NBER WORKING PAPER SERIES

THE INCIDENCE OF ADVERSE MEDICAL OUTCOMES UNDER PROSPECTIVE PAYMENT

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Working Paper No. 4300

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 1993

I am grateful to Jerry Hausman, Larry Katz, Joe Newhouse, Jim Poterba, and Larry Summers for useful discussions, to Glenn Sueyoshi for providing computer programs, to Abt Associates for the use of the data, and to the Alfred P. Sloan Foundation and National Institutes on Aging for research support. This paper is part of NBER's research programs in Aging, Health Care and Public Economics. Any opinions expressed are those of the author and not those of the National Bureau of Economic Research.

NBER Working Paper #4300
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ABSTRACT

This paper examines the effect of prospective payment for hospital care on adverse medical outcomes. In 1983, the federal government replaced its previous cost-based reimbursement method with a prospective payment system, where reimbursement depends only on the diagnosis of the patient. Hospitals thus lost the marginal reimbursement they formally received for providing additional treatments. In addition, the average price each received changed with fixed reimbursement. This paper related each of these changes to adverse outcomes, with two conclusions. First, there is a change in the timing of deaths associated with changes in average prices. In hospitals with price declines, a greater share of deaths occur in the hospital or shortly after discharge, but by one or two years post-discharge, this difference in mortality rates disappears. Second, there is a trend increase in readmission rates caused by the elimination of marginal reimbursement. This appears to be due to accounting changes on the part of hospitals, however, rather than true changes in morbidity.

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Recent years have witnessed large changes in pricing of hospital care. Responding to rising Medicare expenditures, the federal government in 1983 replaced its cost-based hospital reimbursement system with a fixed-price Prospective Payment System (PPS). Prospective payment established a fixed price for each patient, based only on the patient's diagnosis. Since prices are fixed, hospitals now bear the full cost of marginal treatments. In addition, prospective payment changed the average prices that different hospitals received; previously high cost hospitals lost revenue, and previously low cost hospitals increased revenue.

This paper examines the effect of marginal and average reimbursement changes on patient outcomes. I use a longitudinal data set of almost 30,000 Medicare recipients, with over 40,000 hospital admissions, in New England between 1981 and 1988. Since Massachusetts began prospective payment later than the other New England states, the data permit a natural experiment of the effect of prospective payment on adverse events. I use mortality and hospital readmission to measure adverse events. The econometric formulation has three risks: death in the hospital; readmission post-discharge; and death post-discharge. I relate each of these events to the marginal and average reimbursement changes.

The results suggest two conclusions. First, hospitals with average price declines have a compression of mortality rates into the immediate post-discharge period. There are more deaths in the hospital and the first two months post-discharge, but there is no increase in mortality for those surviving one or two years. Second, the elimination

of marginal reimbursement led to increased hospital readmissions, but this appears to be due to accounting changes on the part of hospitals making patients appear more likely to be readmitted, rather than true changes in morbidity. There does not appear to be any true change in sickness from the elimination of marginal reimbursement.

The paper proceeds as follows. The first section discusses identifies the marginal and average reimbursement effects of prospective payment. The second section describes the data. The third and fourth sections present the econometric methodology and results. The fifth section considers different explanations of the marginal reimbursement effect, and the sixth section examines long run mortality effects of average price changes. The last section concludes.

I. Prospective Payment and Adverse Outcomes

Prior to prospective payment, Medicare[1] reimbursement to hospitals was essentially cost-plus. Each hospital reported the cost of treating each patient and was reimbursed that amount. Prospective payment, in contrast, instituted fixed prices per admission. Under prospective payment, each patient is grouped into one of roughly 470 Diagnoses Related Groups, or DRGs. The classification is done predominantly on the basis of the principal diagnosis, although secondary diagnoses are often taken into account.

The hospital's payment for the patient depends on the DRG of

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[1]Medicare recipients are predominantly elderly (90 percent are over 65), with some disabled beneficiaries (about 10 percent). The data I examine contain only elderly recipients.

the patient. Each DRG is assigned a weight (WGT_d) based on the costs of treating patients in that DRG is previous years.[2] The weight is then multiplied by an update factor (P_h) which converts the weight into a price for each hospital. The update factor is relatively uniform across hospitals, although it does vary to reflect local wages and additional payments for sole community hospitals and rural referral centers. Finally, adjustments are made for hospitals with indirect medical education (teaching) costs (IME_h) and hospitals that serve a disproportionate share of poor patients ($DISSH_h$). The price under PPS for any patient is thus given by:[3]

$$P_{1,d,h} = WGT_d * P_h * (1+IME_h) * (1+DISSH_h). \qquad (1)$$

There are two important properties of prospective reimbursement. First, hospitals bear the full marginal cost for each treatment they provide. Under cost-based reimbursement, marginal costs are fully reimbursed; under prospective payment, they are not reimbursed at all. I refer to this as the "marginal reimbursement effect". If marginal cost were known for each patient, one could relate this known marginal cost to adverse outcomes. In practice, however, there is no accurate way to measure differences in marginal cost across patients. I thus assume constant marginal costs and proxy for the marginal reimbursement effect with a post-PPS dummy variable.

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[2]The weight ranges from 0.3 to over 11.

[3]The prices vary slightly each year, reflecting changes in the blend of national and regional weights in the update factor. These changes are relatively minor, however, so I use only the 1988 prices.

Second, prospective payment changed the average price different hospitals received, and across DRGs within a hospital. I refer to this change as the "average reimbursement effect". Denoting $C_{0,d,h}$ as the average cost of treating a patient prior to prospective payment, the expected price in the absence of prospective payment is: $P_{0,d,h}=(1+\pi)C_{0,d,h}$, where π is a common update factor.[4] The change in average price is then given by:

$$\Delta P_{d,h} = \log(P_{1,d,h} / P_{0,d,h}). \quad (2)$$

Changes in both marginal and average reimbursement may influence adverse outcomes. Reductions in average prices force hospitals to cut back on either treatment intensity or other inputs. If either of these affects patient outcomes, reductions in average prices will increase the likelihood of an adverse event. Similarly, eliminating marginal reimbursement increases the hospital's cost of marginal treatments relative to the benefits. This may also lower treatment intensity, and result in worse outcomes.[5]

Testing these effects requires measures of adverse events. I use two -- mortality and hospital readmission. Mortality is the most natural measure of outcomes; as reimbursement becomes less generous, we expect mortality rates to rise. Changes in morbidity may be as important as changes in mortality, however, particularly for marginal

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[4]The update factor is the ratio of 1988 to 1984 costs for patients aged 55-64, who are not covered by Medicare. Since it is common across patients, it will be reflected in the constant term of the estimates.

[5]See Cutler (1990) for more discussion of these issues.

treatments. I proxy for morbidity with the hospital readmission rate. Unlike the prediction about changes in mortality, however, the effect of less generous reimbursement on morbidity is unclear. If the average patient is sicker following prospective payment, morbidity should rise. If there is no increase in average morbidity but the sickest patients die sooner, however, the pool of survivors will be less sick than before prospective payment, and morbidity will fall. The observed effect may be in either direction.

The hypotheses to be tested are thus:

H1: Following the elimination of marginal reimbursement, mortality rates should rise. Readmission rates may increase or decrease, depending on changes in the pool of patients relative to changes in the morbidity of the each patient.

H2: In response to average price reductions, mortality rates should rise. The effect on readmission rates is again ambiguous.

