



Abt Associates Inc.

Cambridge, MA  
Lexington, MA  
Hadley, MA  
Bethesda, MD  
Washington, DC  
Chicago, IL  
Cairo, Egypt  
Johannesburg, South Africa

Abt Associates Inc.  
55 Wheeler Street  
Cambridge, MA 02138

## **Unintended Consequences of Sentencing Policy:**

## **The Creation of Long- Term Healthcare Obligations**

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National Institute of Justice  
810 Seventh Street, N.W.  
Washington, D.C. 20531

*Prepared by*  
William Rhodes  
Patrick Johnston  
Quentin McMullen  
Lynne Hozik

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# Executive Summary

With passage of the Violent Offender Truth in Sentencing Act (VOTIS), Congress attempted to extend the duration of prison for repeat and violent offenders. Unless that extension is counterbalanced by fewer or shorter prison terms for less serious offenders, VOTIS will result in higher prison costs. This report examines one of those costs – expenditures for medical care.

This is an empirical study. The Federal Bureau of Prisons provided data about health care utilization by prisoners. Using those data, we developed statistical models of how costs increased for male offenders based on age when they entered prison and time spent in prison. The estimates are specific to 200 types of medical conditions that occur most frequently among Federal inmates.

Inmates suffer from a variety of medical conditions, but for purposes of modeling, we divided these conditions into three types: intermittent, chronic with intermittent recurrence, and chronic requiring continuous treatment.

Some medical episodes occur, receive treatment, and then the condition disappears; although additional episodes might occur subsequently, they are unrelated to the first episode. We call these intermittent conditions. A sprain provides an illustration. Many offenders never receive treatment for a sprain. Others receive several treatments clustered into a single episode – that is, several treatment events associated with the same episode of having sprained an ankle or other body part. Still other offenders are treated for more than one episode, and each episode represents the recurrence of an injury.

Other medical conditions occur and require more or less continuous treatment. Hypertension is an illustration; cancer is another. We call these chronic conditions with continuous treatment, and we model them differently than we modeled intermittent conditions.

The third category of medical condition is a combination of the first two. It comprises chronic conditions requiring episodic treatments. A bad back is an illustration. Typically a person develops a chronic condition that requires treatment when it first happens, then enters a quiescent period; the condition then recurs periodically.

Although we were able to make preliminary projections for nearly 200 of the most prevalent medical conditions observed among Federal prisoners, we were unable to solve all the technical issues that arose in this study. It is best to consider this report as providing an approach, but not a final solution, to the problem of projecting prisoners' health care needs. Nevertheless, this report contains preliminary estimates that provide both researchers and practitioners with a reasoned basis for figuring how health care costs will increase as VOTIS alters the number and mix of prison inmates.

We had to develop a procedure for distinguishing between medical conditions that were chronic and medical conditions that were not chronic. We proposed two empirical tests, and while they were helpful, we learned that empirical tests alone could not determine how to classify medical conditions. Of course, health care providers could probably do a reliable job of making these classifications, but they too would have missed some interesting findings. Offenders apparently go without medical attention, so that when they enter prison, the need for providing medical care is especially heavy. Dental attention, although not part of our data, would seem to be the prototypical illustration. People

who lack medical insurance because they are unemployed or underemployed probably forego seeking medical care. They may even be so uninterested in their medical condition that they forego care available through free clinics. At any rate, when these people go through prison medical diagnosis, such conditions are detected and treatment is rendered.

Our findings suggest also that predictions of the need for medical care cannot be based upon the prevalence of disease outside of prison. Although we do not make any such comparison, it seems reasonable to assume that prisoners suffer from certain medical conditions at higher rates than do others who are not involved with the criminal justice system. Indeed, for communicable diseases, this is demonstrable – people who go through jails and prisons account for a large proportion of diseases such as HIV, AIDS, TB and Hepatitis B and C. Thus, it seems necessary to base projections on a prisoner population.

Our findings also suggest that prison can retard the onset of certain medical conditions. This is easy to understand. Medical care received in prison can be a preventative, and at the least, early diagnoses can lead to more efficacious treatments. Furthermore, inmates are removed from unhealthy conditions (such as substance abuse) and introduced to healthy conditions (including regular sleep, exercise, food and hygiene). This is not to say that prisons are the healthiest alternative. For example, it is difficult to believe that prisons promote mental health. The point, however, is that the incidence and prevalence of medical conditions among prison inmates should be different from the incidence and prevalence of medical conditions among otherwise similarly situated offenders who are not in prison.

This latter effect – that prisons are more or less conducive to health compared with not being in prison – was difficult to model. Indeed, we were not especially successful. While we could almost always uncover what appeared to be a prison effect on the incidence and prevalence of medical conditions, the effect was often too large to be reasonable.

We think that future study of the incidence and prevalence of medical conditions in an offender population has to deal with this prison effect. To do so, however, we believe that researcher will have to acquire data from a longer period of time. Our “window” was three years of medical records. Although three years would seem to be a long time to study the progression of medical conditions, the apparent length of that window is deceptive. Many offenders enter prison during the window. For them, the window is shorter than three years, and it is shortened even more by the need to discard data from windows that are shorter than six months. Of course, offenders may end their sentences before the end of the window, and for them, the window is necessarily less than three years. A new study needs to examine a window that is as long as possible. With computerized databases, such data are readily available, and the models developed in this study can be used to derive useful estimates.

We also had to deal with the problem of left-hand censoring. This is unavoidable since there is no way to observe the onset of chronic medical conditions that occurred before the beginning of prison. But self-imposition of left-hand censoring, which happens when the window is abbreviated, seems like a needless complication that could be overcome by expanding the width of the data collection window.

Several remaining problems received no attention here. Some diseases either end in death or have a high probability of ending in death. Cancer is an illustration. We did not attempt to model death rates, but of course, it would be unreasonable to assume that someone who entered prison with a

terminal malignancy could serve a twenty-year prison term. More refined models would certainly cut the average life-span at some empirically-derived threshold. We have not done that here.

We spent considerable effort attempting to convert medical treatment into dollar costs, but ultimately, we were not successful. There is a conceptual problem converting medical treatment into costs, and that is that prisons vary greatly in the quality and quantity of treatment given to inmates. The cost of treating condition X in prison A is not the same as the cost of treating condition X in prison B. There is no universal standard. The best way for prison administrators to use the projections developed here probably is to apply judgement about how trends will affect the current delivery of health care services and, in turn, how this will effect costs.

There was an additional practical problem with developing cost estimates. We could not find good translations from ICD-9 codes (the basis for classifying medical conditions and treatment procedures) into estimates of how much it costs to treat the conditions. We were not able to develop a useful algorithm for assigning costs to conditions.

Ultimately, we find it difficult to answer the penultimate questions that motivated this research: How will medical health care costs change as prisoners age? We note that a prison system that has a high turnover of inmates has high medical care costs. This is because inmates enter prison with preexisting medical conditions that require treatment; health care likely diminishes for most inmates following this initial period of relatively high intensity health care. If fewer inmates go to prison for relatively short terms, and if those inmates who go to prison stay for extended periods, prison costs would go down provided everything else were held constant.

Of course, not everything else would be held constant. Some medical conditions actually decrease with age – sprains are an illustration. We assume this happens because young inmates are more active physically, and that physical activity leads to the same ailments inside prison as they do outside prison. However, for the most part, these would seem to be conditions that are relatively inexpensive to treat.

In fact, many serious medical conditions – heart disease, for example – increase with age. These will be increasingly expensive to treat. Thus, while the total number of medical events may decrease (e.g., fewer sprains) the expense of medical costs is still likely to increase (e.g., more heart bypass surgery).

Estimating this increase has been very difficult, for reasons illustrated. Although medical conditions will increase as offenders age, for many medical conditions, prison may be a relatively healthy environment. While few of us would exchange freedom for prison, incarceration does provide regular meals, sleep, and exercise which are often avoided by those with the freedom to choose. For some medical conditions, especially communicable diseases, prison may be unhealthy. We are not promoting prisons as health care spas. The point is simply that making projections of health care needs requires some adequate way of modeling the healthy or unhealthy effects that prisons have on the incidence and prevalence of medical conditions. Although our results are suggestive, we were not able to provide that model. We hope that future studies will, and that those future attempts will be assisted by the work reported here.

# 1.0 Introduction

With passage of the Violent Offender Truth in Sentencing Act (VOTIS), Congress attempted to extend the duration of prison for repeat and violent offenders. Unless that extension is counterbalanced by fewer or shorter prison terms for less serious offenders, VOTIS will result in higher prison costs. This report examines one of those costs – expenditures for medical care.

This is an empirical study. The Federal Bureau of Prisons provided data about health care utilization by prisoners. Using those data, we developed statistical models of how costs increased for male offenders based on age when they entered prison and time spent in prison. The estimates are specific to 200 types of medical conditions that occur most frequently among Federal inmates.

For reasons discussed in this report, estimating dollar costs for providing health care was impractical, and anyway, seemed unnecessary. Instead, we have attempted to estimate how the incidence and prevalence of medical conditions change as inmates age. The presumption is that as the prevalence of a disease doubles, the cost of treating that condition also doubles, at least approximately.

Although we were able to make preliminary projections for nearly 200 of the most prevalent medical conditions observed among Federal prisoners, we were unable to solve all the technical issues that arose in this study. It is best to consider this report as providing an approach, but not a final solution, to the problem of projecting prisoners' health care needs. Nevertheless, this report contains preliminary estimates that provide both researchers and practitioners with a reasoned basis for figuring how health care costs will increase as VOTIS alters the number and mix of prison inmates.

## 2.0 Data

The Federal Bureau of Prisons had previously provided data about prisoner health care to Abt Associates for an evaluation of telemedicine.<sup>1</sup> We reassembled those data and augmented them with additional information about inmates and their prison stays.

The data reported all medical events that occurred within a three-year window (actually January 1, 1995 through March 28, 1998) for 57,593 male offenders in U.S. Federal prisons, and the medical diagnoses and treatment events of these inmates comprised the sample analyzed.

We found it useful to distinguish between medical events and medical episodes. An event happens every time an inmate seeks medical attention by visiting a clinic or otherwise consulting with a physician or other medical practitioner. An episode is a cluster of related events. For example, if an inmate contacted the flu and saw a physician three times during a short period, then there were three events but just one episode. We modeled episodes, not events, in this study.

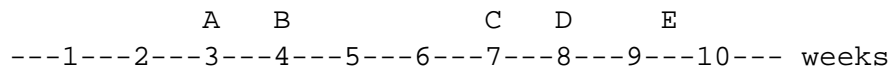
This approach required an empirical criterion for assigning events to episodes. Two medical events that were separated by more than two weeks were considered to contribute to two separate episodes, while two medical events within two weeks were considered to contribute to the same episode.

