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THE INCIDENCE OF ADVERSE MEDICAL OUTCOMES UNDER PROSPECTIVE PAYMENT

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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, under which reimbursement depends only on the diagnosis of the patient. Hospitals thus lost the marginal reimbursement they formerly received for providing additional treatments. In addition, the average price each hospital received for patients with different diagnoses changed. This paper relates 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 year post-discharge, mortality is no higher. 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.

Keywords: Prospective Payment, mortality, hospital readmission, competing hazards.

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). Under Prospective Payment, hospitals are paid a fixed payment for each patient, based only on the patient's diagnosis, not the hospital's cost of treatment. Since prices are fixed, hospitals bear the full cost of marginal treatments. In addition, since hospitals had very different costs prior to PPS, there are large changes in prices for different hospitals and for different diagnoses within hospitals.

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 change in the percentage of patients who have died after one year. Second, the elimination of marginal reimbursement led to

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increased hospital readmissions, but this appears to be due to hospital practices of coding patients who they readmit into higher priced diagnoses, rather than true changes in morbidity. There does not appear to be any change in sickness from the elimination of marginal reimbursement.

The paper proceeds as follows. The first section 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 examines long run mortality effects of average price changes.

1. PROSPECTIVE PAYMENT AND ADVERSE OUTCOMES

Prior to Prospective Payment, Medicare[2] 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 (DRGs), based on the diagnosis of the patient. Each DRG groups many individual diagnoses. The mapping between diagnoses and DRGs is not unique, however. Patients with the same diagnosis may be coded into different DRGs, depending on whether or not they have surgery, and whether the patient has complications and/or comorbidities.

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.

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 in DRG d at hospital h 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.[3] The change in average price is then given by

$$(1) \qquad \Delta P_{d,h} = \log\left(P_{1,d,h}/P_{0,d,h}\right).$$

The price under Prospective Payment ($P_{1,d,h}$) depends on the patient's DRG. Each DRG is assigned a weight (WGT_d) based on the costs of treating patients

[2] 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.

[3] 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.

in the DRG in previous years.[4] The weight is then multiplied by a hospital-specific 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 (DSH_h). The price under PPS for any patient is thus given by[5]

$$(2) \qquad P_{1,d,h} = WGT_d * P_h * (1 + IME_h) * (1 + DSH_h).$$

Changes in both marginal and average reimbursement may influence adverse outcomes. Reductions in average prices may 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.[6] Similarly, eliminating marginal cost payment may also lower treatment intensity, and result in worse outcomes.

To measure adverse outcomes, I use data on mortality and hospital readmission. Mortality is the most natural measure of outcomes; as reimbursement become less generous, we expect mortality rates to rise. Changes in morbidity may be as important as changes in mortality, however, particularly for marginal treatments. I proxy for morbidity with the hospital readmission rate. Because the mix of survivors may change with changes in reimbursement, 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 sickness of survivors relative to changes in the percentage of people surviving.

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

It is important to note that these predictions do not allow for any changes in readmission or mortality because of changes in hospital coding practices, a factor that is considered in Section V.

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

[5] 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.

[6] Alternatively, hospitals could respond by increasing prices to other charge-based payers, with no reduction in costs. In this case, there would be no effect on adverse outcomes.

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 (1988) 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 (Rodgers 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 trend reduction 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.

2. THE DATA

The data on adverse outcomes are formed from Medicare and Social Security records. 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 naturally 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 of a 25 percent random sample of hospitals in the state; (2) the patient's social security number was in one of a 20 percent random 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 admissions 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,

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

[8] These diagnoses were selected by a panel of physicians as most likely to be responsive to changes in state rate-setting procedures (Gaumer and Coelen (1989)). The sample may thus not be representative 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 preceded by a readmission that year.

including those unrelated to a hospitalization.[10] I define readmission as any subsequent admission to any hospital in the sample, for any of the included diagnoses.[11]

