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TECHNICAL REPORT

Preliminary Analyses of Changes in Coding and Case Mix Under the Inpatient Rehabilitation Facility Prospective Payment System

Grace M. Carter, Susan M. Paddock

Supported by the Centers for Medicare and Medicaid Services

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PREFACE

The Balanced Budget Act (BBA) of 1997 says that the Centers for Medicare and Medicaid Systems (CMS) may set the classification and weighting factors of the Inpatient Rehabilitation Facility (IRF) Prospective Payment System (PPS) so that changes in aggregate payments are a result of real changes in case mix and are not a result of changes in coding. This report covers the RAND Corporation's analysis of the extent to which payments during the first year of the IRF PPS were affected by coding change and by real change in case mix. Implementation of the IRF PPS began January 1, 2002.

For some analyses in this report, we estimated the costs of IRF services provided to Medicare beneficiaries in 2002. To make these estimates, we generally used cost report information in the public use files that matched the date of the beneficiary's discharge (in other words, for a beneficiary discharged June 1, 2002 we used the IRF's cost report that included June 1, 2002, assuming it was available on the file). After this report was completed, but during the public comment period on the proposed rule updating the IRF PPS effective October 1, 2005, HealthSouth, a large chain organization, notified CMS that its IRFs did not include any home office costs in their cost reports for cost reporting periods beginning on or after October 1, 2001 and before October 1, 2003. Home offices of chain organizations such as HealthSouth usually furnish central management and administrative services such as centralized accounting, purchasing, personnel services, management, and other services to support patient care services furnished by its member providers. The reasonable costs of these services are normally included in the provider's cost report and reimbursed as part of the provider's costs. The home office costs for HealthSouth are approximately 13 percent of total costs for its IRFs. The home office costs were included in the cost reports used to estimate 1999 costs for HealthSouth IRFs but were omitted from their cost reports covering 2002 discharges. The HealthSouth hospitals cared for about 19 percent of the cases in our sample hospitals and we estimate that analyses in this report are based on costs per case that were understated by approximately 1.6 percent on

average, and by about 6 percent for freestanding IRFs. For further information on this issue, see the IRF PPS final rule (Department of Health and Human Services, Centers for Medicare and Medicaid Services, "Medicare Program; Inpatient Rehabilitation Facility Prospective Payment System for FY 2006; Final Rule," *Federal Register,* Vol. 70, No. 156, August 15, 2005, p. 47884).

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The report benefited greatly from the work of David Adamson, a RAND communications analyst. His insightful questions and suggestions for presentation greatly improved the clarity of the document.

We thank the members of our Technical Expert Panel, whose names are listed on the next page, for their support and guidance throughout this phase of our project. Members of the TEP reviewed an earlier version of this report, helped with interpretation of the data, and pointed out places where the text and the analysis needed clarification.

Remaining problems of presentation and analysis are, of course, the responsibility of the authors.

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EXECUTIVE SUMMARY

The Balanced Budget Act (BBA) of 1997 mandated use of a prospective payment system (PPS) to pay for Medicare patient stays at inpatient rehabilitation facilities (IRFs). The act also stated that changes in the payment amounts should accurately reflect changes in IRFs' patient case mix—that is, the true cost of treating patients—and not be influenced by changes in coding practices, since such coding changes could overstate IRF resource needs and not reflect actual changes in patient costs.

This report covers our analysis of IRF case mix during 2002, the first year of the IRF PPS, and compares it with case mix under the old system in 1999. The report analyzes the extent to which case mix changes were due to coding change versus real change in the resource needs of IRF patients.

BACKGROUND

The IRF PPS assigns a payment amount to each Medicare rehabilitation patient based on that patient's assignment to a Case Mix Group (CMG). At any given IRF, assignment to a CMG and tier (and thus payment amounts) for almost all cases are determined by four patient characteristics at admission: impairment, functional independence, comorbidities, and age. The amount of the payment for such a patient is calculated by taking the standard payment conversion factor ($12,525 in fiscal year 2004) and adjusting it by multiplying by a relative weight, which depends on the patient's CMG and tier. So, for example, an 80-year-old hip replacement patient with a motor score between 47 and 54 and no comorbidities is assigned a relative weight of 0.5511. Further payment adjustments are made based on the facility characteristics (area wage index, rural location, and share of low-income patients). Payments are reduced for short-stay transfers, defined as cases that are transferred to a hospital or nursing home before the expected length of stay in the patient's CMG.