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<sup>1</sup> McDonald, C., Hassol, A., Carlson, K., McCullough, J., Fournier, E. and Yap, J., Telemedicine Can Reduce Correctional Health Care Costs, National Institute of Justice, Research Report, March 1999.

Although the precise definition is to some extent arbitrary, our definition had empirical justification in that inter-event times of more than two weeks were extremely uncommon compared to inter-event times of, say, a few days. In addition, in this study we are primarily interested in the degree to which the occurrence of medical episodes increased or decreased with age, and while our definition might bias the number of episodes, it would not bias age-related trends.

To illustrate our definition of episode, consider the five medical events A, B, C, D and E depicted below. A and B comprise one episode, while C, D, and E comprise another episode. Note that the second episode is longer than two weeks but the times between sequential events are always less than two weeks.



One or more medical conditions were identified from the ICD-9 code reported by the physician or physician-equivalent (e.g. nurse) that provided the diagnosis or treatment.<sup>2</sup> Although codes had up to five digits, we combined all conditions according to the first three digits of the five-digit set. For example, our category *diabetes* (code 250) includes the five-digit subcategories diabetes, insulin dependent; diabetes, non-insulin dependent; and diabetes, uncontrolled. The disadvantage of combining these subgroups is that we cannot make projections based on finer categories that might be of interest. However, as a practical matter, the reporting physician does not always seem to distinguish the subcategories, so combining them may not be more accurate, especially when assigning events to episodes. Furthermore, many of the subcategories were reported so infrequently that we could not analyze them. As we will show, even combining events into three-digit groups provides too few observations to support reliable analysis for some of the top 200 diagnoses.

We excluded some of the ICD-9 codes from the analysis. Firstly, some of the ICD-9 codes identified medical procedures (these started with a blank in the first digit field), rather than medical conditions. Since we could not unambiguously assign medical procedures to specific medical conditions, procedures were dropped from the data. Secondly, we dropped a miscellaneous category (counseling examination not elsewhere classified, and so on) because we could not associate the ICD-9 to a specific medical condition. Thirdly, a few additional decisions were made to eliminate ICD-9 codes that were not informative about specific medical conditions.

There were a few issues with the quality of the database. Firstly, in cases where there were multiple medical conditions, physicians were supposed to record all conditions, which were entered into a database by clerks. We are uncertain that the physicians actually complied. Secondly, there were definitely some recording errors, because uniquely female medical conditions nevertheless appeared in what was an all male sample. Whether these were recording errors by physicians, who reported by circling a list of items on a form, or by data entry clerks, we cannot be sure.

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<sup>2</sup> The International Classification of Diseases, Ninth Revision, Clinical Modification, ICD-9-CM, is a classification system that groups related disease entities and procedures for the reporting of statistical information. The clinical modification of the ICD-9 was developed by the National Center for Health Statistics for use in the United States. This definition and other details can be found at [www.icd-9-cm.org](http://www.icd-9-cm.org).

## 3.0 Models of Medical Conditions

Inmates suffer from a variety of medical conditions, but for purposes of modeling, we divided these conditions into three types: intermittent, chronic with intermittent recurrence, and chronic requiring continuous treatment. We define and illustrate each of these three in this section.

Before describing each of these three model types, however, we need to say more about the information available for estimating each model's parameters. Thinking of the general population of people who are involved with the criminal justice system,<sup>3</sup> let  $F(\text{AGE})$  represent the rate at which those people experience the need for medical attention as a function of age. For some medical conditions, such as body sprains, we would expect  $F(\text{AGE})$  to decrease with age; for other conditions, such as hypertension, we would expect  $F(\text{AGE})$  to increase with age.

Consider a medical condition for which  $F(\text{AGE})$  increases with AGE. We cannot estimate  $F(\text{AGE})$  using data from a prison population, because prisoners are not a random sample of people involved with the criminal justice system (CJS). This is easy to illustrate. Roughly 40 percent of Federal prisoners are between 25 and 35; only 18 percent are between 40 and 50. Clearly people who are involved with the CJS run a lessened risk of going to prison as they age, presumably because they reduce their crime commission. Whatever the explanation, the important point is that we cannot estimate  $F(\text{AGE})$  from a prisoner sample; instead, we can only estimate  $f(\text{AGE})$  – which is  $F(\text{AGE})$  adjusted for differential imprisonment probabilities. The adjustment is not observable.

For example, we expect  $F(\text{AGE})$  to be monotonically increasing for hypertension; although this may be the case for  $f(\text{AGE})$  as well, it need not be if those who suffer from hypertension are least likely to continue offending. The fact that we estimate  $f(\text{AGE})$  and not  $F(\text{AGE})$  is not problematic, of course, because for present purposes we are interested in  $f(\text{AGE})$  not  $F(\text{AGE})$ . The reason for the discussion is that our findings will illustrate many medical conditions for which  $f(\text{AGE})$  does not conform with expectations about  $F(\text{AGE})$ , a fact that should be remembered when assessing results.<sup>4</sup>

Now,  $f(\text{AGE})$  is relatively easy to estimate by examining inmates' ages and the rate at which they receive attention for various medical conditions. Indeed, our models, which always include an inmate's age as an explanatory variable, provide that type of estimate. This is not exactly what we are after, however, because we seek to learn how the incidence and prevalence of medical conditions change while an offender is in prison. That is not what  $f(\text{AGE})$  tell us.

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<sup>3</sup> A precise definition of “people involved with the criminal justice system” is unnecessary. We mean people who were involved with crime sometime and were likely to have been caught and sent to prison at some time. An imprecise definition is acceptable because we only mean to distinguish a group who has medical needs that are very different from the needs in a larger population. This is a consequence of the high level of indigence, the low level of health insurance and medical attention, and high-risk lifestyles. Also for present purposes we assume that membership in this group is permanent. That is, one cannot leave the group simply by stopping crime commission.

<sup>4</sup> We apologize to readers for whom this discussion was unnecessary. We researchers failed to appreciate this difference for some time, however, so we assume that this subtle point could otherwise be missed. It is important for interpreting the findings.

Specifically,  $f(\text{AGE})$  is estimated from cross-sectional data. To illustrate, suppose that the data comprised 1,000 inmates who were 20 years old, another 1,000 who were 30 years old, and still another who were 40 years old. Suppose that 20 percent of the 20 year olds suffer from hypertension, 30 percent of the 30 year olds, and 40 percent of the 40 year olds. Based on these cross sectional data, we might infer that the incidence of hypertension is about 1 percent per year between the ages of 20 and 40. Thus, we would express  $f(\text{AGE})$  to reflect that progression.

But suppose that we could actually observe inmates who entered prison when they were 20 years old through 10 years of prison. Prisoners benefit from regular sleep, adequate diet, healthy exercise, and of course regular medical attention. Given this healthy living, perhaps at the end of 10 years we would observe that only 25 percent of them suffered from hypertension. For convenience, express that progression as  $g(\text{AGE}|\text{20})$ , where the 20 denotes that the relationship between medical conditions and age is conditional on when an inmate entered prison (age 20 in this illustration), and “AGE” is the inmate’s current age.

In this illustration,  $g(40|30) < f(40)$ . That is, a time-series that controls for age when an offender entered prison can provide a very different answer than a cross-section across inmates. Of course, given that we are interested in changes in medical conditions as offenders age, we are most interested in estimating  $g(\text{AGE}|\text{age entered prison})$ . In theory, this could be done by including the age when an offender entered prison as a control variable and by examining how the diagnosis and treatment of medical conditions change as the offender ages.

Theory aside, the estimation of  $g(\text{AGE}|\text{age entered prison})$  was difficult to do. At a maximum, the time-series could last for about three-years, the length of the window. In fact the time-series is usually much shorter. The window is abbreviated when an offender begins or ends his term during a window. The brevity of the window led to imprecise parameter estimates, and some findings that were difficult to interpret. This was especially problematic when seeking to use those findings to make projections five, ten, fifteen and twenty years into the future. Consequently, in what follows, we present models based on both  $f(\text{AGE})$  and  $g(\text{AGE}|\text{age entered prison})$ .

Returning now to the three models, we repeat that we identified as three types: intermittent, chronic with intermittent recurrence, and chronic requiring continuous treatment. For each of these, we estimated a version of  $f(\text{AGE})$  and  $g(\text{AGE}|\text{age entered prison})$ . We discuss the modeling next.

Some medical episodes occur, receive treatment, and then the condition disappears; although additional episodes might occur subsequently, they are unrelated to the first episode. We call these *intermittent conditions*. A sprain provides an illustration. Many offenders never receive treatment for a sprain. Others receive several treatments clustered into a single episode – that is, several treatment events associated with the same episode of having sprained an ankle or other body part. Still other offenders are treated for more than one episode, and each episode represents the recurrence of an injury.

We modeled the episode rate for intermittent conditions. We used an overdispersed Poisson model that accommodated for the fact that inmates were observed for different durations (from one day to over three years). Let:

$N_{ij}$  the number of treatment episodes experienced by the  $i^{\text{th}}$  offender during the year when that offender was age  $j$ .

- $A_{ij}$  age of the  $i^{\text{th}}$  offender at the point when the treatment episode was experienced.
- $AP_i$  age the  $i^{\text{th}}$  offender began his prison term.
- $X_i$  a row vector of explanatory variables for the  $i^{\text{th}}$  offender.
- $T_{ij}$  the proportion of year  $j$  that was observed during the window period for the  $i^{\text{th}}$  offender. That is, the proportion of the year when the offender was age  $j$  and incarcerated during the period of the window.
- $\gamma$  parameter to be estimated.
- $\delta$  a column vector of parameters corresponding to  $X_i$ .

Then the expected value and variance of the number of episodes for the  $i^{\text{th}}$  offender during the  $j^{\text{th}}$  year is written:

$$E(N_{ij}) = \exp(\ln(T_{ij}) + Z_{ij})$$

$$V(N_{ij}) = \alpha E(N_{ij})$$

$$\text{where } Z_i = \beta_0 + \beta_1 A_{ij} + \beta_2 (A_{ij})^2 + X_i \delta + ((A_{ij} - AP_i) \gamma).$$

Explanatory variables were the age when a person entered prison, the length of time he spent in prison, race (black and other), and offense seriousness (projected length of time served). For some specifications we included age-squared. When we included age-square, we constrained  $\beta_2$  to equal zero; that is, the time spent in prison did not enter the model. This is the version corresponding to 90 f(AGE), as discussed earlier. For other specifications, we included time spent in prison,  $(A_{ij} - AP_i)$ , and excluded the age-squared term. That is, in this second specification,  $\gamma$  was a free parameter. This is the version that corresponds to g(AGE|age entered prison) as discussed above. Using either model, if the offender entered prison when he was age  $A$ , and if he remained in prison for 10 years, then we expect that he would experience EPISODE <sub>$i$</sub>  during those ten years:

$$\text{EPISODE}_i = \sum_{j=A}^{A+9} E(N_{ij})$$

Given a prison population of known size  $I$ , and given the age when those offenders entered prison and how long they remained, we could estimate the total number of treatment episodes as:

$$\text{EPISODE} = \sum_{i=1}^I \text{EPISODE}_i$$

We tried various alternative models to estimate the episode rate.<sup>5</sup> However, the approach outlined above, while statistically inefficient, was practical and was able to provide consistent parameter estimates. Figure 1 illustrates how the frequency of intermittent conditions occur for a typical medical problem – sprains. The figure shows  $f(\text{AGE})$ .