The final data issue is the measure of average price changes for each diagnosis. This is complicated for two reasons. First, the price after PPS depends on the DRG to which the patient is assigned, and I do not know this information exactly (because of missing information on secondary diagnoses). In addition, forming the price before Prospective Payment requires the average cost of all the patients in that DRG. This large sample data is only available for Massachusetts, however.[12]

To form the average price variable, I thus proceed in two steps. First, I compute the price change for each DRG at each hospital. Second, I compute from the large sample data the DRGs to which a patient with each diagnosis in my sample was assigned, and use this information to form a weighted average of the price changes for each diagnosis.[13] Because the pre-PPS cost data are only available for Massachusetts, I am limited to Massachusetts for measuring average price effects.[14]

The average price increased by 0.6 percent after Prospective Payment, with a standard deviation of 19 percent. About one-half of the variation in prices is explicable through hospital and diagnosis effects, with most of this variation associated with hospital effects. This is expected since narrowing the variation across hospitals was one of the goals of the system. Among different diagnoses, price increases were most pronounced for nervous disorders (especially seizures) and diseases of the hepatobiliary system. Price decreases were most pronounced for patients with kidney and musculoskeletal problems.

Trends in Readmission and Mortality

Table I presents evidence on cumulative readmission and mortality probabilities. The table reports the probability of either event for fixed periods up to 1

[10] Almost all mortality records had the exact day of the month on which death occurred. A small sample of deaths (4 percent) had known death records but did not identify the exact day of the month on which the patient died. For these patients, I recorded the death rate 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.

[12] The discharge data are for 1984 and are from the state Rate Setting Commission. Massachusetts is one of the few states that collects complete discharge data. Since the data contain hospital charges and not costs, I deflate them using a hospital-specific cost to charge ratio, obtained from the Health Care Financing Administration. 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 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.

[14] 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 variable, to include the observations for which the price data are missing. The estimated marginal reimbursement effects were very close to the ones reported here.

TABLE I
CUMULATIVE DISTRIBUTION OF ADVERSE EVENTS

Days from Discharge	Probability of: Readmission	Mortality	At Least One Adverse Event	Censored
In-Hospital	0.0%	9.8%	9.8%	0.0%
15 days	3.3	11.6	14.6	0.5
30 days	5.4	13.4	18.1	1.0
60 days	8.4	16.2	23.2	1.8
180 days	14.8	23.0	33.8	4.8
365 days	19.6	29.8	42.4	8.5

Note: The table shows the cumulative probability of readmission, mortality, or censoring for various periods post-discharge. The data are for the 1981–1988 period.

year post discharge; Figure 1 shows the 6 month readmission and mortality rates annually. 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.

Table II presents some first evidence on trend changes in adverse events associated with PPS (the marginal reimbursement effect). The first three columns of the table present the cumulative probability of readmission (the upper panel) or mortality (the lower panel) for the federal PPS states, and the second three