There were three reasons why we expected that the relative weights and payment rates in the IRF PPS would need refining.

First, better data are available. The earlier sample over-represented freestanding facilities, and consequently under-represented distinct part units of hospitals.

Second, implementation of the IRF PPS was likely to cause important changes in coding. We expected more accuracy and consistency in coding across hospitals now, because of the educational programs that were implemented in 2001 and 2002 and because items that previously did not affect payment (such as comorbidities) are now important factors in determining payment. There were also changes in instructions for using some impairment codes and some measures of functional independence, so that the same patient may be correctly coded differently now than in 1999. Furthermore, there is now a significant incentive to code ambiguous cases in a way that provides the most payment.

It is worth emphasizing that coding can change significantly for a variety of reasons, and often without dishonesty or gaming. However, regardless of the reasons behind coding changes, CMS can use the BBA language to adjust future payments to eliminate the effect of coding changes because the resource requirements of the patients have not increased.

Third, the IRF PPS also provides an incentive to accept a costlier mix of cases. Under the old system (created in 1982 under the Tax Equity and Fiscal Responsibility Act or TEFRA), the same average payment rate applied to all patients and thus there was a strong incentive to admit less costly patients into any IRF where costs exceeded the TEFRA limit. Under the IRF PPS, hospitals will receive more compensation for patients who are more costly due to their impairment, lower function, and/or relevant comorbidities. Thus, many hospitals will have a greater incentive than they had under TEFRA to admit expensive patients. Higher payments that reflect an increase in severity of case mix are appropriate.

METHODS

The Case Mix Index (CMI) is the average relative weight used to pay for the case. In computing this average, short-stay transfers are counted as only a fraction of a case.

This analysis addresses two key questions: (1) How much did the CMI (and therefore payment per IRF case) change between 1999 and 2002? (2)

To what extent were changes due to changing patient resource needs and to what extent to changes in coding?

To address the first question, we derived aggregate totals using CMS bills and matched patient assessments from 1999 and 2002. To address the second question, we analyzed the determinants of the CMI. We analyzed weight per discharge (WPD) separately from changes in short stay transfers.

Because it was not possible to observe directly the coding of each patient, we used information from the patient's preceding acute care hospitalization to predict coding during the IRF hospitalization. We believe that the introduction of the IRF PPS had minimal effect on coding of acute care patients within acute care facilities. Thus changes over time in the acute care records should reflect real change in the rehabilitation population. Therefore, we partitioned changes in WPD into real change and coding change, using information from acute hospitalizations that preceded the rehabilitation admission.

We used two different approaches to estimating real and coding change using statistical models and acute care data. The first approach underestimates real change and overestimates coding change. The second approach overestimates real change and underestimates coding change. Thus we are confident that the truth lies somewhere between these two estimates.

First Set of Estimates

The first approach derived estimates based on the following two working hypotheses, illustrated in Figure S.1:

- Changes over time in characteristics recorded during the acute hospitalizations preceding inpatient rehabilitation are the result of real change in rehabilitation case mix.
- Changes over time in IRF coding of patients that had similar acute characteristics reflects coding change

If the acute care characteristics were perfect predictors of rehabilitation characteristics and acute care coding did not change, these two hypotheses would necessarily be true.