This figure shows the number of treatment episodes per year for sprains. The horizontal axis is the inmate's age. The vertical axis is the average number of treatment episodes per year for sprains. The trend is apparent. Young inmates are treated most frequently for sprains, presumably because they are more active physically than are older inmates, and thus, at higher risk. The prevalence of sprains falls as inmates age.

Other medical conditions occur and require more or less continuous treatment. Hypertension is an illustration; cancer is another. We call these chronic conditions with continuous treatment, and we model them differently than we modeled intermittent conditions.

The Poisson model is of interest even for chronic conditions with continuous treatment, but for these conditions modeling the time to onset is more fundamental. After onset, it is likely that treatment would vary less with age than in the case of other types of conditions (intermittent, and chronic with intermittent recurrence). Our approach was to estimate a logistic probability model of the condition's onset as a function of the offender's age. Define:

- $P_i$  the probability that the condition had an onset by age  $A_i$ .
- $T_i$  time measured from the offender's 18<sup>th</sup> birthday.
- $AP_i$  age at the time that prison began
- $TP_i$  time when the offender entered prison.
- $X_i$  a row vector of control variables comprising race and time to be served in prison.
- $\delta$  parameters to be estimated.
- $\gamma$  parameter to be estimated.

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<sup>5</sup> In the approach described here, one offender can contribute more than one observation to the data, depending on his age during the window period. For example, if he entered the window when he was 20 and stayed until he was 22, then he contributed three observations: a partial year when he was 20, a full year when he was 21, and a partial year when he was 22. Our approach treats those three observations as if they were independent, which seems unlikely.

As an alternative, we tried introducing a fixed effect specific to each individual into the model. However, this model proved problematic in both computational and substantive ways. Because of the large number of inmates in the study, the fixed effect model contained over 57,000 parameters, and thus could not be estimated in a standard computing environment. Although we devised a methodological solution to this difficulty, the solution remained computationally intensive and led to results very close to those produced by the approach actually employed.

A second alternative approach used a conditional nonhomogeneous Poisson model. Programmed in GAUSS, this model provided estimates that were very similar to those reported here for selected diseases. The conditional nonhomogeneous Poisson model was unavailable in SAS, however, which raised two problems. The first was that we had to estimate and test the model for many different medical conditions, and this was most suitably achieved using SAS. The second was that GAUSS is unavailable to many other researchers who might seek to replicate these findings.

Overall, then, the estimation procedure used here was the most practical for our application; it had several benefits and apparently no large costs.

figure 1

Then the model specification is:

$$P_i = 1/(1+\exp(-Z_i))$$

$$\text{where } Z_i = \beta_0 + \beta_1 T_i + \beta_2(T_i-30) + \beta_3(T_i-40) + \beta_4(T_i-50) + X_i \delta + ((T_i-AP_i)$$

This specification used a linear spline to model the probability of developing a specified chronic condition by the age  $T_i$ . Note that this is not a cumulative probability distribution, because  $f(\text{AGE})$  is not the same as  $F(\text{AGE})$ . The latter would be a cumulative probability;<sup>6</sup> the former may not be because it depends on how people get “selected” for prison. The estimate of  $P$  could decrease over some ranges of age.

Each of the terms in parentheses is set to zero when otherwise they would be negative. The term  $X_i \beta_7$  introduces two covariates – race and offense seriousness – into the regression.

One version of this model constrains  $\gamma$  to zero. This version corresponds to  $f(\text{AGE})$ . An alternative version allows  $\gamma$  to be a free parameter. That alternative version corresponds to  $g(\text{AGE}|\text{age entered prison})$ .

This is a logistic regression. The dependent variable is the observation that a chronic condition began at least by age  $A$ , where  $A$  is the earliest age at which treatment for that condition was observed. The chronic condition may have started earlier, but the data are censored on the left, so we cannot observe the actual starting date. If we did not observe it during the window, we assume that the data were censored on the right, that is, that the chronic condition had not yet started.

The length of the window varied from offender to offender. The window lasted three years for most offenders, but for those who entered or left prison during the window, it was shorter. For the logistic regression to provide a reliable estimate, the window must be of sufficient duration that we could unambiguously conclude that a chronic condition did or did not exist by the window’s end. We could not do that for very short windows, because treatment events might be spaced such that no treatment event was observed despite a chronic condition’s being extant. Therefore we only used observations where the offender’s prison term overlapped the window by at least six months. The choice of six months was somewhat arbitrary, but the only cost of selecting a relatively long window is the loss of observations.<sup>7</sup> Figure 2 illustrates the probability of a typical chronic condition – hypertension – as a function of age.

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<sup>6</sup> Actually,  $F(A)$  is a cumulative probability only if nobody dies. Given that we are analyzing medical conditions, some of which are terminal,  $F(A)$  is not really a cumulative probability either.

<sup>7</sup> Selecting a window of at least 6 months has some justification. A hazard is the rate of occurrence of an event per number of people who are at risk of having that event occur for the first time. When we select just those offenders who begin their prison term sometime during the window, we can define the hazard as the first occurrence of a specified chronic disease – such as hypertension – for each month spent in prison. For hypertension, the hazard is very low for the first two months in prison and is comparatively high during months three through eight. The hazard is fairly constant thereafter. Apparently what happens is that inmates have a comprehensive physical during the early stages of prison, during which preexisting chronic conditions are diagnosed and treatment begun. If we included data from windows that were much less than six months, then the failure to detect a chronic condition may have resulted from the fact that the physical had not yet been completed so the condition had not yet been diagnosed. We would erroneously classify that outcome as right-hand censoring.

figure 2

The horizontal axis is the inmate's age. The vertical axis is the probability that an inmate will have been diagnosed with hypertension as of a given age. Again the pattern is distinctive. The onset of hypertension increases with age, so that by age 50 an inmate has better than a 0.30 probability of being diagnosed with hypertension.

The third category of medical condition is a combination of the first two. It comprises chronic conditions requiring episodic treatments. A bad back is an illustration. Typically a person develops a chronic condition that requires treatment when it first happens, then enters a quiescent period; the condition then recurs periodically.

Modeling this type of medical condition does not require much additional discussion. Because the condition has an onset, we model the time until onset the same way that we did for chronic conditions such as hypertension, and because the condition recurs periodically, we modeled the recurrence rate via the basic Poisson model discussed earlier. This provides an approximate but suitable way of combining the following two steps: model the time until the first occurrence of the condition, and then, after discarding the first episode, model the rate at which additional episodes happened.<sup>8</sup>

Figures 3 and 4 illustrate models for back disorders. These correspond to the  $f(\text{AGE})$  version of the model. Back disorders comprise two ICD-9 codes, one for lower back pain, the second for other back diagnosis. In figure 3, the horizontal axis represents the inmate's age, and the vertical axis represents the probability that the condition had an onset as of that age. The apparent decrease after age 50 is not statistically significant, so it is reasonable to conclude that chronic back conditions are unlikely to have an onset after the age of 50.

Figure 4 reports the average number of treatment episodes per year per inmate. This figure corresponds to a model with age and age-squared terms, and shows back disorders increasing with age, and then decreasing for the oldest inmates. The apparent decrease after age 50 is almost certainly the result of the fact that only a small percentage of inmates fall into this age category (less than 10% averaging over all conditions), so the quadratic model obtains most of its shape from the younger age categories.

### 3.1 Distinguishing between Chronic and Non-Chronic Conditions

A necessary step was to classify medical conditions as chronic or non-chronic. We reasoned that a preexisting chronic condition would be detected during the first few months of a prison term when each inmate goes through a series of medical examinations. To explain this approach, let:

$N_{ij}$  the number of inmates who had not been treated for medical condition  $i$  by month  $j$ . This number either decreased or remained the same from one month to the next. It remained the same from month  $j$  to month  $j+1$  only when no inmate was treated for condition  $i$  for the first time in month  $j$ .

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<sup>8</sup> Because the Poisson model is estimated conditional on the first event having occurred, the first event is uninformative about the Poisson process.

figure 3

insert figure 4

$T_{ij}$  the number of inmates who were treated for medical condition  $i$  for the first time (while in prison) during month  $j$ .

The hazard is a function of months, so that the hazard for month  $j$  is:

$$H_{ij} = T_{ij}/N_{ij}$$

We could only estimate the hazard when the offender entered prison during the window period. Otherwise, he might have been treated for the condition before we could observe his within prison medical history. Furthermore, there were few medical events during the first two months of a prison term. This may be because physicals are delayed, or perhaps because inmates stay in local jails pending transfer to prison. We are unsure of the reason, but the answer does not matter here. We dropped the first two months of prison and computed the hazards for the following eighteen months. Of course, some medical histories were censored on the right when offenders were released before twenty months and when offenders began their prison terms within twenty months of the end of the window. The  $N_{ij}$  term included only those offenders who remained in prison at time  $j$ .

We also used a parametric survival model (based on the assumptions that the survival distribution was Weibull) to test whether or not the risk of a diagnosis was large during the first few months in prison and then became more or less constant over time. The Weibull's shape parameter indicates whether the hazard is increasing (shape > 1) or decreasing (shape < 1). In very broad terms, a shape parameter of less than about 0.8 appeared to indicate a chronic condition, while a shape parameter of greater than 0.8 indicated a non-chronic condition.

The two ways of looking at these data (nonparametric hazards and parametric survival) generally agreed, but sometimes they did not. Hypertensive heart disease is an illustration. The nonparametric hazard curves show an average hazard of 0.083 during months 2–8, an average hazard of 0.019 during months 9–15, and an average hazard of 0.013 during months 16–20. This pattern implies a chronic condition, but the shape parameter is 1.63, implying a non-chronic condition. We necessarily had to exercise judgement when the two approaches disagreed.

Figures 5 and 6 show estimated Weibull hazards for hypertension and sprain. Hypertension has a decreasing hazard (Weibull shape = 0.5), while sprain has a constant hazard (Weibull shape = 1.0).