Almost all previous work on hospital responses to prospective payment has focused on marginal reimbursement effects, generally proxied by time trends. Fitzgerald, Moore and Dittus (1989) found an increase in long term nursing home utilization and a reduction in physical movement for patients with hip fractures following prospective payment. This result has not been confirmed for other groups of patients, however (Kahn et al, 1990; Palmer et al, 1989; Gerety, Soderholm-Difatte, and Winograd, 1989). A much larger study (Brook et al, 1990), examined detailed clinical conditions for about 10,000 Medicare hospitalizations in five diagnoses before and after prospective payment, and found an increased incidence of instability at discharge.

This was offset, however, by a general decline in mortality rates among the elderly, so there was no long term mortality increase. Staiger and Gaumer (1990) is the only other paper to use average as well as marginal price changes. They find that hospitals with a greater decrease in Medicare revenues had an increase in post-admission mortality rates. That paper uses reimbursement changes for the entire hospital; I examine within-hospital changes as well. In addition, I examine morbidity as well as mortality changes.

II. The Data

The data on adverse outcomes are formed from Medicare and Social Security records.[6] The initial sample is a complete census of Medicare hospitalizations for the elderly (age 65+) in the six New England states (Massachusetts, Maine, New Hampshire, Vermont, Rhode Island, and Connecticut) from 1981 through 1988. Prospective payment was instituted in Massachusetts in fiscal year 1986[7], and in the latter five states (termed "federal PPS" states), in fiscal year 1984. The eight year period thus natually divides into three samples: 1981-83 (prior to prospective payment in all states); 1984-85 (federal prospective payment only); and 1986-88 (prospective payment in all states).

Hospital records were selected if: (1) the admission was in one

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[6]The data were prepared by Abt Associates and are discussed in more detail in Gaumer et al (1989).

[7]Throughout the paper, I refer to fiscal years instead of calendar years.

of a 25 percent random sample of hospitals in the state; (2) the last digit of the patient's social security number matched one of two choices (a 20 percent sample); and (3) the admission was in one of 67 principal diagnoses.[8] These diagnoses represent approximately 20 percent of all hospital admissions, so that the final data contains about 1 percent (.25*.20*.20) of Medicare admissions in these states over the eight year period. This results in 16,308 admissions in the state of Massachusetts, and 24,373 in the federal PPS states. Each record was then matched with Social Security death records through 1989.[9] All known deaths are noted on the file, including those unrelated to a hospitalization.[10] I define readmission as any subsequent admission to the set of diagnoses in the sample.[11]

The final data issue is the measure of average price changes.

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[8]These diagnoses were selected by a panel of physicians as most likely to be responsive to changes in state rate setting procedures (evaluated in the mid-1980s). The sample may thus not be respresentative of the average response under prospective payment. Nevertheless, under the null hypothesis of no increase in adverse effects, the sampling choice is immaterial.

[9]In the sickness equations, I censor deaths at the end of 1988 since it is impossible to determine if a death in 1989 was preceeded by a readmission that year.

[10]A small sample of records (965 observations) had known deaths but did not identify the exact day of the month on which the patient died. For these patients, I recorded the death date as the last day of the month of death.

[11]I also experimented with a readmission measure limited to similar diagnoses. The results were quite close to those reported here.

This is difficult to compute because it requires a complete sample of patients admitted to each DRG prior to prospective payment. For the state of Massachusetts, I obtained data for the entire set of admissions in 1984, two years prior to prospective payment, which I use to form costs.[12] Unfortumately, the cost data are not available for the other states; I am thus limited to Massachusetts for measuring average price effects.[13]

The appropriate price change for any patient is the change in the reimbursement for that patient's DRG. To determine the DRG exactly sometimes requires knowledge of secondary diagnoses in addition to the primary diagnosis, which my data do not contain.[14] I thus cannot form an exact price change for each patient. Instead, I use the empirical distribution of which DRGs a patient with that principal

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[12]The data from before PPS contain charges rather than costs. I deflate them to costs using the hospital-specific cost-to-charge ratio. For 91 admissions, I was unable to compute the price change due to too few elderly admissions in the base period. The hazard models thus contain 40,590 observations.

[13]I have estimated the sickness model using only the Massachusetts sample, to test the importance of pooling the states for the average price response. The results are virtually identical to those reported here. I have also estimated the model without the price change, to test the sensitivity of the marginal reimbursement terms to the missing price data. These results were also very close to the ones reported here.

[14]For example, patients with complications and/or comorbidities will often be assigned to a different DRG than patients without complications and/or comorbidities. Also, patients who have surgery are in different diagnoses than patients who do not have surgery, but the hospital may not know if the patient will require surgery at the time of admission.

diagnosis was assigned to in 1984 to form a weighted average of the price changes for those DRGs.[15] Each patient receives the price change associated with this average of the DRG-specific price changes.

The average price increased by 0.7 percent after prospective payment, with a standard deviation of 28 percent. Since many hospitals have only a few patients in some DRGs, the pre-prospective payment average price is measured with some error. For standard reasons, this suggests that the effect of price changes on adverse events will be understated.[16]

A. Trends in Readmission and Mortality

Table 1 presents evidence on changes in readmission rates (the upper panel) and mortality rates (the lower panel) after the implementation of prospective payment. The table reports the probability or either event for fixed periods up to 1 year;[17] Figure 1 shows the 6 month readmission and mortality rates annually. For each adverse event, the first three columns present the probability of that

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[15]I took only those DRGs which accounted for at least 10 percent of the 1984 admissions. There were 22 diagnoses with only 1 DRG matching this criterion, 30 with 2 DRGs, and 13 with 3 or more DRGs.

[16]While it is possible to extend this framework to the instrumental variables case, there are no obvious instruments.

[17]The 1 year cutoff was chosen largely because of data limits; there are not enough spells before and after prospective payment to estimate adverse events over longer periods. Since readmission rates only rise by about 6 percentage points in the second year, however, this limit may not be very important.

outcome for the federal PPS states, and the second three present the results for Massachusetts.[18]

Both mortality and readmission are substantial risks for the elderly. The probability of death in the hospital is almost 10 percent, and rises to 30 percent by one year. Similarly, there is a three percent chance of readmission within 15 days, rising to almost 20 percent by one year. The probability of some adverse event in the first year is 42 percent.

To summarize the effects of prospective payment, I use a linear probability model:

$$Event_j = \sum_{s=0}^{S} \beta_{0,s,j} + \sum_{t=1}^{T} \beta_{1,t,j} + \beta_2 * Post\text{-}PPS_j + \epsilon_j. \qquad (3)$$

where $Event_j$ is an indicator variable for the presence of an adverse event, β_0 is a set of state-specific identifiers, β_1 a set of time-specific identifiers, and β_2 the PPS effect. The last two columns report β_2 from equation (3), where I have separated the response in the federal PPS states from the response in Massachusetts.

Importantly, equation (3) is identified only because of the staggered implementation dates of prospective payment. The time dummy variables capture the average adverse event probability each year; the Post-PPS variables reflect only the change in the federal PPS states relative to Massachusetts after 1983, and the change in Massachusetts relative to the federal PPS states after 1985.

Both readmission and mortality rates appear to have changed

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[18]The standard errors for the three year averages are about 0.4.

after prospective payment, but in opposite directions. Readmission rates increased after prospective payment in both groups of states, although they subsequently declined in the federal PPS states. The increase in the 6 month readmission rate is about 1.7 to 3.1 percentage points. In contrast, mortality rates, particularly in-hospital, fell after the implementation of prospective payment, by about 2.5 percentage points. Mortality rates remain low, although they do increase by 0.5 to 1.0 percentage points in the next year. The fact that readmission and mortality rates moved in opposite directions suggests that a simple model of increased sickness after prospective payment is not a complete description of events. I return to this issue in Section V.