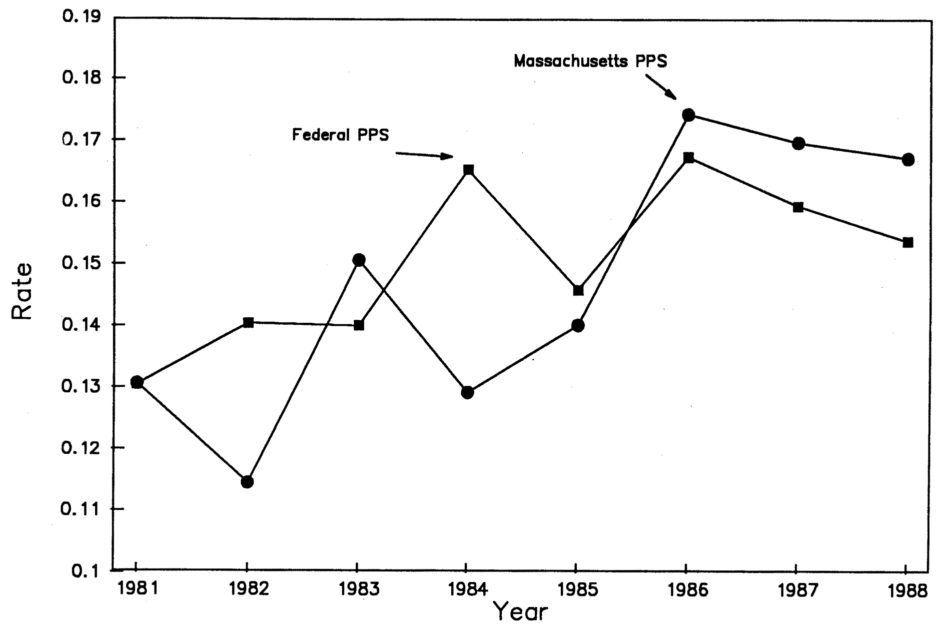

FIGURE 1(a).—6 month readmission rate.

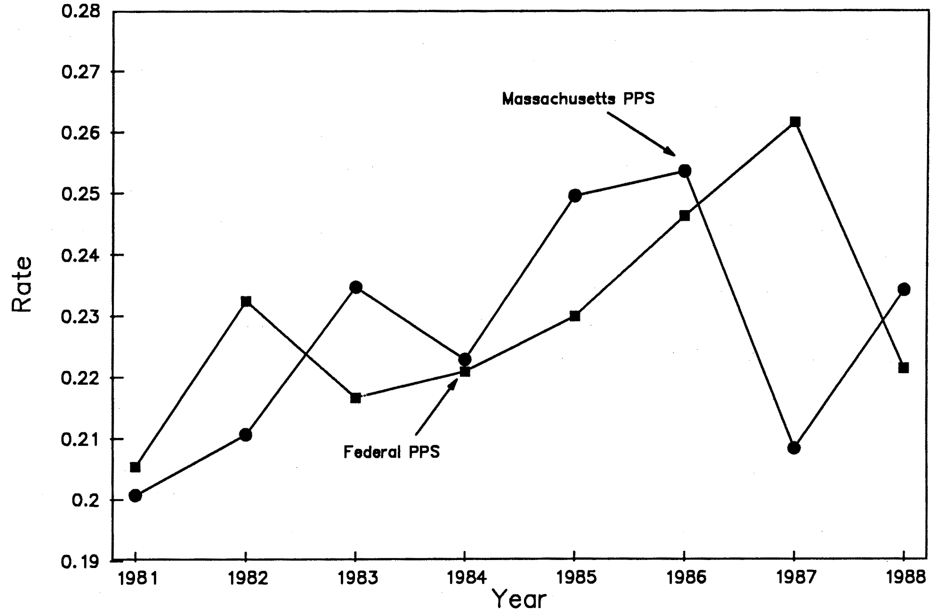

FIGURE 1(b).—6 month mortality rate.