Table 1 summarizes results. The recoded three-digit ICD-9 code appears in column one; a description of the medical condition is reported in column two. The third column reports the number of inmates who were treated for the specified medical condition sometime during the window period. The next three columns reported the average hazard for months 3–8, months 9–14, and months 15–20, respectively. Most entry physicals appear to be completed between months 2 and 8. Column seven reports the shape parameter from the Weibull survival analysis, and the last column reflects our judgement that the condition should or should not be designated as chronic. We provide reasoning for how we made that judgement below.

**Table 1**

**Distinguishing Between Chronic and Non-Chronic Conditions**

ICD-9	Medical Condition	Prevalence	average hazard month 3-8	average hazard month 9-14	average hazard month 15-20	Shape	Chronic indicator
440	DIABETES MELLITUS	2,481	0.034	0.005	0.003	0.46	C
191	HODGKINS DISEASE	34	0.000	0.000	0.000	0.50	C
239	ESSENTIAL HYPERTENSION	52	0.000	0.001	0.000	0.51	C
117	MENTAL RETARDATION NOS	27	0.000	0.000	0.000	0.52	C
367	HIV RELATED	907	0.012	0.003	0.002	0.54	C
272	OTH CHR ISCHEMIC HRT DIS	58	0.000	0.000	0.000	0.58	C
403	ASTHMA	3,219	0.034	0.011	0.009	0.59	C
319	DRUG DEPENDENCE	571	0.005	0.002	0.002	0.60	C
301	EPILEPSY	188	0.001	0.001	0.000	0.61	C
054	SCHIZOPHRENIC DISORDERS	24	0.000	0.000	0.000	0.61	C
305	ACQUIRED HYPOTHYROIDISM	260	0.002	0.001	0.001	0.62	C
345	EARLY SYMPTOMATIC SYPHIL	611	0.007	0.002	0.002	0.62	C
351	HEART FAILURE	700	0.005	0.003	0.002	0.63	C
244	NEUROTIC DISORDERS	56	0.001	0.000	0.000	0.64	C
372	AFFECTIVE PSYCHOSES	928	0.010	0.003	0.002	0.65	C
362	GOUT	713	0.006	0.002	0.002	0.65	C
297	THYROTOXICOSIS	174	0.001	0.001	0.001	0.65	C
098	HYPERTENSIVE RENAL DIS	25	0.000	0.000	0.000	0.65	C
404	OTH CIRCULATORY DISEASE	3,543	0.026	0.012	0.010	0.67	C
185	OTH LIVER DISORDERS	31	0.000	0.000	0.000	0.68	C
381	OBESITY/HYPERALIMENT	1,597	0.014	0.007	0.005	0.69	C
401	PEPTIC ULCER SITE NOS	2,651	0.020	0.010	0.007	0.71	C
112	MALIGNANT NEOPLASM COLON	26	0.000	0.000	0.000	0.71	C
382	DEPRESSIVE DISORDER NEC	2,233	0.023	0.009	0.008	0.71	C
153	ACUTE MYOCARDIAL INFARCT	30	0.000	0.000	0.000	0.71	C
216	ALCOHOL DEPENDENCE SYNDR	43	0.000	0.000	0.000	0.71	C
307	SENILE/PRESENILE PSYCHOS	263	0.002	0.001	0.001	0.71	C
380	OTH ENDOCARDIAL DISEASE	1,522	0.014	0.006	0.003	0.72	C
378	NONDEPENDENT DRUG ABUSE	932	0.011	0.004	0.003	0.72	C
298	OTH NONORGANIC PSYCHOSES	181	0.001	0.001	0.001	0.73	C
302	MALIGNANT NEOPLASM NOS	201	0.001	0.001	0.000	0.73	C
052	CARDIAC DYSRHYTHMIAS	22	0.000	0.000	0.000	0.73	C
198	HYPERTEN HEART/RENAL DIS	34	0.000	0.000	0.000	0.74	C
414	PERSONALITY DISORDERS	5,063	0.050	0.022	0.014	0.75	C
405	HEARING LOSS	3,674	0.021	0.015	0.014	0.77	C
388	CONDUCT DISTURBANCE NEC	2,480	0.026	0.013	0.009	0.77	C
366	ANEMIA NEC/NOS	823	0.005	0.003	0.002	0.78	C
368	CHR AIRWAY OBSTRUCT NEC	918	0.005	0.003	0.003	0.79	C
278	OLD MYOCARDIAL INFARCT	68	0.000	0.000	0.000	0.80	C
411	VIRAL HEPATITIS	4,166	0.032	0.017	0.011	0.80	C
304	SPECIAL SYMPTOM NEC	212	0.002	0.001	0.000	0.80	C
344	CNS DISORDER NEC/NOS	582	0.006	0.002	0.002	0.81	C
436	BACK DISORDER NEC NOS	16,622	0.129	0.083	0.066	0.81	C
428	ARTHROPATHIES NEC/NOS	7,178	0.048	0.030	0.025	0.82	C
287	CANDIDIASIS	89	0.000	0.000	0.000	0.83	C

ICD-9	Medical Condition	Prevalence	average hazard month 3-8	average hazard month 9-14	average hazard month 15-20	Shape	Chronic indicator
011	MALIGNANT NEOPLASM BRAIN	22	0.000	0.000	0.000	0.83	C
410	DIS OF LIPOID METABOLISM	3,799	0.021	0.014	0.014	0.83	C
389	OTH ACQ LIMB DEFORMITIES	2,636	0.017	0.012	0.010	0.84	C
280	OTH FEMALE GENITAL DIS	68	0.000	0.000	0.000	0.86	C
229	OTHER BREAST DISORDERS	43	0.000	0.000	0.000	0.86	C
282	DISEASES OF ESOPHAGUS	82	0.000	0.000	0.000	0.87	C
435	JOINT DISORDER NEC NOS	14,178	0.097	0.070	0.060	0.87	C
199	HEMORRHOIDS	35	0.000	0.000	0.000	0.87	C
412	SEBACEOUS GLAND DISEASE	4,489	0.027	0.020	0.018	0.88	C
402	STRABISMUS	3,163	0.016	0.014	0.012	0.90	C
365	RENAL/URETERAL CALCULUS	806	0.004	0.003	0.002	0.91	C
300	CURVATURE OF SPINE	183	0.001	0.001	0.001	0.91	C
349	OTH AC ISCHEMIC HRT DIS	634	0.004	0.003	0.002	0.91	C
091	HEREDIT HEMOLYTIC ANEMIA	25	0.000	0.000	0.000	0.91	C
425	CHRONIC SINUSITIS	6,995	0.038	0.032	0.027	0.92	C
162	IMPAIRED RENAL FUNCTION	30	0.000	0.000	0.000	0.92	C
424	OSTEOARTHRITIS ET AL	5,084	0.028	0.021	0.019	0.92	C
433	OTH BONE CARTILAGE DIS	11,121	0.071	0.053	0.051	0.93	C
274	ABNORMAL BLOOD FINDINGS	58	0.000	0.000	0.000	0.94	C
250	MAL NEO TRACHEA/LUNG	57	0.000	0.000	0.000	0.94	C
379	PARANOID STATES	1,148	0.012	0.005	0.003	0.95	C
303	OTH GALLBLADDER DISORDER	203	0.001	0.001	0.001	0.95	C
311	UNSPECIFIED NEOPLASM	418	0.002	0.002	0.001	0.96	C
309	ILL-DEFINED HEART DIS	289	0.002	0.001	0.001	0.96	C
312	FACIAL NERVE DISORDERS	540	0.003	0.002	0.003	0.96	C
079	MALIGN NEOPL TESTIS	25	0.000	0.000	0.000	0.97	C
285	MALIGN NEOPL PROSTATE	84	0.000	0.000	0.000	0.97	C
276	CARDIOMYOPATHY	63	0.000	0.000	0.000	0.99	C
078	OSTEOMYELITIS	24	0.000	0.000	0.000	1.00	C
242	CHR LIVER DIS/CIRRHOSIS	53	0.000	0.000	0.000	1.08	C
201	GLAUCOMA	40	0.000	0.000	0.000	1.11	C
295	RETINAL DISORDERS NEC	122	0.001	0.000	0.001	1.13	C
413	HYPOTENSION	4,882	0.025	0.018	0.016	1.16	C
429	ABNORMAL FUNCTION STUDY	9,535	0.111	0.029	0.029	1.18	C
214	PRECEREBRAL OCCLUSION	40	0.000	0.000	0.000	1.21	C
186	SEC MALIG NEO OTH SITES	32	0.000	0.000	0.000	1.30	C
132	SECONDARY MAL NEO GI/RESP	28	0.000	0.000	0.000	1.32	C
290	SECONDARY HYPERTENSION	94	0.001	0.000	0.000	1.32	C
070	OTH PERIPH VASCULAR DIS	24	0.000	0.000	0.000	1.33	C
110	CHRONIC ULCER OF SKIN	25	0.000	0.000	0.000	1.35	C
197	DISORDERS OF REFRACTION	34	0.000	0.000	0.000	1.37	C
136	CHRONIC RENAL FAILURE	29	0.000	0.000	0.000	1.41	C
296	ATHEROSCLEROSIS	162	0.001	0.001	0.001	1.44	C
427	HYPERTENSIVE HEART DIS	7,145	0.083	0.019	0.013	1.63	C
053	ACQ DEFORMITIES OF TOE	22	0.000	0.000	0.000	1.77	C
575	GONOCOCCAL INFECTIONS	59	0.001	0.000	0.000	0.47	N
550	POIS-MEDICINAL NEC/NOS	47	0.000	0.000	0.000	0.52	N
588	VIRAL INF IN OTH DIS/NOS	75	0.001	0.000	0.000	0.53	N