III. Econometric Specification

I assume that an individual admitted to the hospital has a latent measure of sickness S_j, which is a function of individual frailty characteristics and the treatment the hospital provides (both summarized in the vector X_j). The probability of an adverse outcome is increasing in the level of sickness. There are three potential adverse events. First, the person could die in the hospital. It is natural to separate this risk from the post-discharge risks since the probability of this event is much larger than the other two and since there may be a more immediate relation between reimbursement and in-hospital mortality. I model in-hospital mortality as a logit model:[19]

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[19]One could also estimate the in-hospital mortality equation as a hazard model, using length of stay as the time measure. Because length of stay is endogenous, however, I do not follow this approach.

$$P^{*}_{Hj} = X_j * \beta_H + \epsilon_{Hj}, \qquad (4)$$

where ϵ_H has a logistic distribution (denoted $G(\epsilon_H)$). The patient dies if $P^{*}_{H,j} > 0$.

An individual discharged from the hospital may either be readmitted [P_R], may die without readmission [P_M], or may live without adverse incident.[20] A natural specification of these two probabilities is a proportional hazard model: $\lambda_{i,j}(t) = \lambda_{0,i}(t) * \exp(X_j(t) * \beta_i)$, where $\lambda_i(t)$ is the instantaneous probability of risk i, conditional on survival to t, and $\lambda_{0,i}(t)$ is the baseline hazard. The hazard can be rewritten as a non-linear equation for the failure time t^* (Kalbfleisch and Prentice, 1980):

$$\log\left(\int_0^{t^*} \exp(X_j(s) * \beta_i) * \lambda_{0,i}(s)\, ds \right) = \epsilon_{i,j}, \qquad (5)$$

where ϵ_i has an extreme value distribution (denoted $F(\epsilon_i)$). Assuming that $X_j(s)$ is constant within each period, this can be rewritten as:

$$\delta_{i,j}(t^*) = \log\left(\sum_{s=1}^{t^*} \exp(X_j(s) * \beta_i + \gamma_{s,i}) \right) = \epsilon_{i,j}. \qquad (6)$$

The term $\gamma_{s,i} = \log\left(\int_{s-1}^{s} \lambda_{0,i}(\tau) d\tau \right)$ is the integrated baseline hazard.

Assuming the in-hospital and post-discharge risks are

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[20]If the probabilities were a function of a well-defined scalar sickness level, there would be non-linear restrictions on the parameters in the three equations. I instead allow the coefficients to differ, to minimize potential specification bias.

independent,[21] the probabilities can be written as:

$$P_{1j} = Prob[in\text{-}hospital\ mortality] = G(X_j * \beta_H)$$

$$P_{2j} = Prob[censored\ in\ week\ t^*] = [1-G(X_j * \beta_H)] * [1-F(\delta_{Rj}(t^*-1))] * [1-F(\delta_{Mj}(t^*-1))] \quad (7)$$

$$P_{3,kj} = Prob[event\ k\ in\ week\ t^*] = [1-G(X_j * \beta_H)] * [F(\delta_{kj}(t^*))-F(\delta_{kj}(t^*-1))] * [1-F(\delta_{-kj}(t^*-1))]$$

where k in the last equation is either readmission or death and -k is the other.[22] The likelihood thus factors into a logit equation for in-hospital mortality and a competing risks model for readmission and death.

Defining d_j as an indicator for in-hospital mortality and c_j as an

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[21]Alternatively, one could allow for correlation of the error terms in the three equations. As Han and Hausman (1990) show, however, hazard models with unknown error correlations are identified only if there are time-varying covariates, exclusion restrictions in one of the equations, or at least two continuous variables. Since the model does not suggest any natural exclusion restrictions, and there is only 1 continuous variable, the correlation of the errors is unidentified. I explore alternative heterogeneity specifications below.

[22]The equation for $P_{3,k}$ is consistent but not fully efficient. Since the hazard function is known for each period, fullly efficient estimation would integrate over the joint probability of event k occurring and event -k not occurring during the t^*-1 to t^* period. The specification here uses less information--only the knowledge that event -k occurred after t^*-1. Because the one week hazard for both events is very small and the integration over several thousand observations would be computationally difficult, I do not perform the within week integration.

indicator for censored observations, the likelihood function is:

$$L = \prod_{j=1}^{N} P_{1j}^{d_j} \; P_{2j}^{c_j} \; P_{3,k\,j}^{(1-c_j-d_j)} \qquad (8)$$

I estimate equation (8) using standard maximum likelihood techniques.

IV. Readmission and Mortality Estimates

As covariates in the sickness model, I include four age dummies (65-69, 22 percent; 70-74, 24 percent; 75-79, 21 percent; 80+, 33 percent), a sex dummy (50 percent of the patients are male), a dummy for whether the current admission is a readmission to the hospital (15 percent of admissions), a dummy for being in Massachusetts, year dummy variables, and dummy variables for nine types of admission.[23] The underlying sickness equation is:

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[23]The types are: surgical emergencies; potential surgical emergencies; medical emergencies; potential medical emergencies; intracranial emergencies; traumatic injury to vital organs, and serious and potentially serious fractures; serious burns, potential emergencies due to physical agens, and emergencies due to allergic reactions; complex diagnostic entities; and elective surgical procedures. I do not include dummy variables for each diagnosis because the 160 additional variables (60 variables in three equations) would be too many to estimate. I have examined a number of subsamples of the data to test the importance of this assumption. Restricting the sample to diseases of the circulatory system, where there are many observations (including the two largest diagnoses) and where mortality rates are high enough to allow diagnoses-specific dummy variables, has no appreciable effects on the results. I also grouped the diagnoses by organ system rather than type of admission, again with very similar results. This suggests that the absence of diagnosis-specific dummy variables should not affect the results.

$$S_j = \alpha_0 + \sum_{i=2}^{4} \alpha_{1,i} AGE_{i,j} + \alpha_2 MALE_j + \alpha_3 READMIT_j + \alpha_4 MASS_j + \sum_{i=2}^{9} \alpha_{5,i} DIAG_{i,j} + \sum_{t=2}^{T} \alpha_{6,t,j} + \beta_1 \Delta P_j + \beta_2 Post\text{-}PPS_j. \quad (9)$$

Importantly, equation (9) does not contain person-specific effects. In the presence of such effects, estimation would be done over persons as opposed to admissions, conditional on the entire medical history (Chamberlain, 1980). Since the data contain only limited patient histories, however, I do not use this specification.

Table 2 present estimates of the sickness model. The first column is the logit equation for in-hospital mortality. The next two columns present the post-discharge hazards, assuming the baseline follows a Weibull distribution:[24] $\lambda_{0,i}(t) = \alpha_i t^{\alpha_i - 1}$. The coefficients on the demographic variables are similar for the three equations. Relative to patients aged 65-69, all three risks increase in probability with increasing age, with especially pronounced effects for the mortality equations. Males are more likely to suffer post-discharge adverse outcomes. Patients readmitted to the hospital are more likely to suffer all types of adverse events, particularly subsequent readmission. Patients in Massachusetts are less likely to die in the hospital than patients in other states.

The remaining rows show the effects of prospective payment

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[24]Weibull models are fequently used for adverse events since they have a natural bioactuarial interpretation (Manton, Vaupel, and Stallard, 1986).

on readmission and mortality. Both marginal and average reimbursement changes affect adverse outcomes. In response to average price reductions, in-hospital mortality increases, and this result is statistically significant. The coefficient (-.317) suggests a mortality increase of about 0.5 percentage points in response to a one standard deviation decline. Since in-hospital mortality is about 6 percent, this is almost a ten percent mortality increase. In contrast, the readmission probability decreases with price reductions, although this result is only statistically significant at the 10 percent level. The coefficient (.158) suggests a four percent decrease in the readmission hazard in response to a one standard deviation reduction in price. There is no change in the post-discharge mortality hazard following averge price reductions.