TABLE II

READMISSION AND MORTALITY RATES, BEFORE AND AFTER PROSPECTIVE PAYMENT

Days from [2u Discharge	Federal Prospective Payment 1981–83	Federal Post-PPS 1984–85	Federal Post-PPS 1986–88	Mass. Prospective Payment 1981–83	Mass. 1984–85	Mass. Post-PPS 1986–88	PPS Effect Fed. PPS (v. Mass.)	PPS Effect Mass. PPS (v. Fed.)
				A. Readmission Probability				
30	4.6%	5.8%	5.8%	4.5%	4.7%	6.3%	1.0%	1.5%
	(0.3)	(0.3)	(0.2)	(0.3)	(0.4)	(0.3)	(0.6)	(0.5)
180	13.8	15.6	16.1	13.5	13.5	17.1	1.7	3.1
	(0.4)	(0.4)	(0.4)	(0.5)	(0.6)	(0.4)	(1.0)	(0.8)
365	19.6	21.3	21.4	18.0	19.1	22.4	0.4	3.1
	(0.5)	(0.5)	(0.5)	(0.6)	(0.6)	(0.6)	(1.1)	(1.0)
				B. Mortality Probability				
0	9.6%	9.1%	10.2%	8.9%	11.0%	9.6%	−2.7%	−2.4%
	(0.4)	(0.4)	(0.3)	(0.4)	(0.5)	(0.3)	(0.9)	(0.8)
30	13.4	12.8	14.1	12.4	14.1	13.0	−2.3	−2.3
	(0.4)	(0.4)	(0.3)	(0.5)	(0.5)	(0.4)	(1.0)	(0.9)
180	21.9	22.5	24.1	21.8	23.7	23.2	−1.2	−2.0
	(0.5)	(0.5)	(0.4)	(0.6)	(0.7)	(0.5)	(1.2)	(1.1)
365	28.5	29.3	30.7	28.7	30.8	30.3	−1.3	−1.9
	(0.5)	(0.6)	(0.4)	(0.7)	(0.7)	(0.5)	(1.3)	(1.2)

Note: The table shows readmission and mortality probabilities post hospitalization. The readmission rate is based on noncensored observations. The last two columns report the change in readmission or mortality from a logit model controlling for state and year effects. Standard errors are in parentheses.

columns present the results for Massachusetts. To summarize the effects of Prospective Payment, the last two columns report changes in the probability of each event associated with the implementation of PPS. These latter two columns are from a logit regression, with state and year controls.

Both readmission and mortality rates appear to have changed after Prospective Payment, but in opposite directions. Readmission rates increased after Prospective Payment in both groups of states, although they subsequently decline 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 1.5 percentage points in the next year.

3. ECONOMETRIC SPECIFICATION

I assume that an individual j 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:[15]

$$(3) \qquad P^*_{H,j} = X_j \beta_H + \epsilon_{H,j},$$

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. 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 nonlinear equation for the failure time t_i^*:

$$(4) \qquad \log\left(\sum_{s=1}^{t_i^*} \exp\left(X_j(s)\beta_j + \gamma_{s,i}\right)\right) = \epsilon_{i,j},$$

where $\gamma_{s,i} = \log(\int_{s-1}^{s} \lambda_{0,i}(T)\,dT)$ is the integrated baseline hazard, ϵ_i has an extreme value distribution (denoted $F(\epsilon_i)$), and $X_j(s)$ is assumed constant within each period. I define the logarithm of the integrated hazard in the left-hand side of equation (4) as $\delta_{i,j}(t_i^*)$.

[15] 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 likely to be endogenous, however, I do not follow this approach.

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

Assuming for the moment that the in-hospital and post-discharge risks are independent, the probabilities can be written as:

$$
\begin{aligned}
(5) \qquad P_{1,j} &= \text{Prob[in-hospital mortality]} = G(X_j\beta_H), \\
P_{2,j} &= \text{Prob[censored in week } t^*] \\
&= [1 - G(X_j\beta_H)] * [1 - F(\delta_{R,j}(t^* - 1))] \\
&\quad * [1 - F(\delta_{M,j}(t^* - 1))], \\
P_{3,k,j} &= \text{Prob[event } k \text{ in week } t^*] \\
&= [1 - G(X_j\beta_H)] * [F(\delta_{k,j}(t^*)) - F(\delta_{k,j}(t^* - 1))] \\
&\quad * [1 - F(\delta_{-k,j}(t^* - 1))]
\end{aligned}
$$

where k is the last equation is either readmission or death and $-k$ is the other. 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 indicator for censored observations, the likelihood function is:

$$
(6) \qquad L = \prod_{j=1}^{N} P_{1,j}^{d_j}(X_j, \beta_H)\ P_{2,j}^{c_j}(X_j, \beta_H, \beta_R, \beta_M)\ P_{3,k,j}^{(1-c_j-d_j)}(X_j, \beta_H, \beta_R, \beta_M).
$$

I estimate equation (6) using standard maximum likelihood techniques.