ICD-9	Medical Condition	Prevalence	average hazard month 3-8	average hazard month 9-14	average hazard month 15-20	Shape	Chronic indicator
573	PEDICULOSIS AND PHTHIRUS	58	0.001	0.000	0.000	0.56	N
717	ADJUSTMENT REACTION	1,199	0.008	0.004	0.005	0.66	N
511	OTH BACTERIAL PNEUMONIA	34	0.000	0.000	0.000	0.67	N
564	PLEURISY	51	0.000	0.000	0.000	0.68	N
565	PULMONARY TUBERCULOSIS	54	0.001	0.000	0.000	0.72	N
714	HYPERPLASIA OF PROSTATE	858	0.005	0.003	0.002	0.75	N
721	OTHER ABDOMINAL HERNIA	1,454	0.009	0.005	0.005	0.78	N
487	OTH PERITONEAL DISORDERS	28	0.000	0.000	0.000	0.78	N
629	OTH INFLAMM POLYARTHROP	266	0.001	0.001	0.001	0.78	N
715	INGUINAL HERNIA	1,063	0.007	0.004	0.003	0.81	N
462	OTH UPPR RESPIRATORY DIS	24	0.000	0.000	0.000	0.82	N
735	DISORDERS OF EAR NEC	3,061	0.015	0.014	0.014	0.82	N
608	DIVERTICULA OF INTESTINE	222	0.001	0.001	0.001	0.83	N
493	OTH PARALYTIC SYNDROMES	29	0.000	0.000	0.000	0.83	N
727	INF/PARASITE DIS NEC/NOS	2,007	0.012	0.008	0.006	0.84	N
560	SPONDYLOSIS ET AL	49	0.000	0.000	0.000	0.85	N
794	GASTRITIS AND DUODENITIS	4,349	0.025	0.019	0.017	0.86	N
722	SEXUAL DISORDERS	1,672	0.010	0.006	0.004	0.86	N
996	DERMATOPHYTOSIS	17,610	0.135	0.095	0.082	0.87	N
729	OTH URINARY TRACT DISOR	2,205	0.012	0.009	0.007	0.87	N
977	DISORDER OF EXTERNAL EAR	13,317	0.094	0.067	0.052	0.87	N
998	OTHER SKIN DISORDERS	21,403	0.159	0.110	0.096	0.87	N
562	EYE DISORDERS NEC	51	0.000	0.000	0.000	0.87	N
728	OTHER VIRAL DISEASE	2,020	0.012	0.009	0.008	0.88	N
919	STOMACH FUNCTION DISORD	6,811	0.038	0.031	0.027	0.88	N
994	OTH RESP SYSTEM DISEASES	15,829	0.107	0.084	0.071	0.89	N
790	MALE GENITAL DIS NEC	3,866	0.022	0.016	0.013	0.89	N
702	URETHRITIS/URETHRAL SYND	491	0.003	0.002	0.002	0.89	N
726	DISEASES OF NAIL	1,810	0.011	0.009	0.007	0.89	N
532	CHICKENPOX	40	0.000	0.000	0.000	0.89	N
716	HERPES SIMPLEX	1,171	0.007	0.005	0.005	0.90	N
553	REPLACE GRAFT COMPLIC	47	0.000	0.000	0.000	0.90	N
736	OTH GASTRODUODENAL DIS	3,445	0.017	0.015	0.012	0.91	N
598	CVA	95	0.000	0.000	0.000	0.91	N
463	SPRAIN OF KNEE LEG	25	0.000	0.000	0.000	0.91	N
959	CONTACT DERMATITIS	12,578	0.080	0.059	0.058	0.92	N
742	ACUTE TONSILLITIS	3,811	0.020	0.018	0.016	0.92	N
701	GASTROINTESTINAL HEMORR	488	0.003	0.002	0.001	0.93	N
HIV	AC URI MULT SITES/NOS	24,114	0.196	0.164	0.135	0.93	N
816	OTH DIS SYNOV/TEND/BURSA	4,877	0.025	0.020	0.018	0.93	N
495	ANKLE FRACTURE	29	0.000	0.000	0.000	0.93	N
930	FUNCT DIGESTIVE DIS NEC	7,630	0.036	0.030	0.028	0.93	N
995	DIS OF MUSCLE/LIG/FASCIA	16,675	0.112	0.092	0.078	0.94	N
465	DISORDERS OF CONJUNCTIVA	26	0.000	0.000	0.000	0.94	N
733	CORNS AND CALLOSITIES	2,440	0.014	0.012	0.010	0.94	N
537	METACARPAL FRACTURE	44	0.000	0.000	0.000	0.94	N
709	PROSTATIC INFLAMMATION	824	0.004	0.003	0.003	0.95	N
848	CERTAIN ADVERSE EFF NEC	5,777	0.035	0.029	0.029	0.95	N

ICD-9	Medical Condition	Prevalence	average hazard month 3-8	average hazard month 9-14	average hazard month 15-20	Shape	Chronic indicator
719	URTICARIA	1,379	0.007	0.007	0.005	0.96	N
604	VISUAL DISTURBANCES	189	0.001	0.001	0.001	0.96	N
535	OTH SURGICAL COMPL NEC	40	0.000	0.000	0.000	0.97	N
459	TRANSIENT CEREB ISCHEMIA	24	0.000	0.000	0.000	0.97	N
496	INTESTINAL OBSTRUCTION	31	0.000	0.000	0.000	0.97	N
737	OTH INTESTINAL DISORDERS	3,458	0.015	0.015	0.013	0.98	N
844	NONSUPPUR OTITIS MEDIA	5,686	0.034	0.024	0.023	0.98	N
682	BENIGN NEOPLASM NEC/NOS	338	0.002	0.001	0.001	0.98	N
558	AC LARYNGITIS/TRACHEITIS	49	0.000	0.000	0.000	0.98	N
603	HYDROCELE	168	0.001	0.001	0.001	0.99	N
824	BRONCHITIS NOS	4,891	0.025	0.026	0.021	0.99	N
706	OTITIS MEDIA SUPPUR/NOS	585	0.003	0.003	0.003	0.99	N
730	OTHER CELLULITIS/ABSCESS	2,368	0.012	0.012	0.011	0.99	N
601	EFFECT EXTERNAL CAUS NEC	147	0.000	0.000	0.000	0.99	N
931	ACUTE PHARYNGITIS	7,843	0.041	0.039	0.033	1.00	N
593	OTHER JOINT DERANGEMENT	85	0.000	0.000	0.000	1.00	N
836	OTHER MYCOSES	5,193	0.028	0.025	0.025	1.01	N
829	OTH NONINF GASTROENTERIT	4,935	0.025	0.025	0.023	1.02	N
949	SPRAIN NEC	10,568	0.060	0.060	0.055	1.02	N
519	IRON DEFICIENCY ANEMIAS	36	0.000	0.000	0.000	1.04	N
815	PERIPH ENTHESOPATHIES	4,675	0.022	0.021	0.019	1.05	N
692	DISLOCATION NEC	432	0.002	0.003	0.001	1.05	N
611	HERPES ZOSTER	262	0.001	0.001	0.001	1.05	N
571	OTH NERVOUS SYSTEM ANOM	57	0.000	0.000	0.000	1.07	N
839	SUPERFICIAL INJ OTH SITE	5,506	0.025	0.028	0.025	1.07	N
793	INFLUENZA	3,898	0.015	0.018	0.016	1.07	N
597	INTESTINAL MALABSORPTION	92	0.000	0.000	0.000	1.08	N
568	CATARACT	56	0.000	0.000	0.000	1.08	N
578	OTHER LUNG DISEASES	71	0.000	0.001	0.000	1.08	N
724	FRACTURE NOS	1,687	0.008	0.008	0.008	1.09	N
703	BENIGN NEOPLASM OF SKIN	545	0.002	0.002	0.003	1.09	N
718	BURN UNSPECIFIED	1,310	0.007	0.007	0.007	1.10	N
879	CONTUSION LEG OTH SITE	6,192	0.029	0.034	0.030	1.10	N
473	ANAL FISSURE FISTULA	27	0.000	0.000	0.000	1.10	N
708	ORCHITIS EPIDIDYMITIS	730	0.003	0.003	0.003	1.11	N
574	EXT ALLERGIC ALVEOLITIS	58	0.000	0.000	0.000	1.11	N
802	INJURY NEC/NOS	4,635	0.020	0.022	0.022	1.12	N
569	FLUID/ELECTROLYTE DIS	57	0.000	0.000	0.000	1.13	N
486	DUODENAL ULCER	28	0.000	0.000	0.000	1.14	N
707	FOREIGN BODY EXTERN EYE	612	0.002	0.003	0.002	1.15	N
443	ACUTE APPENDICITIS	22	0.000	0.000	0.000	1.15	N
700	PNEUMONIA ORGANISM NOS	474	0.001	0.002	0.002	1.16	N
600	CHOLELITHIASIS	143	0.000	0.001	0.001	1.17	N
599	FOREIGN BODY IN EAR	105	0.000	0.000	0.000	1.19	N
924	OPEN WOUND SITE NEC	7,027	0.028	0.037	0.038	1.19	N
478	OTHER DERMATOSES	27	0.000	0.000	0.000	1.27	N
455	ABN FIND-BODY STRUCT NOS	22	0.000	0.000	0.000	1.32	N
533	OTH SKIN HYPERTRO/ATROPH	40	0.000	0.000	0.000	1.32	N

ICD-9	Medical Condition	Prevalence	average hazard month 3-8	average hazard month 9-14	average hazard month 15-20	Shape	Chronic indicator
540	ANGINA PECTORIS	45	0.000	0.000	0.000	1.38	N
592	INTERVERTEBRAL DISC DIS	77	0.000	0.000	0.000	1.40	N
464	PURPURA OTH HEMOR COND	26	0.000	0.000	0.000	1.47	N
482	FRACTURE OF FACE BONES	27	0.000	0.000	0.000	1.54	N
536	OTH RENAL URETERAL DIS	41	0.000	0.000	0.000	1.54	N
585	OTHER SOFT TISSUE DIS	72	0.000	0.000	0.000	1.61	N
458	LIPOMA	24	0.000	0.000	0.000	1.69	N
490	FRACTURE PHALANGES HAND	28	0.000	0.000	0.000	1.72	N
579	INTERNAL DERANGEMNT KNEE	72	0.000	0.000	0.000	1.78	N
530	DISLOCATION OF KNEE	39	0.000	0.000	0.000	1.96	N
518	URETHRAL STRICTURE	34	0.000	0.000	0.000	2.09	N

As mentioned, we established the criterion that a condition was chronic if the shape parameter was less than 0.8. This critical value was judgmental and we will say more about that decision later. For example, using that criterion, asthma was judged to be a chronic condition; acute tonsillitis was judged to be non-chronic.

This criterion was not definitive, however, and for many medical conditions, it was wrong. One problem was that certain medical conditions were relatively rare, so the estimate of the shape parameter was unreliable. Even discounting estimates of the shape parameter for small sample size, an inference based exclusively on the shape parameter estimate sometimes led to erroneous classification. One difficulty is that inmates fail to seek medical treatment before entering prison for some conditions that are non-chronic, so that when those offenders arrive at prison the condition is detected and treated for the first time.<sup>9</sup> The hazard is large during the early prison months, but this does not imply a chronic condition. An Inguinal hernia would seem to illustrate that problem. We used our judgement to change these to non-chronic conditions even when the estimate of the shape parameter was less than 0.8.

Other factors entered into the decision to classify a condition as chronic or not. For example, an “Adjustment Reaction” to entering prison has a high initial hazard, but this does not distinguish a chronic condition. We used judgement to put all medical conditions into either the chronic or non-chronic category. The last column shows our final judgement about whether or not a condition was chronic.

Table 1 has been sorted so that all the conditions that we deem chronic appear at the beginning of the table and all the conditions that we deem not to be chronic appear at the end of the table. Within the chronic/non-chronic categories, the table is sorted by the Weibull shape parameter.