The response to average price changes suggests a natural sickness interpretation: sicker individuals die closer to a hospital admission and thus are not subsequently readmitted to the hospital. The composition effect of average price changes on the pool of survivors thus appears to be larger than the change (if any) in the average morbidity of patients. These results also imply, however, that the long run response of mortality will be smaller than the short run response, since the individuals who die shortly after the hospital visit are not at risk for readmission and subsequent death. I return to the question of the long run effects of average price changes in Section VI.

Eliminating marginal reimbursement has opposite effects on outcomes from price declines. In-hospital mortality falls in response to the elimination of marginal reimbursement, by about 25 percent. This reduction is statistically significantly different from zero. The

mortality reduction appears to be permanent; there is no evidence of an increase in the post-discharge mortality hazard over time. The readmission hazard increases in response to the elimination of marginal reimbursement, although this result is only statistically significantly different from zero at the 10 percent level. The estimates suggest an increase of about 1.3 percentage points at 180 days.

The marginal reimbursement effects are more difficult to interpret in a sickness framework than the average reimbursement effects. Increased sickness should certainly be manifest in increased mortality, but the effect here is to lower mortality. This suggests looking beyond the sickness hypothesis to explain these results. I return to this issue in Section V.

The last two columns of Table 2 re-estimate the post-discharge hazards, using a semi-parametric baseline in place of the Weibull baseline.[25] The X^2 tests of the equality of the baseline specifications reject the Weibull assumption (the 5 percent critical value is 124.3). As Figure 2 indicates, this rejection is predominantly due to an overestimate by the Weilbull model of the true baseline hazard in the first week after discharge and an underestimate in the next several weeks. Substantively, however, there are no important differences between the two sets of estimates. The coefficients on the reimbursement variables are essentially unchanged, as are those on the individual characteristics. I thus use the Weibull model in the

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[25]In each case, the three equations are estimated jointly; since the in-hospital mortality risk is independent of the post-discharge risk, the estimates for that equation are identical. equation model.

remainder of the paper.

A. Unobserved Heterogeneity

The most obvious difficulty with equations (4) and (6) is the potential for unobserved heterogeneity. Individuals who are intrinsically sicker will be more likely to die or be readmitted to the hospital. If unobserved sickness is correlated with demographic or hospital variables, the coefficients on these variables will be biased. Heterogeneity can be modelled as an additional source of error in the in-hospital and post-discharge equations:

$$\begin{aligned} P^{*}_{hj} &= X_j * \beta_H + \epsilon_{Hj} + \omega_H \\ \delta_{ij}(t^{*}) &= \epsilon_{ij} - \omega_i . \end{aligned} \tag{10}$$

If one were willing to specify a functional form for ω (for example Gamma), one could jointly estimate the parameters of the heterogeneity distribution and the sickness equation. An alternative formulation, suggested by Heckman and Singer (1984), is to estimate the distribution of ω non-parametrically, as a discrete set of points (mass points) and the probability that a patient has that value of ω. I pursue this second option.

I assume for each equation that there are L discrete values of ω (mass points). The probability of any event can then be factored into the probability conditional on ω and the probability of each value of ω. The set of ω's are denoted $\omega_H=\{\omega_h,\ h=1,\ldots,L\}$, $\omega_R=\{\omega_r,\ r=1,\ldots,L\}$, and $\omega_M=\{\omega_m,\ m=1,\ldots,L\}$. The probability of each event is thus:

$$P_{1j} = \sum_{h=1}^{L} G(X_j * \beta_H + \omega_h) * Pr[\omega_H = \omega_h]$$

$$P_{2j} = \sum_{h=1}^{L} \sum_{r=1}^{L} \sum_{m=1}^{L} [1 - G(X_j * \beta_H + \omega_h)] * [1 - F(\delta_{Rj}(t^* - 1) + \omega_r)] *$$

$$[1 - F(\delta_{Mj}(t^* - 1) + \omega_m)] * Pr[\omega_H = \omega_h] * Pr[\omega_R = \omega_r] * Pr[\omega_M = \omega_m]$$

$$P_{3j} = \sum_{h=1}^{L} \sum_{k=1}^{L} \sum_{-k=1}^{L} [1 - G(X_j * \beta_H + \omega_h)] *$$

$$[F(\delta_{kj}(t^*) + \omega_k) - F(\delta_{kj}(t^* - 1) + \omega_k)] * [1 - F(\delta_{-kj}(t^* - 1) + \omega_{-k}))] *$$

$$Pr[\omega_H = \omega_h] * Pr[\omega_K = \omega_k] * Pr[\omega_{-K} = \omega_{-k}]$$

The likelihood function is the same as in equation (8).

In preliminary estimation, all 3 equations had one mass point become increasingly large and negative, so that there is no probability of an adverse event. To allow for this, I fix one point at an arbitrary large, negative value (-25), so that the probability of an adverse event will be effectively zero. The values of the other mass points, along with their associated probabilities, are chosen optimally.

Table 3 shows estimates of the sickness model with three mass points.[26] For all 3 equations, there is some unobserved heterogeneity. The mass points are statistically significantly different from each other, with probabilities greater than zero. In addition, the baseline hazard parameters increase, reflecting the reduction in mixed populations. In

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[26]I attempted to estimate models with additional points, with little success. There were a number of local maxima.

the post-discharge equations, there is a 20 to 30 percent probability of no adverse event. There is a 60 percent probability of no in-hospital mortality risk. Beyond the differentiation between some and no risk, however, there is much less heterogeneity. The probability of a second, non-zero mass point is never above 7 percent. Thus, a two or three point distribution appears to characterize the unobserved heterogeneity well.

Most importantly, the conclusions about the reimbursement effects are not altered by adding the heterogeneity terms. The coefficients on the reimbursement variables are actually greater in magnitude with the heterogeneity correction than without it. The coefficients in the in-hospital equation, for example, are 60 to 100 percent larger than those in Table 2. The standard errors also increase substantially, however. In most cases, it is impossible to reject constancy of the coefficients in Table 3 with those in Table 2. Because the coefficients without the heterogeneity correction are estimated much more precisely than those with the heterogeneity correction, I use the equations without the heterogeneity correction in the subsequent sections. It does not appear that unobserved heterogeneity explains the results above.

B. Alternative Specifications of the Reimbursement Terms

Since changes in morbidity may occur at different periods post-discharge, a natural generalization of equation (9) is to allow for time variation in the reimbursement terms. I divide the reimbursement variables into four splines (1-4 weeks, 5-8 weeks, 9-26 weeks, and 27-

52 weeks) and estimate separate effects for each. Table 4 presents the results.[27]

The estimates suggest some differences in the response at different points in time; a X^2 test rejects the specification in Table 2 in favor of that in Table 4. The decline in readmission rates following average price reductions occurs principally after the first two months. Between two months and one year, the estimates suggest a 5 to 10 percent reduction in the readmission hazard in response to a one standard deviation price decline. The coefficients on the 1-4 week and 5-8 week splines, in contrast, are small and statistically insigificant. The trend increase in readmission rates associated with the elimination of marginal reimbursement occurs principally in the first two months post-discharge. The coefficient on the 1-4 week and 5-8 week splines are positive and statistically significant. The coefficients on the other two variables are smaller, and the effect in the second half of the year is in the opposite direction. Finally, as in Table 2, there are no large effects of marginal or average reimbursement changes on post-discharge mortality. The estimates are generally statistically insignificant and of varying signs. This evidence clearly implies an important dynamic element in the sickness process. I return to the importance of this in Section VI.