4. READMISSION AND MORTALITY ESTIMATES

As covariates in the sickness model, I include four age dummy variables (65–69, 22 percent; 70–74, 24 percent; 75–79, 21 percent; 80 +, 33 percent), a sex dummy variable (50 percent of the patients are male), a dummy variable for whether the current admission is a readmission to the hospital (15 percent of admissions), a dummy variable for being in Massachusetts, year dummy variables, and dummy variables for nine types of admission.[16] The underlying

[16] 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 agents, and emergencies due to allergic reactions; complex diagnostic entities; and elective surgical procedures. I do not include dummy variables for each diagnosis because the 180 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.

sickness equation is[17]

$$(7)\qquad S_j = \alpha_0 + \sum_{j=2}^{4} \alpha_{1,j} AGE_{i,j} + \alpha_2 MALE_j + \alpha_3 READMIT_j$$
$$+ \alpha_4 MASS_j + \sum_{j=2}^{9} \alpha_{5,j} DIAG_{i,j}$$
$$+ \sum_{t=2}^{T} \alpha_{6,t} YEAR_{t,j} + \beta_1 \Delta P_j + \beta_2 Post - PPS_j.$$

The price change (ΔP) is defined in equation (1).

Table III presents 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:[18] $\lambda_{0,i}(t) = \alpha_i t^{a_i - 1}$. 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 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 price 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 average 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

[17] Equation (6) does not include hospital dummy variables. Since there are 68 hospitals in the sample, including these variables would involve an additional 201 coefficients, a prohibitively large number. The most important issue is whether hospital effects explain the average price results, since average price changes are correlated within a hospital. To examine this, I have estimated the equations for the Massachusetts sample only, including hospital indicators. These results are similar to those reported, with slightly larger effects of average price changes. I thus work with the lower-bound estimates for the full sample.

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

TABLE III

ESTIMATES OF SICKNESS EQUATIONS

Variable	In-Hospital Mortality	Post-Discharge Hazard: Weibull Baseline Readmission	Weibull Baseline Mortality	Semi-Parametric Baseline Readmission	Semi-Parametric Baseline 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 5 percent critical value for 102 degrees of freedom is 124.3.

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 6.

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 significant. There is no evidence of an increase in the post-discharge mortality hazard over time, although the readmission hazard increases in response to the elimination of marginal reimbursement (statistically significant at the 10 percent

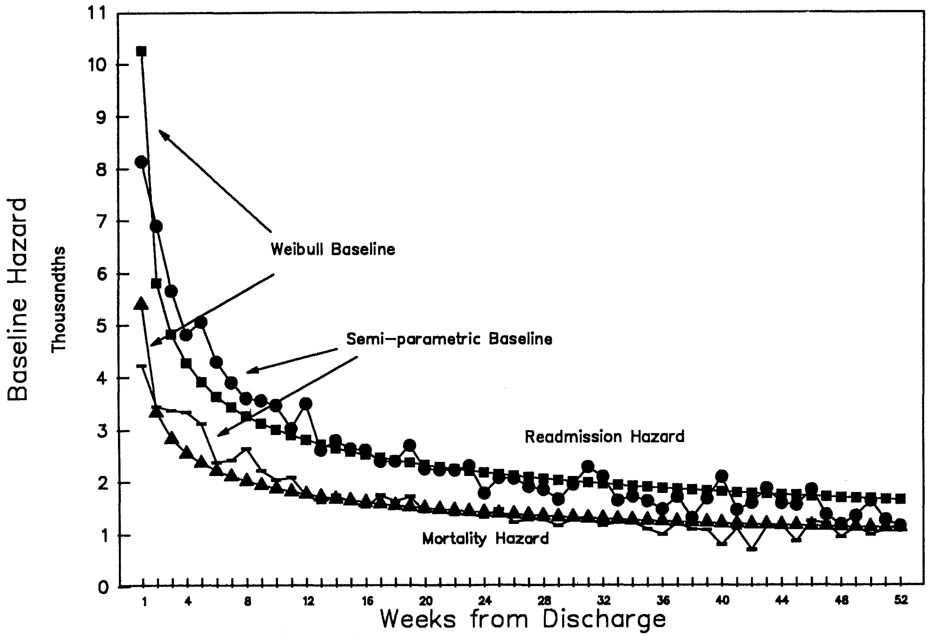

FIGURE 2.—Readmission and mortality baseline hazards.