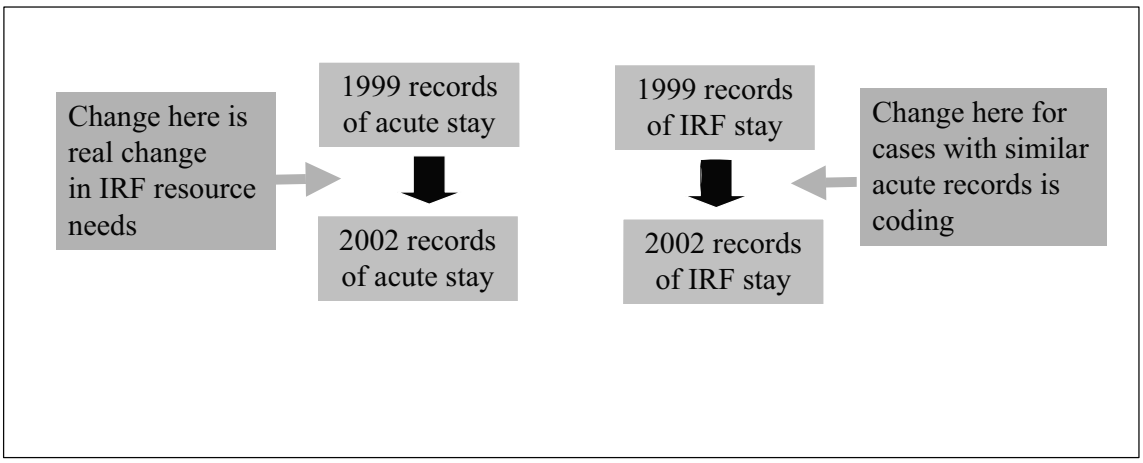

Figure S.1 Using Acute Care Records to Predict Real and Coding Changes in IRF Records

To illustrate the assumptions of this first set of estimates, suppose, for example, that IRFs recorded a greater number of patients on dialysis in 2002 than in 1999. If we find that more patients received dialysis during their acute care stay in 2002 than in 1999, then it is likely that IRFs were treating a greater number of patients with dialysis. Conversely, if the number of patients receiving dialysis in acute care did not change, but the IRFs reported dialysis for a greater percentage of the dialysis patients found in the acute care record, it is likely that the increase is due to coding changes, since it is unlikely that patients in rehabilitation are developing a need for dialysis that was not present during acute care.

We began with four models to predict each of the IRF stay characteristics that determine case weight: Rehabilitation Impairment Category (RIC), comorbidity tier, motor score (the measure of functional independence that most determines relative weight), and transfer status. Each of the first three models is based on characteristics found in the preceding acute stay. We predicted RIC based on the principal diagnosis of the acute stay and on major procedures performed during the stay (e.g., joint replacement, amputations, etc.). We predicted comorbidity tier based on all diagnoses during the acute stay and on a small set of procedure codes (e.g., hemodialysis, tracheostomy, etc.). We predicted motor score based on our predictions of RIC, predictions of tier, age, and a selected set of additional comorbidities. We predicted transfer

status from Medicare bills and nursing home assessments for the day of IRF discharge.

We then regressed weight per discharge in 1999 on all the variables that predict any of these rehabilitation characteristics:

- predicted RIC
- predicted tier
- age
- additional comorbidities found in acute care
- predicted transfer status

We then took the acute care characteristics of each 2002 discharge and predicted its weight using the coefficients from the 1999 regression. *If coding in 2002 of cases with each set of acute care characteristics was similar to coding in 1999 and if there were no patient selection within acute care groups*, then the difference between the model's prediction and the 1999 actual average weight per discharge is the increase in weight per discharge due to real case mix. This is our first estimate of real change. Further, the difference between the actual 2002 weight per discharge and the model's prediction is our first estimate of coding change because the sum of coding change and real change must add to the total change.

If the acute care characteristics were unbiased predictors of weight per discharge, this procedure would give us unbiased estimates of real and coding change. However, it is possible that hospitals might have selected patients during 2002 that had a higher weight from among all patients with the same acute care characteristics than were selected in 1999. If hospitals did in fact select in this way, this first set of estimates will underestimate real change and overestimate coding change. Thus the first estimate of real change is really only a lower bound on real change, while the estimate of coding change is an upper bound. The lower bound estimate of real change is the minimum amount of real change that occurred (the actual number could be higher) and the upper bound on coding is the maximum amount by which coding changed the CMI (the actual number could be lower).

Second Set of Estimates

Our second set of estimates of real and coding change accounts for possible patient selection by IRFs from among possible patients with

similar acute care characteristics. In this method, we attempted to model the results of a plausible selection process. When the observed data contradict what we see as a plausible selection process, we attribute that difference to coding change and thus get our second estimate of coding change and real change. In using this second approach we treat all change as real change except that which is not consistent with selection. Thus the biases in the estimate run in the opposite direction from those of the first set of estimates, and we therefore expect both real change and coding change to lie between the two estimates of real and coding change. Separate models were used for changes in RIC, tier comorbidities, and motor score.

DATA

We compared change in WPD between calendar year (CY) 2002 and the 1999 data that were used to develop the weights. The 1999 discharges in our analytic sample were bundled according to the interrupted stay rules, resulting in 247,461 cases that were used to calculate weights. Further information about this sample may be found in Carter et al. (2002).