As a final specification of the reimbursement terms, I included a complete set of year dummy variables for Massachusetts and the federal PPS states. The difference between these estimates and those

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[27]The in-hospital mortality equation is the same as in Table 2, since there are no time varying parameters in this case.

in Table 2 is a specification test for the marginal reimbursement terms.

The X^2 test from the estimation rejects the restrictions imposed in Table 2.[28] Most of the qualitative conclusions from the unrestricted model, however, are similar to those in Table 2. To determine the marginal reimbursement effect, one can compute a difference-in-differences estimate using the year dummy variables. The change in the adverse event probability associated with the implementation in Massachusetts, for example, is the difference in the year effects in Massachusetts before versus after prospective payment, relative to the change in the federal PPS states before versus after prospective payment: MA-PPS = $[M_{86\text{-}88}-M_{84\text{-}85}]-[F_{86\text{-}88}-F_{84\text{-}85}]$, where M and F are the average year effects for the two groups of states. The difference between the federal PPS states and Massachusetts between 1981-83 and 1984-85 is a second estimate of the marginal reimbursement effect.

For the in-hospital mortality equation, the implementation in Massachusetts and the federal PPS states are associated with decreases of -.294 (.087) and -.349 (.099) in the sickness propensity. These results are statistically indistinguishable from the -.298 reported in Table 2. Similarly, both estimates suggest little change in the post-discharge mortality hazard. The effects are -.042 (.071) and .065 (.076) for the Massachusetts and federal PPS experiments, compared to -.002 in Table 2. The one qualitative difference between the two experiments is in the readmission hazard. This probability rises in the Massachusetts experiment [.162 (.056)] but is unchanged in the federal

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[28]The likelihood ratio for the augmented model is -87,662. The test statistic, 38, exceeds the 5 percent critical value of 28.9.

PPS experiment [-.019 (.063)]. The estimate in Table 2 (.095) is an average for these two groups.

These results thus suggest some caution in interpreting the increase in the readmission hazard. The effect is clearly important for one state, but less important for the other states. Since there are only eight years of data in the sample, there is no way to look for other experiments using aggregate data. Instead, I examine data in different diagnoses to test the importance of the marginal reimbursement effects noted above. I turn to this next.

V. Explaining Marginal Reimbursement Effects

There are three potential explanations for the marginal reimbursement effects above.[29] First, they may be due to randomness associated with the short period over which the data are measured. Second, they may signal true changes in sickness. The decline in in-hospital mortality argues against this explanation, although this decline may be caused by other factors. Finally, the response may reflect accounting changes on the part of hospitals to prospective payment, without any change in underlying sickness. Prospective payment gave hospitals many ways to increase reimbursement by making only accounting changes. The most common is through what is termed DRG upcoding (Carter, Newhouse, and Relles, 1990). Suppose that

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[29]An earlier version of this paper also considered the hypothesis that hospitals responded to prospective payment by discharging patients sooner and then readmitting them to collect additional reimbursement. I found no support for this model, however, so I omit it here.

a hospital takes a patient that was formerly in a low-weighted DRG and records the patient with a more severe diagnosis. Since sicker patients may be placed in higher weighted DRGs, this increases reimbursement. Because my sample contains mostly more severe diagnoses, I may observe increases in readmission rates that are due only to coding changes, not true changes in morbidity. This might also explain the decline in mortality, because the newly coded patients will be less severely ill than were patients in that diagnosis prior to prospective payment.

The most natural test of these theories is to examine the correlation between changes in readmission and mortality rates across diagnoses. The sickness explanation suggests that changes in readmission and mortality rates should be positively correlated across diagnoses, even if aggregate mortality rates fall after prospective payment. The coding explanation, in contrast, suggests that the two will be negatively correlated, as more marginal readmissions are counted in that diagnosis. The randomness explanation suggests no relation between readmission and mortality changes across diagnoses.

To test these hypotheses, I examine outcome changes for the 17 largest diagnoses (containing 35,005 admissions).[30] To find the

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[30]These diagnoses are those with over 200 admissions in both sets of states in the eight year sample. They are: (1) aortic aneurysm; (2) cholelithiasis with acute cholecystitis; (3) cholecystitis and cholangitis without mention of calculus; (4) acute myocardial infarction; (5) paroxysmal atrial fibrillation; (6) grand mal seizure; (7) left ventricular failure; (8) congestive heart failure; (9) fracture of pelvis; (10) status asthmaticus (asthma); (11) secondary and unspecified malignant neoplasm of respiratory and digestive system; (12) cholecystectomy;

marginal reimbursement effects, I estimated the sickness model allowing for diagnoses-specific PPS effects. I then find the percentage point change in in-hospital mortality and readmission rates in the first week implied by the estimates.

Figure 3 graphs the change in readmission and mortality rates for the different diagnoses, along with the predictions from a linear regression.[31] While the reimbursement estimates are highly variable, the evidence from Figure 3 appears more consistent with the coding explanation than the morbidity explanation. Diagnoses with large increase in readmission rates tend to have reductions in mortality rates. The correlation between the two is -.203. With only 17 observations, this is not statistically different from zero. The correlation is thus consistent with either the coding explanation or the randomness explanation. Importantly, however, it is not consistent with an explanation of increase morbidity. I find no evidence that changes in marginal reimbursement affect sickness in these data.

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(13) repair of inguinal hernia; (14) transurethral resection of prostate; (15) hysterectomy; (16) excision/destruction of local lesion of bladder; and (17) mastectomy.

[31]The regression coefficient and correlation coefficient are adjusted for sampling error. For two variables $x=x^*+\epsilon$ and $y=y^*+\eta$, the sample covariance is given by $cov(x,y)= cov(x^*,y^*)+cov(\epsilon,\eta)$, and the sample variances are $\sigma^2_x=\sigma^2_{x^*}+\sigma^2_\epsilon$ and $\sigma^2_y=\sigma^2_{y^*}+\sigma^2_\eta$. To estimate $\sigma^2_{x^*}$, for example, I form the difference between the variance of my set of x coefficients (σ^2_x) and the average variance of each estimate (σ^2_ϵ). I use a similar procedure to form $cov(x^*,y^*)$ and $\sigma^2_{y^*}$. The regression coefficient and correlation are based on these estimates of the true values.

VI. How Important Are Average Price Responses?

In response to average price reductions, mortality rates initially rise and subsequent readmission rates decline. Since patients who are readmitted to a hospital are at higher risk of death than patients who do not need to be rehospitalized, the long run effect of average price changes on mortality will be smaller than the short run effect.

To examine the long-run mortality effect of average price changes, I simulated the sickness model 100,000 times and generated the empirical mortality distribution.[32] Each simulated admission receives random error terms for the in-hospital mortality equation and the post-discharge hazards. The simulation then follows patients through any subsequent hospital admission and death, up to one and one-half years post discharge. I use the time-varying estimates in Table 4 to perform the simulations.[33] The patient is assumed to be one with the average characteristics in the sample.[34]

Table 5 shows the cumulative mortality rates for the average patient and for a patient in a hospital with a one standard deviation reduction in price. Since the mortality probability is increasing in the

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[32]Alternatively, one could integrate the three equations to find the probability of death at any time. Because of the many possible paths, however, this is impractical.

[33]I assume the coefficients for the 26-52 week spline extend through the next half year.

[34]There are two exceptions to this. First, I consider a patient admitted after prospective payment. Second, I assume the first admission is not a readmission. Any subsequent hospital admissions are counted as readmissions, however.

risk factors, the average simulated patient has a lower mortality rate than the average patient in the sample. The in-hospital mortality rate, for example, is 5 percent. A one standard deviation price reduction raises the in-hospital mortality rate by .29 percentage points. The mortality differential rises over the next two months, to .46 percentage points. After that point, the differential falls, as fewer patients are readmitted to the hospital and thus at risk for the high in-hospital mortality rate. By one-half year after discharge, one-half of the mortality increase has been eliminated, and by one year, almost all of the increase has been eliminated. The simulations suggest that after one or one and one-half years, there is no difference in mortality rates between patients admitted to hospitals with different price changes.