<sup>9</sup> We presume that many offenders are indigent or at least lack health care coverage. Many, such as intravenous drug users, may be unaware of certain medical conditions that are masked by their drug abuse, and many others may for various reasons simply avoid seeking medical attention.

figure 5

figure 6

## 3.2 Unsolved Problems with the Approach

Although this approach to modeling and projecting inmate demands for medical treatment provides useful insight, it suffers from unsolved problems that limit the utility of those projections. We discuss some of those problems here and illustrate them in the next section.

The basic data are the medical events that happened during a three-year window when inmates were incarcerated. From those data, we inferred when medical conditions started and the frequency with which they recurred. The inmate's age was the most important explanatory variable, because we used the relationship between age and medical conditions to predict what would happen as inmates age.

We estimated a series of models where the  $\lambda$  parameter was constrained to equal zero. (See the discussion on model specification from above.) The problem with this approach is that it assumes that the onset and recurrence of medical conditions vary with age but are invariant to the length of time that an inmate was actually in prison. However, medical conditions are sensitive to diet, exercise, and a host of other environmental conditions that surely change when a person enters prison. A better model would recognize those differences and allow  $\lambda$  to be a free parameter.

Consequently, we estimated a series of related models where  $\lambda$  was a free parameter. (See the discussion on model specification from above.) In theory, this approach should have allowed us to determine the prevalence of medical conditions in a non-prison cohort (estimated from the prevalence of a preexisting condition when those people entered prison) and how the prevalence of that condition changed over time while in prison. In fact, this was sometimes a useful approach, as we will show with some illustrations in the next section.

For many medical conditions, however, this alternative approach did not work. We expected that the onset of most diseases should not be greatly affected by incarceration. But in fact, when we allowed  $\lambda$  to be a free parameter, the resulting projections were at variance with that expectation – many were so different that we could not accept this model specification as providing a better view of the onset of chronic medical conditions.

We are left with the problem that neither model does the job; both have notable deficiencies. We are uncertain why that is the case, but we suspect that it happens because the window is too narrow. That is, three years is too little time to draw inferences about what would happen as offenders age, especially since the early months in prison are atypical of latter months. There is no reason to constrain the data to a three-year period, other than the fact that adequate data were not available prior to 1995. A future study with cases from a more expansive window might be able to resolve this problem. We cannot do so here.

Another problem is that we wish to project the onset of medical conditions for inmates who are 50, 60 and 70 years old. In fact, very few inmates are that old. Fifty percent of this sample was younger than 34 at the time of the window; ninety percent were younger than 49. Only 5 percent were older than 55, 2 percent were older than 60, and fewer than 1 percent were older than 64. This is a small basis for making inferences, and we caution the reader that projections beyond the age of 50 are imprecise. In some cases, they are outrageously poor. We will note instances in the following section.

Still another problem is unique to specific diseases. Comparing the prevalence of disease across age cohorts can sometimes create results that are unhelpful for making projections. HIV and AIDS provide one illustration. The prevalence of those diseases is especially high in the age 30 cohort and it is comparatively low in the age 50 cohort. Of course, this does not say that the prevalence of this chronic condition decreases with age, but rather, that the younger age cohort was at especially high risk because HIV/AIDS is epidemic. Our approach does not work well for medical conditions that are epidemic.

Mental illness provides another illustration of a chronic condition where cohort comparisons seem not to work well. The prevalence of mental illness is relatively high in the age 30 cohort, but it is lower in the age 50 cohort. Perhaps this is because those with mental illness are “cured” by the time they reach an older age, but more likely something happens to the chronically mentally ill – perhaps they die early – so that they do not appear with the same frequency among older cohorts. We are unsure, but this is a clear illustration of how  $f(\text{AGE})$  can differ from  $F(\text{age})$

These are serious problems that constrain the inferences that otherwise might be made with these data. We think they could be overcome with longer windows, so that inferences could be based on the time-series progression of disease as inmates age, rather than cross-cohort comparisons. That will have to await a future study.

## 4.0 Results

The results are organized by type of medical condition: intermittent and chronic. Chronic is further divided into chronic with continuous treatment and chronic with intermittent treatment. Two types of tables of parameter estimates are given: Poisson-based estimates for the number of episodes per year are given for all conditions (tables A1 and A2), and logistic-based estimates for the probability of onset by a given age are given for chronic conditions (tables A3 and A4). The first table for each model type corresponds to a model with age variables but no time in prison variable (tables A1 and A3). These correspond to the  $f(\text{AGE})$  variant of the model. The second table for each type corresponds to a model with age variables and a time in prison variable (tables A2 and A4). This is the  $f(\text{AGE}|\text{age entered prison})$  model specification, from above. These tables can be found in appendix A.

We begin by discussing particular examples for intermittent conditions, chronic conditions requiring continuous treatment, and chronic conditions with intermittent recurrences.

### 4.1 Intermittent Conditions

Earlier we showed that the frequency of sprain decreased with age, as we would expect. On average, sprains occur at a rate of 0.16 treatment episodes per inmate per year at age 30 and about 0.08 per year at age 45. Abdominal Hernia, shown in figure 7, provides another example of results we would expect. In this case the rate increases with age, doubling from 0.02 per year at age 35 to 0.035 per year at age 45.

figure 7

The above results are based on models containing age and age-squared terms, and for these medical conditions it seems unnecessary to add time in prison. However, for certain other medical conditions, a model with time in prison seemed more plausible. For example, for digestive disorders (FUNCT DIGESTIVE DIS NEC, ICD-9 564), the graph corresponding to the model containing age and age-squared terms (figure 8) shows an increasing episode rate up to age 50, followed by a decreasing episode rate.

This non-monotonic relationship is not borne out by the model containing age and time in prison shown in figure 9. In this improved model there is an increasing episode rate for inmates over the entire age range. (The Akaike Information Criterion (AIC) for a given model is defined as deviance plus two times the number of parameters in that model; in this case, the reduction in the AIC is 69.48, causing us to prefer the second model to the first.) For example, a 40 year old inmate who started prison at age 35 experiences digestive disorders at an annual rate of 0.1 treatment episodes, and 20 years later he may expect a rate of 0.6.<sup>10</sup>

Although the AIC criterion provides some assistance, judging whether or not the  $f(\text{AGE})$  version is better than the  $f(\text{AGE}|\text{age entered prison})$  version is uncertain. For reasons already discussed, each model has its strengths and weaknesses. Table A1 in appendix A reports all the parameter estimates for the  $f(\text{AGE})$  version of the model. The variable AGE2 is age squared. TSERV is expected time served in prison; BLACK is a dummy variable denoting race. Table A2 reports comparable parameter estimates for the  $f(\text{AGE}|\text{age entered prison})$  variation. In this table, TIP represents time in prison. An asterisk associated with the TIP variable denotes that time in prison is a significant predictor of changes medical needs as a function of time in prison. This does not necessarily mean that  $f(\text{AGE}|\text{age entered prison})$  is a better model than  $f(\text{AGE})$ , however, because these two models are not nested. Although we drew the corresponding figures, it was impractical to include more than a few illustrations. We invite the reader to draw others that interest him. This can be done easily with a spreadsheet program.

## 4.2 Chronic Conditions Requiring Continuous Treatment

Table A3 reports results from the logistic model. The first two columns identify the ICD-9 code and diagnosis. The third column reports the number of incidents of that medical condition reported in the data. Note that some conditions are rare, and for them, estimates are likely to be unreliable. The rest of the columns report parameter estimates for variables identified in the main text. Table A4 is the counterpart to A3 that includes time in prison (TIP) in the model specification.

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<sup>10</sup> Incidentally, the model indicates that time in prison contributes to digestive disorders: the earlier the age when the prison term began, the higher the episode rate for an inmate of a given age. The apparent downward trend from the model with age and age squared can be understood as follows. The approximately correct model indicates that the age effect is small and the time in prison effect is positive. Because age and time in prison are positively correlated (correlation = 0.28), the exclusion of the time in prison variable would induce a positive relationship between the episode rate and age. In fact, the relationship between age and time in prison is not only positive, but also bending *upward*. Thus, the exclusion of the time in prison variable induces a positive but *downward* bending relationship between the episode rate and age, the relationship we see in figure 8.

figure 8

figure 9

We first illustrate the relationship between the probability of onset and age estimated via the logistic model. Earlier, in figure 2, we showed that the onset of hypertension increases with age, as expected. By age 40 an inmate's chance of being diagnosed with this condition is about 0.1, and this increases to 0.3 by age 50. Arthritis (Arthropathies NEC/NOS ICD-9 716), shown in figure 10, provides another example of an expected increasing relationship with age: the probability of onset by age 40 is about 0.12, and by age 50 this doubles to 0.24.

These results do not account for the effect of time in prison. For hypertension, figure 11 shows that adding this variable has no additional effect. However, for arthritis the effect of time in prison is positive ( $p < 0.0001$ ), and this is shown in figure 12. We now estimate that, for an inmate starting prison at age 35, the probability of onset by age 40 is 0.14, and by age 50 this increases to 0.35.

HIV shows the effect of time in prison in a more dramatic way. If the time in prison variable is excluded, onset by age 50 (0.015) is supposedly about half that of onset by age 40 (0.027). This is shown in figure 13. Of course, this is impossible for a homogeneous population. However, the cohort that was 40 in 1998 has a higher prevalence of HIV than the cohort that was 50 in 1998, and thus the exclusion of a "cohort" variable could easily induce the curve in figure 13. To some extent, the inclusion of time in prison deals with this problem of heterogeneity, for if we follow the trajectory of inmates starting prison at a given age, we are actually following a cohort rather than, as in the previous model, moving between cohorts. For example, as shown in figure 14, inmates starting prison at age 35, have a slightly higher HIV prevalence 15 years later (0.30 at age 50) than 5 years later (0.28 age 40).

Figure 14 also illustrates a problem with the  $f(\text{AGE}|\text{age entered prison})$  model. It seems unlikely that large numbers of federal inmates would become HIV positive while under federal custody, yet the  $f(\text{AGE}|\text{age entered prison})$  variation of the logistic model implies that the infection rate is very high. We cannot be pleased with either the  $f(\text{AGE})$  or  $f(\text{AGE}|\text{age entered prison})$  version of this model.

Figures 15 and 16 show onset graphs excluding and including time in prison for schizophrenia. These patterns are typical for mental disorders, and they are qualitatively similar to those for HIV. Without time in prison (Figure 15), we are again presented with a lower onset by age 50 compared to the onset by age 40. As with HIV, this situation could be induced by the prevalence of the condition decreasing with cohort, and this type of prevalence-cohort relationship appears to be taken into account by a model containing time in prison (figure 16). In addition, one would ideally wish to define the homogeneous population as a cohort of inmates not ultimately transferred from prison to hospital because of their schizophrenic disorder.