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 in-hospital 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 5.

The last two columns of Table III re-estimate the post-discharge hazards, using a semi-parametric baseline in place of the Weibull baseline.[19] A likelihood ratio test rejects the equality of the two baseline specifications (the 5 percent critical value is 124.3). As Figure 2 indicates, this rejection is predominantly due to an overestimate by the Weibull 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 remainder of the paper.

[19] 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.

Unobserved Heterogeneity

The most obvious difficulty with equations (3) and (4) is the potential for unobserved heterogeneity to bias the results. Individuals who are intrinsically sicker will be more likely to die or be readmitted to the hospital. If these differences are not accounted for, estimates of the reimbursement variables may be biased. Unobserved heterogeneity can be modelled as an additional source of error in the in-hospital and post-discharge equations:

$$(8) \qquad P^*_{h,j} = X_j\beta_H + \epsilon_{H,j} + \omega_H,$$

$$\delta_{i,j}(t^*_i) = \epsilon_{ij} - \omega_i.$$

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 nonparametrically, 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 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 any event can then be factored into the probability conditional on any set of ω's and the probability of each combination of ω. The likelihood is thus

$$(9) \quad L = \prod_{j=1}^{N} \sum_{h=1}^{L} \sum_{r=1}^{L} \sum_{m=1}^{L} P_{1,j}^{d_j}(X_j, \beta_H, \omega_h)\, P_{2,j}^{c_i}(X_j, \beta_H, \beta_R, \beta_M, \omega_h, \omega_r, \omega_m)$$

$$* P_{3,k,j}^{(1-c_j-d_j)}(X_j, \beta_H, \beta_R, \beta_M, \omega_h, \omega_r, \omega_m)$$

$$* \Pr[\omega_H = \omega_h, \omega_R = \omega_r, \omega_M = \omega_m].$$

Table IV shows estimates of the sickness model with two mass points.[20] For all 3 equations, there is some unobserved heterogeneity. The mass points are statistically significantly different from each other. In addition, the baseline hazard parameters increase, reflecting the reduction in population mixing.

In principle, there are eight potential probabilities (2 mass points for each of three equations). In practice, however, only three of the probabilities were estimated to be greater than zero. These are detailed in the last rows of the table. These mass point combinations have natural economic interpretations.

[20] For the in-hospital mortality equation, one of the mass points became large and negative. In the final estimates, I held this constant at a level corresponding to zero probability of in-hospital death. I attempted to estimate models with additional points, with little success. There were a number of local maxima.

TABLE IV

ESTIMATES OF SICKNESS EQUATIONS WITH NON-PARAMETRIC HETEROGENEITY

Variable	In-Hospital Mortality	Post-Discharge Hazard Readmission	Post-Discharge Hazard Mortality	Probability
Demographics				
Constant	—	—	—	—
Age 70–74	.304	.147	.212	—
	(.065)	(.043)	(.056)	—
Age 75–79	.497	.235	.491	—
	(.066)	(.044)	(.057)	—
Age 80 +	.953	.389	.964	—
	(.071)	(.043)	(.055)	
Male	.053	.239	.351	—
	(.039)	(.029)	(.035)	
Current Readmission	.222 (.051)	1.058 (.037)	.712 (.046)	—
Massachusetts Sample	−.118 (.045)	−.007 (.033)	−.031 (.040)	—
Financial				
ΔPrice	−.340	.171	.080	—
	(.161)	(.117)	(.150)	
Post-PPS	−.336	.110	.024	—
	(.088)	(.063)	(.076)	
Heterogeneity				
Mass Point 1	−25*	−6.09	−6.97	—
		(0.15)	(0.19)	
Mass Point 2	−1.73	−3.58	−4.24	—
	(0.22)	(0.11)	(0.14)	
Baseline				
Baseline Parameter	—	.850 (.017)	.935 (.023)	—
Probabilities				
Combination 1	1	1	1	.243
				(.059)
Combination 2	2	1	1	.557
				(.093)
Combination 3	2	2	2	.200
N		40,590		
log(Likelihood)		−87,509		

