMPLOY	0.402**	-0.302**	CNTY-LTPH	-0.061	0.207
	(0.056)	(0.109)		(0.093)	(0.169)
DEMENTIA	0.000		CNTY-GH	-0.017	-0.009
				(0.014)	(0.028)
PARANOID	0.698		CNTY-AEDU	-0.741**	0.272
	(0.326)			(0.312)	(0.524)
SCHIZAFF	0.716**		CNTY-PCI	0.006	0.004
	(0.207)			(0.007)	(0.015)
SCHIZ	0.753**		CNTY-URB	-0.429**	0.177
	(0.198)			(0.132)	(0.264)
ORGANIC	0.797**		CNTY-RUR	-0.320**	0.044
	(0.205)			(0.069)	(0.156)
BIPOLAR	0.943**		CNTY-BLK	0.024	-0.370
	(0.201)			(0.159)	(0.298)
OTH-PSYTIC	0.977**		CNTY-JAIL	-0.038	0.077
	(0.204)			(0.111)	(0.232)
DEPRESS	1.194**		JAIL	0.061**	0.015*
	(0.203)			(0.005)	(0.008)
PERSNLTY	1.217**		SLOPE-1	0.153**	-0.110**
	(0.220)			(0.013)	(0.028)
SUBSTABU	1.505**		SLOPE-2	0.025**	-0.017
	(0.209)			(0.009)	(0.022)

Table 6 (continued)

ADJUST	1.617**		SLOPE-3	-0.024**	-0.028**
	(0.204)			(0.005)	(0.011)
ALCOHOL	1.947**		SLOPE-4	-0.015**	0.003
	(0.200)			(0.005)	(0.010)
OTHER	1.410**		SLOPE-5	-0.020**	-0.013
	(0.203)			(0.009)	(0.015)
LNPSP/100		0.137**	SLOPE-6	-0.002**	-0.004**
		(0.053)		(0.000)	(0.001)
NHSPS	-0.173**	0.036**	CD-SPIKE	1.751**	
	(0.055)	(0.001)		(0.068)	
COMMDYS/100	-1.256**		TDO-SPIKE	0.201**	
	(0.373)			(0.050)	
LGST	0.363**	0.129	SIGMA	0.741**	1.052**
	(0.057)	(0.106)		(0.063)	(0.103)
			Log Likhd	-2186.2	-7791.2

Notes:

1) Items in parentheses are standard errors. Single starred items are significant at the 10% level, and double starred items are significant at the 5% level.

2) There are 5662 psychiatric hospital stays and 4797 community stays. See Table 1 for the distribution of censored episodes.

3) Slopes: (1 for first 7 days; 2 for days 8-15; 3 for days 16-31; 4 for days 32-50; 5 for days 51-60; 6 for days after 60).

4) There are 8 hospital dummies for each equation whose coefficients are not reported to save space. In general, they are not significantly different from each other in either equation.

5) DEMENTIA is set equal to 0.0, and the coefficients on other diagnoses in the hospital equation should be interpreted as the effect of that diagnosis relative to dementia.

Table 7
Comparison of Results with Unobserved Heterogeneity

Variable	No Left Censoring Correction		3-Point Left Censoring Correction	
	Hospital	Community	Hospital	Community
BLACK	0.022 (0.043)	0.142* (0.081)	0.027 (0.043)	0.138* (0.078)
FEMALE	-0.126** (0.040)	0.009 (0.081)	-0.117** (0.040)	-0.015 (0.078)
MARRY	0.307** (0.053)	-0.331** (0.108)	0.345** (0.055)	-0.285** (0.106)
AGE/100	-1.988** (0.138)	0.284 (0.313)	-2.039** (0.143)	0.488 (0.302)
EMPLOY	0.405** (0.057)	-0.344** (0.112)	0.380** (0.060)	-0.220** (0.110)
DEMENTIA	0.000		0.000	
PARANOID	0.660** (0.333)		0.637* (0.335)	
SCHIZAFF	0.684** (0.211)		0.707** (0.211)	
SCHIZ	0.727** (0.203)		0.734** (0.202)	
ORGANIC	0.776** (0.208)		0.811** (0.207)	
BIPOLAR	0.911** (0.204)		0.916** (0.204)	
OTH-PSYTIC	0.969** (0.208)		0.993** (0.207)	
DEPRESS	1.161** (0.207)		1.172** (0.206)	

Table 7 (continued)