Reductions in average prices thus appear to compress the mortality distribution rather than increase it permanently. Individuals that would have died within one or two years after a hospital admission now die closer to the date of admission, generally within two months. For individuals who survive beyond about one year, however, there does not appear to be a large increase in mortality risk.

The conclusion that only the timing of death and not the long run mortality probability is affected by average price changes has some support in the literature. Garber, Fuchs, and Silverman (1984) examined outcome differences between faculty and community physicians at a hospital with both types on staff, and found that although the patients treated by faculty physicians had one-half the in-hospital mortality rate (and greater cost) of the patients treated by community physicians, there was no difference in the mortality rate at

9 months. Similarly, Staiger and Gaumer (1990) show that since the mid-1970s, mortality reductions have been concentrated almost entirely in in-hospital mortality and mortality within forty-five days of admission. There has been no change in one year mortality rates. While the price changes here cannot explain the trend mortality change they present (since the equations include time trends), this evidence does suggest that non-uniform mortality reductions are a common feature of medical change.

VI. Conclusions

The evidence suggests two important conclusions. First, in response to average price changes, there is a compression of the mortality distribution. Mortality rates increase up to 2 months post-discharge, but patients who survive beyond one year have no increased mortality. Second, there is a trend increase in readmissions and decrease in in-hospital mortality associated with marginal reimbursement changes. This increase, however, appears to be due to accounting changes on the part of hospitals, rather than true increases in morbidity.

These results leave two unanswered questions. First, the evidence is necessarily vague about the welfare consequences of these changes. If the non-hospital days of patients that formerly survived the hospital visit were not greatly valued, the mortality increase may have little loss in social welfare. If they were valued highly, the loss could be large. Further work using direct measures of living standards is needed to examine this question.

Second, since prospective payment has been in place for less than a decade and reimbursement was relatively generous for much of that period, there has been little experience with prolonged reductions in prices. Some evidence indicates that recent changes in Medicare reimbursement are having greater effects on hospital revenues than past changes (Prospective Payment Assessment Commission, 1991). It would clearly be worthwhile to revisit these issues after several years of tighter reimbursement policy.

References

Brook, Robert H. et al., "The Effects of the DRG-Based Prospective Payment System on Quality of Care for Hospitalized Medicare Patients", (and related articles), Journal of the American Medical Association, October 17, 1990, 1953-1994.

Carter, Grace M., Joseph P. Newhouse and Daniel A. Relles, "How Much Change in the Case Mix Index is DRG Creep?" Harvard University mimeo, June 1990.

Chamberlain, Gary, "Analysis of Covariance with Qualitative Data", Review of Economic Studies, 1980, 225-238.

Cutler, David M., "Empirical Evidence on Hospital Delivery Under Prospective Payment", 1990, MIT mimeo.

Feldstein, Martin, "Quality Change and the Demand for Hospital Care", Econometrica, 1977, 1681-1702.

Fitzgerald, John F., Patrcia S. Moore and Robert S. Dittus, "The Care of Elderly Patients with Hip Fractures", New England Journal of Medicine, 1988, 319:1392-1397.

Fuchs, Victor, "Health Care and the United States Economic System", in The Health Economy, Cambridge, MA: Harvard University Press, 1986.

Garber, Alan M., Victor R. Fuchs and James F. Silverman, "Case Mix, Costs and Outcomes: Differences Between Faculty and Community Services in a University Hospital", New England Journal of Medicine, 1984, 310:1231-1237.

Gaumer, Gary et al, "Effects of State Prospective Reimbursement Programs on Hospital Mortality", Medical Care, July 1989, 724-736.

Gerety, M.B., V. Soderholm-Difatte, and C.H. Winograd, "Impact of Prospective Payment and Discharge Location on the Outcome of Hip Fracture", General Internal Medicine, 1989, 4:388-391.

Guterman, Stuart, Paul W. Eggers, Gerald Riley, Timothy F. Greene, and Sherry A. Terrell, "The First 3 Years of Medicare Prospective Payment: An Overview", Healthy Care Financing Review, Spring 1988, 67-77.

Hadley, Jack, Earl P. Steinberg and Judith Feder, "Comparison of Uninsured and Privately Insured Hospital Patients", Journal of the American Medical Association, 1991, 265:374-379.

Han, Aaron and Jerry A. Hausman, "Flexible Parametric Estimation of Duration and Competing Risk Models", Journal of Applied Econometrics, 1990, 1-28.

Harris, Jeffrey, "The Internal Organization of Hospitals: Some Economic Implications", Bell Journal of Economics, 1977.

Heckman, James J., and Burt Singer, "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data", Econometrica, March 1984, 271-320.

Kalbfleisch, J.D., and R.L. Prentice, The Statistical Analysis of Failure Time Data, New York: Wiley & Sons, 1980.

Kahn, Katherine L. et al, "Comparing Outcomes of Care Before and After Implementation of the DRG-Based Prospective Payment System", Journal of the American Medical Association, 1990, 264:1984-1988.

Manton, Kenneth G., Eric Stallard and James W. Vaupel, "Alternative models for the Heterogeneity of Mortality Risks Among the Aged", Journal of the American Statistical Association, September 1986, 635-644.

Newhouse, Joseph P., The Economics of Medical Care: A Policy Perspective, Reading, MA: Addison Wesley, 1978.

Palmer, R.M., R.M. Saywell Jr., T.W. Zollinger et al, "The Impact of the Prospective Payment System on the Treatment of Hip Fractures in the Elderly", Archives of Internal Medicine, 1989, 149:2237-2241.

Prospective Payment Assessment Commission, Medicare Prospective Payment and the American Health Care System, Washington, D.C.: Prospective Payment Assessment Commission, June, annually.

Staiger, Douglas and Gary L. Gaumer, "The Impact of Financial Pressure on Quality of Care in Hospitals: Post-Admission Mortality Under Medicare's Prospective Payment System", mimeo, Stanford University, 1990.

Table 1: Readmission and Mortality Rates, Before and After Prospective Payment

Days from Discharge	Federal Prospective Payment			Mass. Prospective Payment			PPS Effect	
		Post-PPS				Post-PPS	Fed. PPS	Mass. PPS
	1981-83	1984-85	1986-88	1981-83	1984-85	1986-88	(v. Mass.)	(v. Fed.)
				A. Readmission Probability				
15	2.7%	3.4%	3.5%	3.0%	3.0%	3.8%	0.8% (0.5)	0.7% (0.4)
30	4.6	5.8	5.8	4.6	4.7	6.3	1.0 (0.6)	1.5 (0.6)
60	7.3	8.7	8.9	7.9	7.5	10.1	1.6 (0.8)	2.4 (0.7)
180	13.8	15.6	16.1	13.5	13.5	17.1	1.7 (1.0)	3.1 (0.9)
365	19.6	21.3	21.4	18.0	19.1	22.4	0.5 (1.1)	3.2 (1.1)
				B. Mortality Probability				
0	9.6%	9.1%	10.2%	8.9%	11.0%	9.6%	-2.6% (0.8)	-2.5% (0.7)
15	11.6	10.9	12.2	10.5	12.8	11.3	-3.0 (0.9)	-2.8 (0.8)
30	13.4	12.8	14.1	12.4	14.1	13.0	-2.3 (0.9)	-2.4 (0.8)
60	16.0	15.8	17.1	14.8	16.8	15.8	-2.1 (1.0)	-2.2 (0.9)
180	21.9	22.5	24.1	21.8	23.7	23.2	-1.2 (1.2)	-2.0 (1.0)
365	28.5	29.3	30.7	28.7	30.8	30.3	-1.3 (1.3)	-1.9 (1.1)

Note: The table shows readmission and mortality probabilities post hospitalization. The readmission rate is based on non-censored observations. The last two columns reports the coefficients β_2 and β_3 from the regression:

$$\text{Event}_j = \Sigma\, \beta_{0,s,j} + \Sigma\, \beta_{1,s,j} + \beta_2 * \text{Fed-PPS}_j + \beta_3 * \text{MA-PPS}_j,$$

where s indexes states and t indexes time.