We combined three sources of 2002 data on each IRF patient. First we used the IRF Patient Assessment Instrument (PAI). This provided impairment group code, a list of up to 10 comorbidities, and measures of functional independence at admission as well as demographic information, provider number, and admission, discharge, transfer, and return dates. Our second source of data was inpatient bills submitted to the Fiscal Intermediaries by the IRFs. These bills contain provider number, beneficiary number, age, admission date, and discharge date, which allow us to match most bills to an IRF PAI record. Our third source of data was other Medicare bills for IRF patients. For most analyses we used only the bill for the acute hospitalization that preceded admission to the IRF, provided it occurred in the month preceding rehabilitation admission. In both 1999 and 2002, 94 percent of IRF cases had a preceding acute care stay. For analyses of changes in transfers we used bills that covered the day of discharge. For completeness, we also use nursing home assessments (MDS records) for patients whose nursing home stay was not paid by Medicare.

RESULTS

Overall

Table S.1 shows the Case Mix Index and weight per discharge in each year. The CMI increased 4.55 percent, and the average WPD increased by 3.4 percent. The difference between these two rates of increase is due to an increase in short-stay transfers and to a decrease in the average LOS of short-stay transfers relative to the expected LOS in their CMG.

Table S.1

Change in Case Mix Index and Average Weight per Discharge between 1999 and 2002

Year	Case Mix Index	Weight per discharge
1999	1.0000	0.9413
2002	1.0455	0.9733
% increase	4.55%	3.40%

We find little evidence that the patients admitted to IRFs in 2002 had higher resource needs than the patients admitted in 1999. Despite the change in payment, most of the changes in case mix that we documented from the acute records imply a case mix with *lower* resource needs in 2002 than in 1999

The last line of Table S.2 shows our estimated bounds on real and coding change under the assumption that all real change would be reflected in changes in the acute care received prior to IRF admission. Based on the acute care records, we estimate that the resource needs of IRF patients, as measured by weight per discharge, declined by 3.45 percent between 1991 and 2002, and that coding change accounted for a 6.84 percent increase in WPD.

The first line of the table shows that most of the decline in real WPD occurred because of a change in the impairments of patients admitted to IRFs. Adding predicted tier, although it is highly statistically significant, has little effect on estimates of either real or coding change. Adding additional predictors of function at admission shows a further small decline in real case mix and the additional real increase in short-stay transfers further decreased WPD.

Table S.2

Lower Bound on Real Change in Weight per Discharge and Upper Bound on Coding Change in Weight per Discharge

Independent variables	Weight per discharge: Estimated real change	Weight per discharge: Estimated coding change	Percent change in WPD: Estimated real change	Percent change in WPD: Estimated coding change
Predicted RIC only	-0.0258	0.0578	-2.74%	6.14%
Predicted RIC and tier	-0.0258	0.0577	-2.74%	6.13%
Predicted RIC, age, tier, and other comorbidities related to function	-0.0282	0.0601	-3.00%	6.39%
Predicted RIC, age, tier, other comorbidities related to function, and transfer	-0.0325	0.0644	-3.45	6.84

The measured decline in case volume from the increase in short-stay transfers and decline in their relative LOS was almost entirely (95.5 percent) real change. Although coding of transfer status on the bills improved substantially between 1999 and 2002, the assessment data that we used to identify transfers in 1999 was just about as accurate as the 2002 bill data used for payment.

Below, we provide details of the changes in WPD, including our second set of estimates of coding change, which we believe are lower than actual coding change.

Impairment

Most of the decline in real weight per discharge occurred because of a change in the impairment of patients admitted to IRFs. Changes in predicted impairment were concentrated in two areas:

(1) a 16-percent decrease in the proportion of IRF patients who came following acute hospitalization for stroke (from 16.42 percent in 1999 to 13.76 percent in 2002). These patients had much higher than average weights in both years, so, all other things equal, this decrease will cause an decrease in WPD.

(2) a 22-percent increase in the proportion of IRF cases who came following a lower extremity joint replacement (from 18.65 percent in 1999 to 22.81 percent in 2002). These patients had much lower than average weights in both years, so, all other things equal, this increase

will cause a decrease in WPD. Changes in RIC assignment mirror this change in predicted impairment.