As a final example for time to onset, figures 17 and 18 show graphs corresponding to models excluding and including time in prison for asthma. The model without time in prison is again untenable: although the slope is positive beyond age 40, it is negative from 18 to 40. Possibly asthma is more prevalent among younger cohorts. In any event, we advocate the time in prison model because, at least to some extent, this controls for the cohort effect, and all cumulative probabilities increase with age.

As noted previously, although age at first onset is fundamental to chronic conditions, the rate at which episodes occur is also of interest, particularly from the viewpoint of total treatment cost. These rates are estimated via the Poisson model. As an example, we consider the rate of hypertension episodes.

figure 10

figure 11

figure 12

figure 13

figure 14

figure 15

figure 16

figure 17

figure 18

Figure 19 shows that the frequency of treatment episodes for hypertension increases with age, from a rate of 0.04 per year at age 40 to 1.1 per year at age 50. We choose the quadratic age model rather than the age with time in prison model because the AIC of the former is 75.80 units less than that of the latter. Combining this with the earlier finding that time in prison had no effect on the age of onset, the implication is that the episode rate conditional on having hypertension is also unrelated to time in prison.

### 4.3 Chronic Conditions with Intermittent Recurrences

The difference between the two types of chronic conditions involves the regularity of treatment episodes once the condition has been contracted. In the case of chronic conditions requiring continuous treatment, the time between episodes for a given patient is thought to be relatively regular, while for chronic conditions with intermittent recurrence, the time between events is widely spaced and almost random. However, the clarity of this distinction is likely to be blurred when we average across patients, and in any event, from a modeling viewpoint, the two types of chronic conditions are indistinguishable. We will consider the example of hemorrhoids.

Figures 20 and 21 show the age of hemorrhoid onset corresponding to models excluding and including time in prison. As a cumulative probability function, figure 20 is reasonable from age 18 to 50, but the figure takes on a negative slope for older ages: the prevalence by age 70 (0.10) is less than that by age 60 (0.11). However, when time in prison is included (figure 21), positive slopes are obtained for all cohorts. In particular, for a 70 year old inmate who started prison at age 55, the prevalence (0.20) is higher than , the prevalence at age 60 (0.12).

Now consider the episode rate graph for hemorrhoids. Figure 22 reports the average number of treatment episodes per inmate year estimated from model with age and age-squared terms. The figure shows hemorrhoids increasing with age up to age 50, and then decreasing for the older inmates. The apparent decrease may be due to the fact that only a small percentage of inmates fall into the older age category (less than 10% averaging over all conditions), so the quadratic model obtains most of its shape from the younger age categories.

Alternatively, the apparent negative relationship with age may be due to the exclusion of the time in prison variable. Figure 23 shows that the effect of time in prison increases the rate of episodes, and the relationship is positive over all ranges. However, although the time in prison parameter is statistically significant, the AIC for the model with time in prison is 46.75 units higher than the AIC for the model with age and age-squared. We would therefore prefer the model without time in prison.

### 4.4 Choosing Between $f(\text{AGE})$ and $f(\text{AGE}|\text{age entered prison})$

We seek to estimate how the incidence and prevalence of medical conditions change as inmates age. One way to do this is to estimate the model denoted  $f(\text{AGE})$ . Usually this model provides reasonable estimate of medical conditions increasing or decreasing monotonically with inmates' ages. As we illustrated above, however, that is not always the case, and sometime  $f(\text{AGE})$  does not provide credible estimates. This should not surprise us, because we know that  $f(\text{AGE})$  does not measure exactly what this study intends to measure. Estimates based on a cross-section of inmates - the basis for  $f(\text{AGE})$  - will not necessarily provide a reliable guide for how medical conditions will change for the same inmates over time.

figure 19

figure 20

figure 21

figure 22

figure 23

Because we were aware of the theoretical deficiencies of the  $f(\text{AGE})$  mode, we estimated a second model, denoted as the  $f(\text{AGE}|\text{age entered prison})$  model. This model does measure what this study intends to estimate, and on that basis, we would always prefer it to the  $f(\text{AGE})$  variation. The problem is that  $f(\text{AGE}|\text{age entered prison})$  is apparently estimated with considerable imprecision. We frequently observe that the incidence of certain medical conditions increase with age at an unreasonable pace. This problem is exacerbated when the projections are extended to fifteen and twenty years into the future. The incidence of HIV infection is an illustration.

This raises the problem: The first model provides estimates that are apparently biased but reasonably precise. The second model provides estimates that are apparently unbiased but imprecise. How should we choose between the two?

There is little sound basis for making the choice in this study, and anyway, the problem is probably not the models but the data. The biggest problem would seem to be the abbreviated length of the window. A longer window should lead to more precise parameter estimates for the  $f(\text{AGE}|\text{age entered prison})$  model. Given the greater reason in theory for preferring  $f(\text{AGE}|\text{age in prison})$  to  $f(\text{AGE})$ , and given the expected improvement in  $f(\text{AGE}|\text{age entered prison})$  that would result from better data, we recommend a future focus on the  $f(\text{AGE}|\text{age entered prison})$  model.

## 5.0 Conclusions

We have attempted to predict changes in health care needs as offenders age. Although we were successful in that mission, we were not totally successful. Believing that social science research is cumulative, we hope that what we have learned will inform future study.

We developed three different generic models of health care needs. The first was a model for intermittent medical conditions, the second a model for chronic conditions requiring continuous treatment, and the third a model for chronic conditions with intermittent recurrence. For each model, we developed two variations. Time in prison did not enter the first variation, which we designate as  $f(\text{AGE})$ ; it did enter the second model, which we designate as  $f(\text{AGE}|\text{age entered prison})$ .

We had to develop a procedure for distinguishing between medical conditions that were chronic and medical conditions that were not chronic. We proposed two empirical tests, and while they were helpful, we learned that empirical tests alone could not determine how to classify medical conditions. Of course, health care providers could probably do a reliable job of making these classifications, but they too would have missed some interesting findings. Offenders apparently go without medical attention, so that when they enter prison, the need for providing medical care is especially heavy. Dental attention, although not part of our data, would seem to be the prototypical illustration. People who lack medical insurance because they are unemployed or underemployed probably forego seeking medical care. They may even be so uninterested in their medical condition that they forego care available through free clinics. At any rate, when these people go through prison medical diagnosis, such conditions are detected and treatment is rendered.

Our findings suggest also that predictions of the need for medical care cannot be based upon the prevalence of disease outside of prison. Although we do not make any such comparison, it seems reasonable to assume that prisoners suffer from certain medical conditions at higher rates than do others who are not involved with the criminal justice system. Indeed, for communicable diseases, this

is demonstrable – people who go through jails and prisons account for a large proportion of diseases such as HIV, AIDS, TB and Hepatitis B and C.<sup>11</sup> Thus, it seems necessary to base projections on a prisoner population.

Our findings also suggest that prison can retard the onset of certain medical conditions. This is easy to understand. Medical care received in prison can be a preventative, and at the least, early diagnoses can lead to more efficacious treatments. Furthermore, inmates are removed from unhealthy conditions (such as substance abuse) and introduced to healthy conditions (including regular sleep, exercise, food and hygiene). This is not to say that prisons are the healthiest alternative. For example, it is difficult to believe that prisons promote mental health. The point, however, is that the incidence and prevalence of medical conditions among prison inmates should be different from the incidence and prevalence of medical conditions among otherwise similarly situated offenders who are not in prison.

This latter effect – that prisons are more or less conducive to health compared with not being in prison – was difficult to model. Indeed, we were not especially successful. While we could almost always uncover what appeared to be a prison effect on the incidence and prevalence of medical conditions, the effect was often too large to be reasonable.

We think that future study of the incidence and prevalence of medical conditions in an offender population has to deal with this prison effect. To do so, however, we believe that researcher will have to acquire data from a longer window. Although three years would seem to be a long time to study the progression of medical conditions, the apparent length of that window is deceptive. Many offenders enter prison during the window. For them, the window is shorter than three years, and it is shortened even more by the need to discard data from windows that are shorter than six months. Of course, offenders may end their sentences before the end of the window, and for them, the window is necessarily less than three years. A new study needs to examine a window that is as long as possible. With computerized databases, such data are readily available, and the models developed in this study can be used to derive useful estimates.

We also had to deal with the problem of left-hand censoring. This is unavoidable since there is no way to observe the onset of chronic medical conditions that occurred before the beginning of prison. But self-imposition of left-hand censoring, which happens when the window is abbreviated, seems like a needless complication that could be overcome by expanding the width of the data collection window.<sup>12</sup>

Several remaining problems received no attention here. Some diseases either end in death or have a high probability of ending in death. Cancer is an illustration. We did not attempt to model death rates, but of course, it would be unreasonable to assume that someone who entered prison with a terminal malignancy could serve a twenty-year prison term. More refined models would certainly cut the average life-span at some empirically-derived threshold. We have not done that here.

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<sup>11</sup> Hammett, T., Harmon, P. and Rhodes, W., The Burden of Infectious Diseases Among Inmates and Releasees from Correctional Facilities, paper prepared by Abt Associates for the National Commission on Correctional Health Care, October 14, 1999.

<sup>12</sup> Likely, some inmates will have entered prison before electronic health records were created. For them, left-hand censoring would remain a problem.

We spent considerable effort attempting to convert medical treatment into dollar costs. Appendix B provides some details, but ultimately, we were not successful. There is a conceptual problem converting medical treatment into costs, and that is that prisons vary greatly in the quality and quantity of treatment given to inmates. The cost of treating condition X in prison A is not the same as the cost of treating condition X in prison B. There is no universal standard. The best way for prison administrators to use the projections developed here probably is to apply judgement about how trends will affect the current delivery of health care services and, in turn, how this will effect costs.

There was an additional practical problem with developing cost estimates. We could not find good translations from ICD-9 codes into estimates of how much it cost to treat the condition. Again, appendix B discusses this issue, but we were not able to develop a useful algorithm for assigning costs to conditions.

Ultimately, we find it difficult to answer the penultimate questions that motivated this research: How will medical health care costs change as prisoners age? We note that a prison system that has a high turnover of inmates has high medical care costs. This is because inmates enter prison with preexisting medical conditions that require treatment; health care likely diminishes for most inmates following this initial period of relatively high intensity health care. If fewer inmates go to prison for relatively short terms, and if those inmates who go to prison stay for extended periods, prison costs would go down provided everything else were held constant.

Of course, not everything else would be held constant. Some medical conditions actually decrease with age – sprains are an illustration. We assume this happens because young inmates are more active physically, and that physical activity leads to the same ailments inside prison as they do outside prison. However, for the most part, these would seem to be conditions that are relatively inexpensive to treat.

In fact, many serious medical conditions – heart disease, for example – increase with age. These will be increasingly expensive to treat. Thus, while the total number of medical events may decrease (e.g., few sprains) the expense of medical costs is still likely to increase (e.g., more heart bypass surgery).