Table 2: Estimates of Sickness Equations

Variable	In-Hospital Mortality	Post-Discharge Hazard			
		Weibull Baseline		Semi-Parametric Baseline	
		Readmission	Mortality	Readmission	Mortality
Demographics					
Constant	-2.06 (0.10)	-4.58 (0.09)	-5.21 (0.11)	---	---
Age 70-74	.290 (.060)	.107 (.034)	.156 (.048)	.107 (.034)	.156 (.049)
Age 75-79	.471 (.060)	.159 (.035)	.389 (.048)	.158 (.035)	.389 (.048)
Age 80 +	.892 (.054)	.232 (.032)	.776 (.043)	.228 (.033)	.773 (.043)
Male	.044 (.036)	.167 (.023)	.266 (.029)	.166 (.023)	.265 (.029)
Current Readmission	.203 (.047)	.869 (.025)	.479 (.036)	.861 (.026)	.472 (.036)
Massachusetts Sample	-.111 (.042)	.003 (.027)	-.029 (.034)	.003 (.027)	-.029 (.034)
Financial					
ΔPrice	-.317 (.148)	.158 (.095)	.054 (.129)	.156 (.095)	.054 (.130)
Post-PPS	-.298 (.081)	.095 (.052)	.002 (.065)	.096 (.052)	.002 (.065)
Baseline					
Baseline Parameter	---	.648 (.008)	.694 (.010)	---	---
Baseline Hazard Specification Test: X^2	---	---	---	221.2	205.1
N		40,590		40,590	
log(Likelihood)		-87,681		-87,526	

Note: All equations include type of admission and year dummy variables, which are not reported. Standard errors are in parentheses. The semi-parametric baseline hazard includes 52 baseline parameters. The X^2 test is for the equality of the semi-parametric and Weibull baseline hazards. The critical value for 102 degrees of freedom is 124.3.

Table 3: Estimates of Sickness Equations
With Non-Parametric Heterogeneity

Variable	In-Hospital Mortality	Post-Discharge Hazard	
		Readmission	Mortality
Demographics			
Constant	----	----	----
Age 70-74	.597	.151	.198
	(.134)	(.047)	(.063)
Age 75-79	1.019	.234	.524
	(.153)	(.048)	(.064)
Age 80 +	2.048	.318	1.019
	(.226)	(.045)	(.063)
Male	.110	.235	.336
	(.081)	(.033)	(.040)
Current Readmission	.466	1.202	.612
	(.116)	(.050)	(.052)
Massachusetts Sample	-.024	.010	-.050
	(.095)	(.037)	(.045)
Financial			
ΔPrice	-.508	.176	.129
	(.332)	(.131)	(.172)
Post-PPS	-.670	.140	.020
	(.192)	(.071)	(.087)
Heterogeneity			
Mass Point 1	-25*	-25*	-25*
Mass Point 2	-1.64	-5.30	-6.31
	(0.30)	(0.17)	(0.21)
Mass Point 3	2.75	-2.91	-3.34
	(0.67)	(0.16)	(0.18)
Probability 1	.632	.343	.229
	(.022)	(.024)	(.019)
Probability 2	.304	.585	.705
	(.028)	(.028)	(.030)
Probability 3	.064	.072	.066
Baseline			
Baseline Parameter	----	.842	.888
		(.024)	(.026)
N		40,590	
log(Likelihood)		-87,575	

Note: All equations include type of admission dummies and year dummy variables, which are not reported. The mass points are for a non-parametric random effect specification. The smallest mass point (*) is held constant. Standard errors are in parentheses.

Table 4: Estimates of Sickness Equations with Time-Varying Covariates

Variable	In-Hospital Mortality	Post-Discharge Hazard	
		Readmission	Mortality
Demographics			
Constant	-2.06	-4.71	-5.32
	(0.10)	(0.09)	(0.11)
Age 70-74	.290	.107	.155
	(.060)	(.034)	(.048)
Age 75-79	.471	.159	.389
	(.060)	(.035)	(.048)
Age 80 +	.892	.230	.774
	(.054)	(.032)	(.043)
Male	.044	.167	.266
	(.036)	(.023)	(.029)
Current Readmission	.203	.865	.475
	(.047)	(.025)	(.036)
Massachusetts Sample	-.111	.002	-.029
	(.042)	(.027)	(.034)
Financial			
ΔPrice	-.317	----	----
	(.149)		
1-4 weeks	----	-.081	.124
		(.182)	(.282)
5-8 weeks	----	.066	-.238
		(.211)	(.336)
9-26 weeks	----	.344	.119
		(.158)	(.220)
27-52 weeks	----	.216	.074
		(.236)	(.239)
Post-PPS	-.298	----	----
	(.081)		
1-4 weeks	----	.214	.076
		(.062)	(.079)
5-8 weeks	----	.255	.236
		(.062)	(.078)
9-26 weeks	----	.117	.018
		(.055)	(.069)
27-52 weeks	----	-.114	-.187
		(.060)	(.074)
Baseline			
Baseline Parameter	---	.684	.726
		(.011)	(.014)
N		40,590	
log(Likelihood)		-87,628	

Note: All equations include type of admission and year dummy variables, which are not reported. Standard errors are in parentheses.

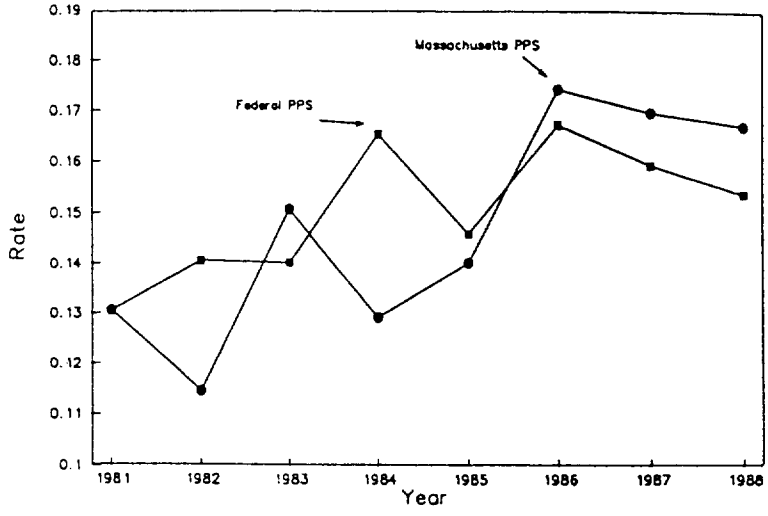
Table 5: Effect of Average Price Change on Cumulative Mortality Probability

Weeks from Discharge	Mortality Rate		Change in Mortality
	Baseline	Price Reduction	
In-hospital	5.0%	5.3%	0.29%
2	7.2	7.5	0.35
4	8.3	8.7	0.38
8	10.3	10.8	0.46
12	11.8	12.2	0.41
26	16.1	16.3	0.25
39	19.0	19.2	0.18
52	21.7	21.8	0.08
78	26.4	26.4	-0.05

Note: The table shows the cumulative mortality distribution from simulating the sickness model in Table 4. The mortality rates are based on 100,000 individuals.