Although most of the change in assignment of RIC was true change, there was also coding change. Our predictions of RIC based on the principal diagnoses and major procedures in the preceding acute stay and our understanding of the rules were correct for about 5 percent more cases in 2002 than in 1999. We believe these corrections were due to improvements in IRF coding of impairment. For example, there was a noticeable decline between 1999 and 2002 in the percent of cases that had an acute principal diagnosis of hip fracture that were incorrectly assigned to the lower extremity joint replacement RIC 8. The net effect of all the RIC corrections was a lowering of weight per discharge by two-tenths of one percent. Table S.3 reports our direct estimates of coding change with the effect of the improved coding of RIC in the first line.

Table S.3

Percent Increase in WPD from Direct Estimates of Coding

Type of coding	Change in WPD	% change in WPD
Impairment improvement	-0.0019	-0.20%
Change in bladder, bowel items	0.0097	1.03%
Change in tier coding		
Tiers not related to cost	0.0011	0.12%
Increased tier coding	0.0088	0.93%
Total lower bound on coding	0.0177	1.88%

Functional Independence

The average motor score declined by 5.8 percent from 1999 to 2002. Lower motor score cases have less functional independence and a higher relative weight. Despite the coded increase in dysfunction, predictors of function at admission show a slight further decline in severity of case mix. An increase of 1 percent in the motor score was predicted from acute care characteristics, including predicted RIC.

The increase in apparent bowel and bladder dysfunction is noteworthy. The interpretation of responses to these items changed between 1999 and 2002. We believe that hospitals would not

differentially select these cases over other functional areas and that therefore, greater 'downcoding' of these two motor items reflects changes in the coding rules rather than an increase in real case mix. If the bowel and bladder items had declined only at the rate of other items, the total motor score decline would have been only 78.5 percent as large as observed. Thus we attribute 21.5 percent of the increase in WPD due to lower motor score to coding.

Comorbidity

There are indications of both real and coding change in comorbidities. Some indications of real change in comorbidity were consistent with a decrease in weight per discharge. For instance, there was a 9-percent decrease in the percentage of cases with an acute care record that indicates a tier 1 comorbidity (from 3.84 percent of cases to 3.55 percent of cases.).

The only sign of real change consistent with an increase in weight per discharge that we found was an increase in the number of cases whose acute care record shows a tier 3 comorbidity. This number increased by 3.5 percent from 20.09 to 20.77. However, because the weight of cases with a tier 3 comorbidity is so much smaller than the weight of cases with a tier 1 comorbidity, the total effect of tier conditions found in acute care is essentially 0.

A set of 10 tier diagnoses was found not to cause greater case cost. Increases in these diagnoses do not affect real resource use and thus should not affect future payments. However, these diagnoses increased much more than average, and therefore we count the effect of this increase on WPD as coding.

Although we cannot test the hypothesis that hospitals might have selected cases with active tier comorbidities from among those with and without indicators of tier comorbidities on their acute record, we believe that a reasonable selection process would have two properties. Increased selection of patients with tier comorbidities should occur at least proportionally from among those with tier comorbidities recorded in acute care as from among those whose acute care record does not record it. Second, hospitals would not discriminate against cases with a tier comorbidity on their acute record. Using these assumptions, we

estimate that coding was responsible for the majority of the effect of the increase in tier incidence on WPD.

Age

Age does not present a coding issue, since it can be assigned accurately. Weight per discharge is somewhat related to age, being slightly U-shaped, with the highest weights found among the oldest and youngest and the lowest weights being in the 65 to 74 age groups. We found that changes in the distribution of the age of IRF patients were quite modest and had little effect on weight per discharge. If we assume that weight per discharge within each age group were, in each year, at the average of the two years, then the weight per discharge would decline by three-hundredths of 1 percent due to the slight change in the age distribution.

IMPLICATIONS

Combining the last lines of Tables S.2 and S.3, we estimate that weight per discharge was between 1.9 percent and 6.8 percent higher in 2002 than in 1999 for reasons unrelated to resource use, largely coding changes. Since the change in the volume of cases due to short-stay transfers was essentially all real, coding increased the CMI by between 1.9 percent and 6.9 percent. Correspondingly, we estimate that the range of real change in the CMI was somewhere between a decline of -2.4 percent (if coding caused a 6.9 percent increase since 1999) and an increase of 2.6 percent (if coding caused only a 1.9 percent increase).