Variable	No Left Censoring Correction		3-Point Left Censoring Correction	
	Hospital	Community	Hospital	Community
PERSNLTY	1.249**		1.339**	
	(0.227)		(0.227)	
SUBSTABU	1.504**		1.509**	
	(0.215)		(0.215)	
ADJUST	1.588**		1.588**	
	(0.209)		(0.209)	
ALCOHOL	1.929**		1.946**	
	(0.205)		(0.207)	
OTHER	1.389**		1.445**	
	(0.207)		(0.207)	
LNPSP/100	-0.905**	-0.092	-1.082**	-0.072
	(0.454)	(0.069)	(0.465)	(0.066)
NHSPS	-0.172**	0.037**	-0.156**	0.038**
	(0.057)	(0.001)	(0.056)	(0.001)
LGST	0.378**	0.151	0.365**	0.005
	(0.059)	(0.108)	(0.059)	(0.106)
CNTY-MD	-0.111	-1.671*	-0.047	-1.686*
	(0.479)	(1.013)	(0.422)	(0.961)
CNTY-PCPSY	5.114	26.237**	5.292	26.113**
	(5.091)	(10.219)	(4.627)	(9.721)
CNTY-RN	0.054	-0.633*	0.105	-0.627
	(0.172)	(0.412)	(0.164)	(0.395)
CNTY-LPN	0.274	0.811	0.216	0.833
	(0.303)	(0.631)	(0.289)	(0.618)

Table 7 (continued)

Variable	No Left Censoring Correction		3-Point Left Censoring Correction	
	Hospital	Community	Hospital	Community
CNTY-LTPH	-0.041	0.114	-0.010	-0.035
	(0.096)	(0.175)	(0.093)	(0.169)
CNTY-GH	-0.017	0.009	-0.022	0.005
	(0.014)	(0.028)	(0.014)	(0.027)
CNTY-AEDU	-0.537*	0.402	-0.598**	0.270
	(0.340)	(0.596)	(0.278)	(0.467)
CNTY-PCI	0.002	0.007	-0.002	0.008
	(0.007)	(0.015)	(0.007)	(0.014)
CNTY-URB	-0.453**	0.178	-0.388**	0.363
	(0.135)	(0.270)	(0.132)	(0.258)
CNTY-RUR	-0.311**	0.047	-0.263**	0.009
	(0.071)	(0.160)	(0.071)	(0.153)
CNTY-BLK	0.040	-0.392	0.073	-0.665**
	(0.162)	(0.305)	(0.159)	(0.298)
CNTY-JAIL	-0.042	0.081	0.021	-0.123
	(0.113)	(0.240)	(0.112)	(0.227)
JAIL	0.063**	0.012	0.064**	0.005
	(0.005)	(0.008)	(0.005)	(0.008)
SLOPE-1	0.157**	-0.113**	0.154**	-0.060**
	(0.014)	(0.028)	(0.014)	(0.028)
SLOPE-2	-0.023**	-0.015	-0.023**	-0.019
	(0.009)	(0.022)	(0.009)	(0.022)
SLOPE-3	0.026**	-0.028**	0.026**	-0.034**
	(0.005)	(0.012)	(0.005)	(0.012)
SLOPE-4	-0.015**	0.004	-0.014**	0.008
	(0.005)	(0.011)	(0.005)	(0.011)

Table 7 (continued)

Variable	No Left Censoring Correction		3-Point Left Censoring Correction	
	Hospital	Community	Hospital	Community
SLOPE-5	-0.019**	-0.013	-0.020**	-0.021
	(0.009)	(0.015)	(0.009)	(0.015)
SLOPE-6	-0.002**	-0.004**	-0.002**	-0.004**
	(0.000)	(0.001)	(0.000)	(0.001)
CD-SPIKE	1.740**		1.755**	
	(0.070)		(0.071)	
TDO-SPIKE	0.204**		0.199**	
	(0.051)		(0.050)	
Sigma	0.913**	1.155**	0.938**	1.074**
	(0.156)	(0.211)	(0.150)	(0.209)
Corr	-0.464**		-0.485**	
	(0.088)		(0.087)	
LogLikhd	-29640.3		-68439.8	

Notes:

1) Items in parentheses are standard errors. Single starred items are significant at the 10% level, and double starred items are significant at the 5% level.

2) There are 5662 psychiatric hospital stays and 4797 community stays. See Table 1 for the distribution of censored episodes.

3) Slopes: (1 for first 7 days; 2 for days 8-15; 3 for days 16-31; 4 for days 32-50; 5 for days 51-60; 6 for days after 60).

4) There are 8 hospital dummies for each equation whose coefficients are not reported to save space. In general, they are not significantly different from each other in either equation.

5) DEMENTIA is set equal to 0.0, and the coefficients on other diagnoses in the hospital equation should be interpreted as the effect of that diagnosis relative to dementia.

Table 8

Left Censoring Node Estimates $\kappa^+(i,j)$

	$j=1$	$j=2$	$j=3$
$i=1$	0.585 (2.389)	-0.695** (0.340)	0.305 8.524
$i=2$	0.173 (4.167)	0.000	0.075 (13.205)
$i=3$	-0.008 (3.870)	-0.304** (0.145)	-0.341 19.136

Table 9
TDO Committal Logit Estimates

Variable	Value	Standard Error
Constant	-0.057**	0.110
BLACK	0.358**	0.082
FEMALE	0.409**	0.074
MARRIED	-0.179**	0.084
AGE/100	0.385	0.261
EMPLOYED	-0.442**	0.091

Notes:

1) There are 1415 observations.
2) Double-starred items are significant at the 5% level.