Estimating this increase has been very difficult, for reasons illustrated. Although medical conditions will increase as offenders age, for many medical conditions, prison may be a relatively healthy environment. While few of us would exchange freedom for prison, incarceration does provide regular meals, sleep, and exercise which are often avoided by those with the freedom to choose. For some medical conditions, especially communicable diseases, prison may be unhealthy. We are not promoting prisons as health care spas. The point is simply that making projections of health care needs requires some adequate way of modeling the healthy or unhealthy effects that prisons have on the incidence and prevalence of medical conditions. Although our results are suggestive, we were not able to provide that model. We hope that future studies will, and that those future attempts will be assisted by the work reported here.

# Appendix A      Tables of Parameter Estimates

## Appendix B      Assigning Dollar Costs of Medical Events

The Health Care Financing Administration recently developed Medicare's Outpatient Prospective Payment System, which is to be implemented fully on July 1, 2000. This payment plan best captures the cost of medically treating prisoners. Each medical record in the data set includes an ICD-9 code (International Classification of Diseases- Version 9) which serves as a basis for determining costs. Using information in the September 8, 1998 Federal Register's Proposed Rule for the Prospective Payment System, we did the following: First, each ICD-9 code was mapped into one of twenty major diagnostic categories (MDC) that are the basis for the payment system. Coupled with the type of visit (clinical or emergency) and level of visit (low, mid, high), the MDC code corresponds to an ambulatory payment class for which there is an associated cost (more specifically, these costs are Medicare's payment rate for these medical events). Unfortunately, the prison medical records do not indicate the type or level of visit. We assume that the events are clinical in nature (versus emergency) and we determined three costs for each APC (these are the costs of a low, mid, and high level visit).

A next step would be to associate these costs with treatment episodes, as defined in this report. Because an episode is a cluster of events, and given that the events identify ICD-9 codes, we could have estimate a cost per episode. This would be the sum of events the comprise the average episode multiplied by the payment class. We did not complete that step, and consequently, we have no practical ways of saying whether or not it would provide useful estimates.

The resulting translation table is too large for inclusion here. We show its first few entries, sorted by the name of the medical condition, as table B-1.

**Table B-1**

**Translation Table from ICD-9 Codes into Dollar Costs**

ICD-9 CODE	MEDICAL EVENT ICD-9 LABEL	COST OF CLINICAL VISITS (dollars)		
		LOW LEVEL	MID LEVEL	HIGH LEVEL
942.29	2ND DEG BURN TRUNK NEC	53.71	53.71	85.63
444.0	ABD AORTIC EMBOLISM	43.07	50.67	72.46
789.34	ABDMNAL MASS LT LWR QUAD	49.66	50.67	76.00
789.33	ABDMNAL MASS RT LWR QUAD	49.66	50.67	76.00
789.06	ABDMNAL PAIN EPIGASTRIC	49.66	50.67	76.00
789.07	ABDMNAL PAIN GENERALIZED	49.66	50.67	76.00
789.02	ABDMNAL PAIN LFT UP QUAD	49.66	50.67	76.00
789.04	ABDMNAL PAIN LT LWR QUAD	49.66	50.67	76.00
789.09	ABDMNAL PAIN OTH SPCF ST	49.66	50.67	76.00
789.03	ABDMNAL PAIN RT LWR QUAD	49.66	50.67	76.00
789.01	ABDMNAL PAIN RT UPR QUAD	49.66	50.67	76.00
789.00	ABDMNAL PAIN UNSPCF SITE	49.66	50.67	76.00
789.40	ABDMNAL RGDT UNSPCF SITE	49.66	50.67	76.00
789.63	ABDMNAL TNDR RT LWR QUAD	49.66	50.67	76.00

MEDICAL EVENT		COST OF CLINICAL VISITS (dollars)		
ICD-9 CODE	ICD-9 LABEL	LOW LEVEL	MID LEVEL	HIGH LEVEL
789.60	ABDMNAL TNDR UNSPCF SITE	49.66	50.67	76.00
441.4	ABDOM AORTIC ANEURYSM	43.07	50.67	72.46
789.9	ABDOMEN/PELVIS SYMP NEC	53.71	53.71	53.71
039.2	ABDOMINAL ACTINOMYCOSIS	49.66	50.67	76.00
790.6	ABN BLOOD CHEMISTRY NEC	53.71	53.71	53.71
794.39	ABN CARDIOVASC STUDY NEC	53.71	53.71	53.71
794.30	ABN CARDIOVASC STUDY NOS	53.71	53.71	53.71
795.2	ABN CHROMOSOMAL ANALYSIS	67.39	61.82	91.71
796.4	ABN CLINICAL FINDING NEC	53.71	53.71	53.71
524.5	ABN DENTOFACIAL FUNCTION	41.04	47.63	66.38
794.02	ABN ELECTROENCEPHALOGRAM	53.71	53.71	53.71
793.6	ABN FIND-ABDOMINAL AREA	53.71	53.71	53.71
793.9	ABN FIND-BODY STRUCT NEC	53.71	53.71	53.71
792.9	ABN FIND-BODY SUBST NEC	53.71	53.71	53.71
793.5	ABN FINDINGS-GU ORGANS	46.11	52.70	65.87
793.0	ABN FINDING-SKULL & HEAD	53.71	53.71	53.71
793.1	ABN FINDINGS-LUNG FIELD	53.71	53.71	53.71
792.2	ABN FINDINGS-SEMEN	46.11	52.70	65.87
793.7	ABN FIND-MUSCULOSKEL SYS	53.71	53.71	53.71
792.1	ABN FIND-STOOL CONTENTS	53.71	53.71	53.71
790.2	ABN GLUCOSE TOLERAN TEST	53.71	53.71	53.71
795.4	ABN HISTOLOGIC FIND NEC	53.71	53.71	53.71
781.0	ABN INVOLUN MOVEMENT NEC	49.66	52.70	76.00
794.4	ABN KIDNEY FUNCT STUDY	46.11	52.70	65.87
794.8	ABN LIVER FUNCTION STUDY	49.66	50.67	76.00
795.0	ABN PAP SMEAR-CERVIX	47.12	53.71	72.46
795.1	ABN PAP SMEAR-OTH SITE	47.12	53.71	72.46
790.5	ABN SERUM ENZY LEVEL NEC	53.71	53.71	53.71
794.5	ABN THYROID FUNCT STUDY	44.08	50.67	71.44
791.9	ABN URINE FINDINGS NEC	46.11	52.70	65.87
794.31	ABNORM ELECTROCARDIOGRAM	53.71	53.71	53.71
790.0	ABNORM RED BLOOD CELL	55.23	52.70	83.60
786.7	ABNORMAL CHEST SOUNDS	53.71	53.71	53.71
787.7	ABNORMAL FECES	49.66	50.67	76.00
796.9	ABNORMAL FINDINGS NEC	53.71	53.71	53.71
701.5	ABNORMAL GRANULATION NEC	42.06	49.66	85.63
783.2	ABNORMAL LOSS OF WEIGHT	44.08	50.67	71.44
796.1	ABNORMAL REFLEX	53.71	53.71	53.71
786.4	ABNORMAL SPUTUM	53.71	53.71	53.71
783.1	ABNORMAL WEIGHT GAIN	44.08	50.67	71.44
704.2	ABNORMALITIES OF HAIR	42.06	49.66	85.63
781.2	ABNORMALITY OF GAIT	49.66	52.70	76.00

MEDICAL EVENT		COST OF CLINICAL VISITS (dollars)		
ICD-9 CODE	ICD-9 LABEL	LOW LEVEL	MID LEVEL	HIGH LEVEL
790.92	ABNRML COAGULTION PRFILE	53.71	53.71	53.71
914.0	ABRASION HAND	53.71	53.71	85.63
910.0	ABRASION HEAD	53.71	53.71	85.63
916.0	ABRASION HIP & LEG	53.71	53.71	85.63
919.0	ABRASION NEC	53.71	53.71	85.63
919.1	ABRASION NEC-INFECTED	53.71	53.71	85.63
540.1	ABSCESS OF APPENDIX	49.66	50.67	76.00
373.13	ABSCESS OF EYELID	49.66	44.08	66.38
572.0	ABSCESS OF LIVER	49.66	50.67	76.00
513.0	ABSCESS OF LUNG	40.54	47.12	67.39
303.00	AC ALCOHOL INTOX-UNSPEC	55.23	55.23	79.55
571.1	AC ALCOHOLIC HEPATITIS	49.66	50.67	76.00
522.4	AC APICAL PERIODONTITIS	41.04	47.63	66.38
540.0	AC APPEND W PERITONITIS	49.66	50.67	76.00
536.1	AC DILATION OF STOMACH	49.66	50.67	76.00
532.00	AC DUODENAL ULCER W HEM	49.66	50.67	76.00
532.10	AC DUODENAL ULCER W PERF	77.02	57.26	95.77
357.0	AC INFECT POLYNEURITIS	49.66	52.70	76.00
411.89	AC ISCHEMIC HRT DIS NEC	43.07	50.67	72.46
534.30	AC MARGINAL ULCER NOS	49.66	50.67	76.00
383.00	AC MASTOIDITIS W/O COMPL	41.04	47.63	66.38
461.0	AC MAXILLARY SINUSITIS	41.04	47.63	66.38
730.07	AC OSTEOMYELITIS-ANKLE	44.08	49.66	69.42
730.06	AC OSTEOMYELITIS-L/LEG	44.08	49.66	69.42
533.20	AC PEPTIC ULC W HEM/PERF	77.02	57.26	95.77
533.00	AC PEPTIC ULCER W HEMORR	49.66	50.67	76.00
420.0	AC PERICARDIT IN OTH DIS	43.07	50.67	72.46
380.01	AC PERICHONDRIITIS PINNA	44.08	49.66	69.42
285.1	AC POSTHEMORRHAG ANEMIA	55.23	52.70	83.60
580.4	AC RAPIDLY PROGR NEPHRIT	46.11	52.70	65.87
295.40	AC SCHIZOPHRENIA-UNSPEC	55.23	55.23	79.55
381.01	AC SEROUS OTITIS MEDIA	41.04	47.63	66.38
531.00	AC STOMACH ULCER W HEM	49.66	50.67	76.00
998.2	ACCIDENTAL OP LACERATION	53.71	53.71	85.63
530.0	ACHALASIA & CARDIOSPASM	49.66	50.67	76.00
726.71	ACHILLES TENDINITIS	44.08	49.66	69.42
536.0	ACHLORHYDRIA	49.66	50.67	76.00
276.2	ACIDOSIS	44.08	50.67	71.44
706.1	ACNE NEC	42.06	49.66	85.63
706.0	ACNE VARIOLIFORMIS	42.06	49.66	85.63