The conversion factor was not based on our case sample alone. CMS' Office of the Actuary projected TEFRA payments to obtain the budget neutral conversion factor. Part of the conversion factor calculation involved using a RIC prediction formula similar to the one used here. It was applied to the entire universe of 1999 IRF cases, and showed that, even in 1999, the population had a distribution of predicted RIC with lower weights than our sample. In response to this finding, CMI used a conversion factor that was 1 percent higher than the conversion factor that would have matched cost just within our sample. Thus, one-third of the approximately 3-percent decline in real case mix from impairment was already taken into account in setting the 2002 rates. This affects our lower and upper bounds on how real and coding change

affected payments. Thus, our final bounds on the causes of the increase in the CMI are:

- coding change between 1.9 percent and 5.9 percent
- real change between a 1.4-percent decline and a 2.4-percent increase

Given these findings, we recommend that CMS either reduce weights by at least 1.9 percent or reduce the conversion factor by at least 1.9 percent below what it otherwise would be in order to ensure that future payments reflect only real changes in resource needs.

1. INTRODUCTION

The BBA of 1997 mandates that the classification, weighting factors, or payment rate of the Inpatient Rehabilitation Facility (IRF) Prospective Payment System (PPS) be set so that changes in aggregate payments are a result of real changes in case mix and are not a result of changes in coding. This report covers our analysis of the extent to which payments during 2002, the first year of the IRF PPS, were affected by coding change and by real change in case mix. Based on the analysis, we developed preliminary recommendations to CMS with respect to refined relative weights and/or the update to the payment rate for the IRF PPS for cases discharged after September 30, 2005.

The IRF PPS assigns a payment amount for each Case Mix Group (CMG). In any given IRF,[1] payment amounts for most cases (all except very short stays and in-hospital deaths) are determined by five factors: impairment, functional independence, comorbidities, discharge destination and, occasionally, age. Further length of stay (LOS) affects the payment of transfer cases. Because date of birth is taken from the Social Security Administration's records, we expect any change in the distribution of age to reflect a real change in case mix. However, changes in the distribution of the other factors—impairment, functional independence, comorbidities, transfer status—could arise from either a real change in the kinds of patients admitted to the IRF or from coding changes.

The Case Mix Index (CMI) is the average relative weight used to pay for each case (in computing this average, short-stay transfers are counted as only a fraction of a case). Because aggregate payments are proportional to the CMI times the volume of cases, the BBA mandate that future aggregate payments be affected only by real change can be met by adjusting future payments to account for how coding and real change affected the past CMI. Thus the goal of this paper is to partition the change in the CMI into real change and coding change.

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[1] A facility-specific adjustment multiplies the national payment rate to account for local area wages and the higher costs incurred by IRFs in rural areas and by lower-income patients.

Implementation of the IRF PPS began January 1, 2002. IRFs are paid under the system beginning with the start of their own fiscal year (FY), so initially the system was used only for hospitals whose FY corresponded to CY 2002. Other hospitals started at different times, and almost all IRFs were paid under the PPS by October 1. The CMGs and their relative weights were developed on a sample of data from CYs 1998 and 1999. Thus we examine change in case mix and coding between our 1999 sample and 2002.

OUTLINE OF THE REPORT

In the next subsection we describe how IRF PPS payments are assigned. Then we conclude this introduction with the reasons why we believe both coding change and real change may have occurred between 1999 and 2002. Section 2 discusses our data and methods. Section 3 reports the amount of change in the CMI and in the average relative weight per discharge (WPD) between 1999 and 2002 and analyzes the determinants of payment. It partitions changes in each determinant into real change and coding change. The last section of the report summarizes our findings and discusses the implications of our findings in light of the way CMS's Office of the Actuary (OACT) set 2002 payments.

IRF PPS PAYMENT

As we have noted, the IRF PPS payment system assigns cases to Case Mix Groups (CMGs) in order to establish payment amounts. The data used to assign CMGs to each IRF patient come from the IRF Patient Assessment Instrument (PAI). In order to assign a case to a CMG, each case is first classified into one of 21 Rehabilitation Impairment Categories (RICs). Most RICs are based on particular body structures (e.g., brain, lower extremity) and/or types of loss (e.g., stroke, fracture).