Note: All equations include type of admission dummies and year dummy variables, which are not reported. The mass points are for a nonparametric random effect specification. The smallest mass point in the in-hospital mortality equation (*) is held constant, at a value corresponding to a probability of zero. Standard errors are in parentheses.

The first and third combinations (the lower and higher value of each point) correspond to individuals with a low or high probability of all of the adverse events. These combinations account for about half of the population. The majority of the population appears to have a high in-hospital mortality probability but low out-of-hospital risk. This would be typical of an emergency situation where the time until the first treatment is applied greatly affects survival, but patients receiving the initial treatment in time are at reasonably low risk for future adverse events.

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, although they are close to those in Table III. I thus conclude that unobserved heterogeneity does not explain the results here.

Alternative Specifications

Since changes in morbidity may occur at different periods post-discharge, a natural generalization of equation (4) 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 V presents the results.[21]

The estimates suggest some differences in the response at different points in time; a X^2 test rejects the specification in Table III in favor of that in Table V. 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 insignificant. 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 III, 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 6.

As a final specification of the reimbursement terms, I included a separate set of year dummy variables for both Massachusetts and the federal PPS states. The difference between these estimates and those in Table III is a specification test for the marginal reimbursement terms. The X^2 test from the estimation rejects the restrictions imposed in Table III.[22] Most of the qualitative conclusions from the unrestricted model, however, are similar to those in Table III. 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 Prospec-

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

[22] The likelihood value for the augmented model is $-87{,}662$. The test statistic, 38, exceeds the 5 percent critical value of 28.9 with 18 degrees of freedom.

TABLE V

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.

tive Payment, relative to the change in the federal PPS states before versus after Prospective Payment: $MA\text{–}PPS = [M_{86-88} - M_{84-85}] - [F_{86-88} - F_{84-85}]$, where M and F are the average 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 III. 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 III. 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 PPS experiment [$-.019$ (.063)]. The estimate in Table III (.095) is an average for these two groups.

The 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.

5. EXPLAINING MARGINAL REIMBURSEMENT EFFECTS

The discussion above interpreted the marginal reimbursement effect in terms of the sickness of the underlying population. An alternative explanation is that these changes reflect merely accounting changes by 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 a hospital takes a patient that was formerly in a low-weighted DRG and records the patient with a more severe (and thus higher weighted) diagnosis. This increases reimbursement to the hospital without any change in costs. 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 diagnoses with readmission increases.