Figure 1

(a) 6 Month Readmission Rate



(b) 6 Month Mortality Rate

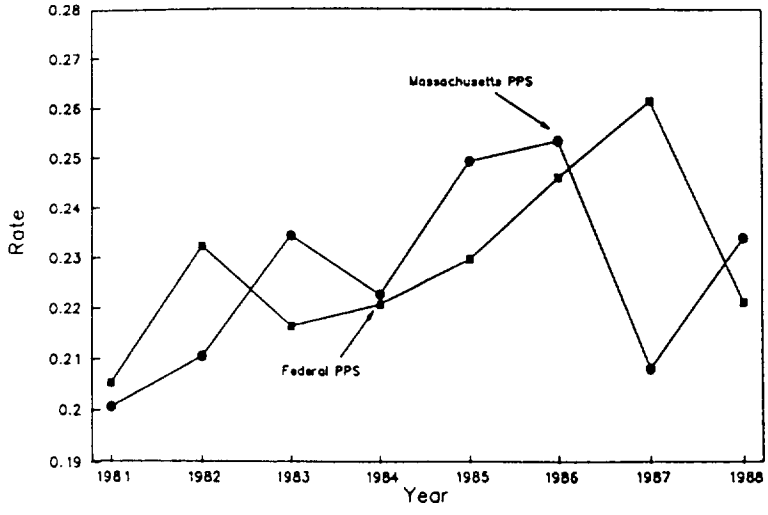


Figure 2

Readmission and Mortality Baseline Hazards

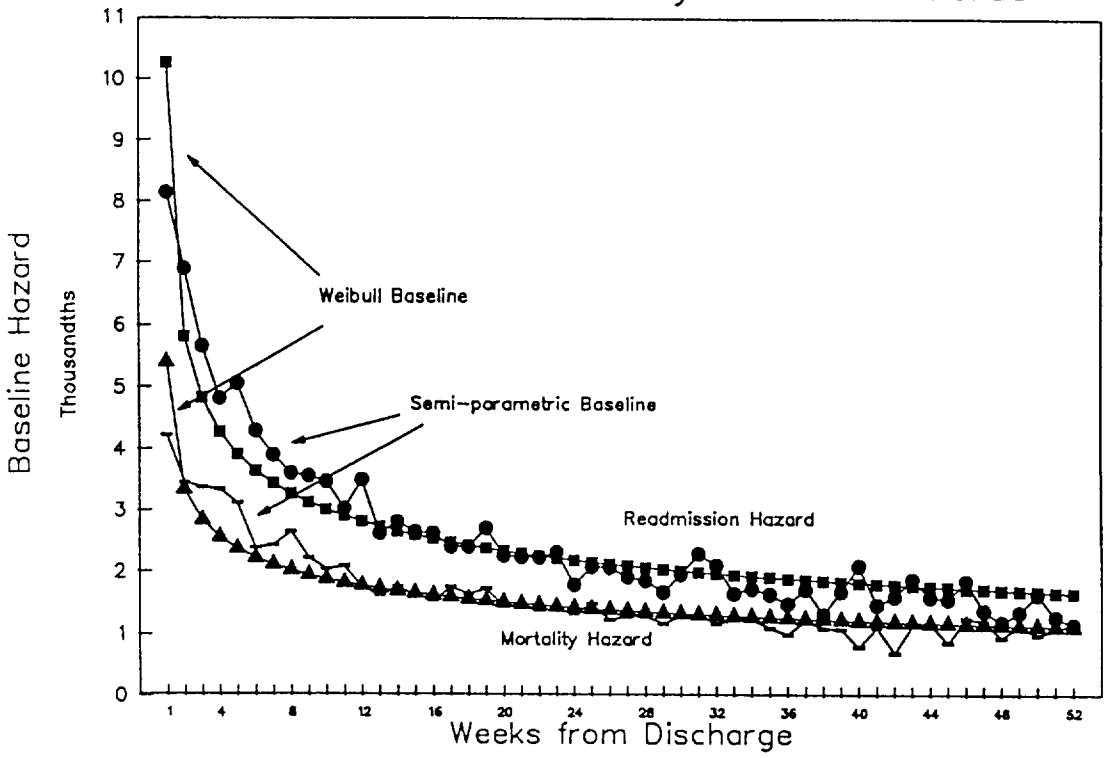
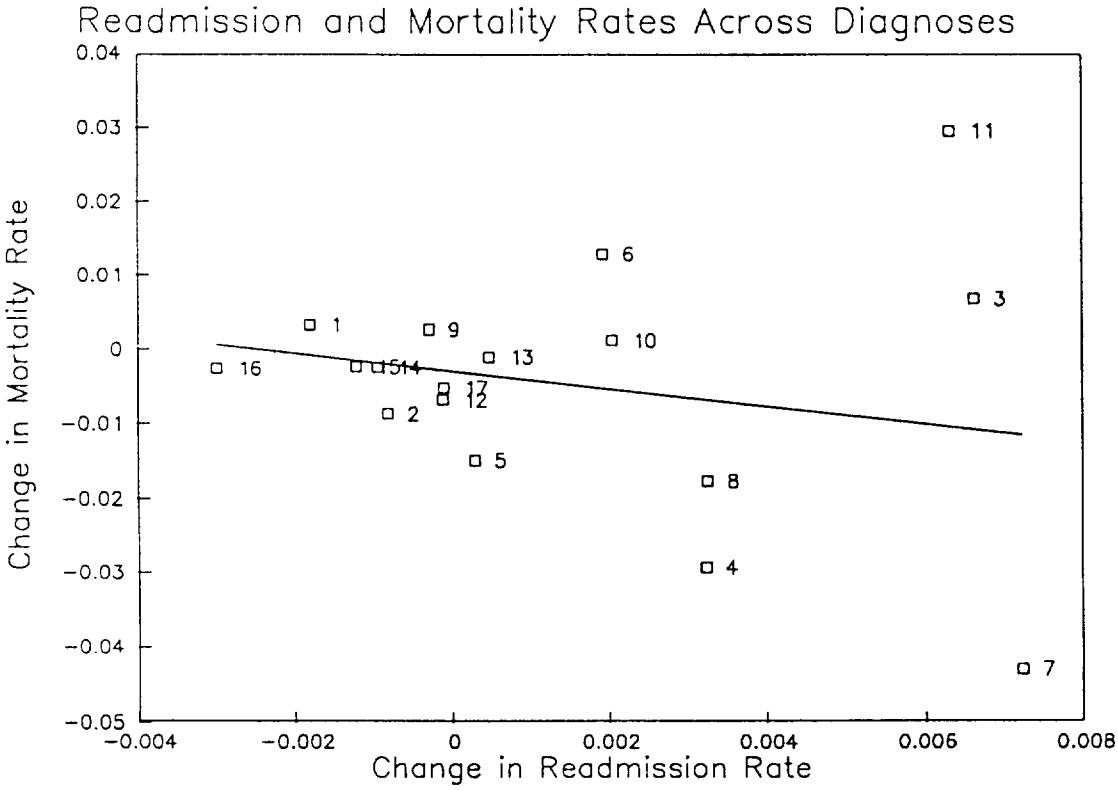


Figure 3


Readmission and Mortality Rates Across Diagnoses
Change in Mortality Rate
Change in Readmission Rate
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.004
-0.002
0
0.002
0.004
0.006
0.008
11
6
3
1
9
10
13
16
2
12
5
8
4
7