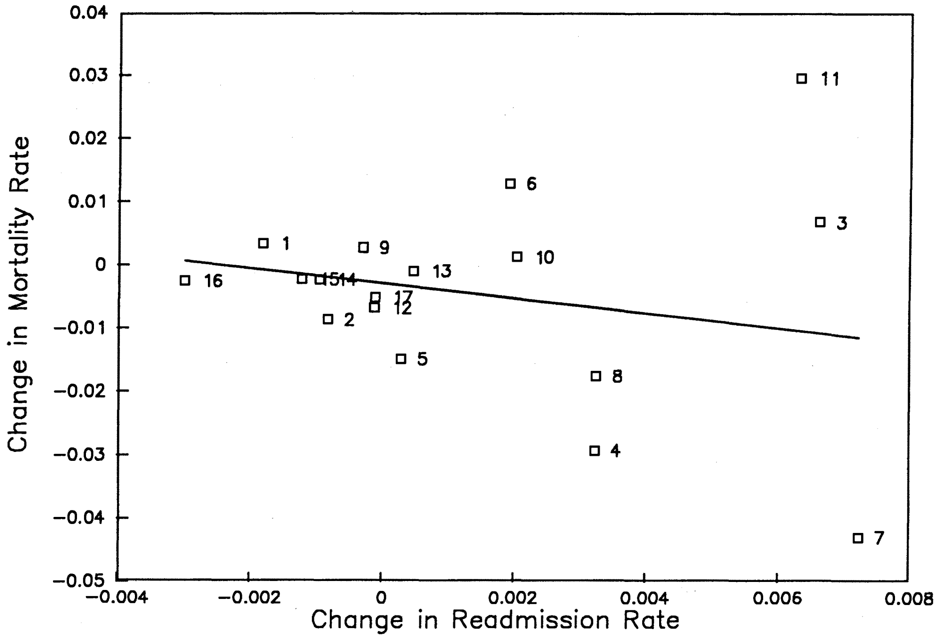

FIGURE 3.—Changes in readmission and mortality rates across diagnoses.

To test these hypotheses, I examine outcome changes for the 17 largest diagnoses (containing 35,005 admissions).[23] To find the 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 (adjusted for the fact that the data are estimated).[24] 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 increases in readmission rates tend to have reductions in mortality rates.

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

[24] 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 $\text{cov}(x, y) = \text{cov}(x^*, y^*) + \text{cov}(\epsilon, \eta)$, and the sample variances are $\sigma_x^2 = \sigma_{x^*}^2 + \sigma_\epsilon^2$ and $\sigma_y^2 = \sigma_{y^*}^2 + \sigma_\eta^2$. To estimate $\sigma_{x^*}^2$, for example, I form the difference between the variance of my set of x coefficients (σ_x^2) and the average variance of each estimate (σ_ϵ^2). I use a similar procedure to form $\text{cov}(x^*, y^*)$ and $\sigma_{y^*}^2$. The regression coefficient and correlation are based on these estimates of the true values.

The correlation between the two is $-.203$, although with only 17 observations, this is not statistically different from zero.

Indeed, examination of the specific diagnoses displayed in Figure 3 is consistent with this interpretation. Most of the diagnoses with large increases in readmission rates are chronic conditions, where readmission is on average more likely, and thus the possibility for upcoding is greater. For example, diagnoses like acute myocardial infarction, where readmission rates increased substantially, have some substitutes in other diagnoses (ischemic heart disease, chest pain, or atherosclerosis) for which coding may be changed. The DRG weight for acute myocardial infarction is about as high as for atherosclerosis or chest pain. In contrast, most of the diagnoses without increases in readmission rates are acute conditions, where patients are generally treated only once, and where upcoding is thus less possible. The evidence thus suggests that the marginal reimbursement effects are more likely due to hospital coding practices than to true changes in underlying sickness.

6. 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.[25] 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 V to perform the simulations.[26] The patient is assumed to be one with the average characteristics in the sample.[27]

Table VI shows the cumulative mortality rates for the average patient and for a patient in a hospital with a one standard deviation reduction in price. 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. A 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

[25] 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.

[26] I assume the coefficient for the 26–52 week spline extends through the next half year.

[27] 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.

TABLE VI

EFFECT OF AVERAGE PRICE CHANGE ON CUMULATIVE MORTALITY PROBABILITY

Weeks from Discharge	Mortality Rate: Baseline	Mortality Rate: Price Reduction	Change in Mortality
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 with time-varying coefficients in Table V. The mortality rates are based on 100,000 individuals.

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 nonuniform mortality reductions are a common feature of medical change.

6. CONCLUSIONS

The evidence suggests two important conclusions. First, in response to average price changes, there is a compression of the mortality distribution into the immediate post-discharge period. 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 nonhospital days of patients that formerly survived the hospital visit were not greatly valued, the mortality compression 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.

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[Footnotes]

[18] **Alternative Models for the Heterogeneity of Mortality Risks Among the Aged**
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