Each RIC is subdivided into CMGs based on functional independence and age. Functional independence is determined by the response to 17 questions on the IRF PAI. The response to each question is used as a number between 1 (least independent) and 7 (most independent).[2] The sum

[2] Unobserved items are recorded as 0, but used as 1 in creating the functional independence scores. These 17 questions cover the same domains of functioning as 17 of the 18 items in the Functional

of 12 items is used to create a motor score, and the remaining five items are summed for a cognitive score. The values of motor and cognitive scores and patient age determine the patient's CMG assignment within RIC. The CMG assignment rules were derived in order to maximize the ability to predict cost under the constraint that payment for care of a patient with a lower score (less independence) is never less than for care of an otherwise similar patient with a higher score.

Comorbidities are used to split most CMGs[3] into four payment subgroups: three comorbidity tiers and a subgroup with no relevant comorbidity. Codes are excluded from tiers in a particular RIC when it is believed that this or a similar condition will afflict many patients in the RIC, and thus the costs should be considered an integral part of the cost of rehabilitation of all patients in the RIC. Except for such RIC-specific exclusions, tiers are defined similarly across all CMGs.[4]

Tier 1 comorbidities are the most costly and have the highest relative weight within the CMG, followed in order by tiers 2 and 3. The least expensive subgroup and the one with the lowest weight within each CMG consists of cases with no relevant comorbidity. Patients that have comorbidities in more than one tier are assigned to the most expensive applicable tier. Multiple comorbidities in the same or lower tiers have no effect on payment.

The IRF PPS payment for a discharge in hospital i in CMG k is given by

$$F = R*A_i*W_k,$$

where R is the national conversion factor, A_i is the facility payment adjustment, and W_k is the CMG relative weight. In FY 2002, R was chosen to meet the statutory budget neutrality constraint that payment under the new RPPS equal what payment would have been under TEFRA, as estimated by the OACT.

This payment is increased by an outlier supplement for very expensive cases. Also, short-stay transfer cases receive a per diem

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Independence Measure (UDSmr, 1997), although the meanings of some responses were changed.

[3] All except for atypically short stays and in-hospital deaths.

[4] The comorbidities in each tier and exclusions are found in both the Federal Register (CMS, 2001) and in Carter et al. (2002a).

payment plus one-half day per diem, where the amount of the per diem depends on CMG.

HYPOTHESES ABOUT CODING CHANGE AND REAL CHANGE

We expected coding to be different in the IRF PAI data than it was in the 1999 data used to determine the relative weights. In the first place, we expected more accuracy and consistency across hospitals, since items that previously did not affect payment are now important factors in the payment determination. For example, as discussed in Carter et al. (2002b), we believe comorbidities were undercoded in the 1998 and 1999 data. In addition, the training in coding of functional items provided by CMS may have increased coding accuracy and reliability.

In the second place, there were changes in instructions for some functional items and some impairments so that the same patient may be correctly coded differently now than in 1999. For example, the bowel and bladder items in the 1998-99 data coded frequency of accidents quite differently than the count of accidents within the seven days preceding the assessment reference date (usually the third day of admission) used in the IRF PAI.

Finally, there is now a significant incentive to code ambiguous cases in a way that maximizes payment. The training and instructions may have led to changes in coding practice even when the instructions did not formally change. For example, at least anecdotally, many hospitals appear to have instituted '24/3 FIM'—using measurements of function observed during night-time activities when the patient may be less capable than during the day. Although this may be within the rules, and perhaps always was, the frequency with which these data are used in the functional assessment may have changed. Indeed, there are some clinicians who believe that this is the most appropriate way to code since it is the patient's weakest performance that constrains discharge home.

It is important to note that coding can change significantly without dishonesty or gaming—it could be simply more accurate due to increased attention to items that now affect payment. Regardless of the underlying reasons for the coding change, the BBA allows CMS to adjust future payments to eliminate the effect of all coding change—even better

coding—because the resource requirements of the patients have not increased. The BBA allows CMS to adjust payments, so increases in payment reflect only real changes in resource needs.

The IRF PPS also provides an incentive to admit a case mix of sicker or lower-functioning patients. Under TEFRA, all patients were paid for at the same average rate. The rate was determined based on actual cost and the TEFRA limit. The limit itself was based on historical costs trended forward. Thus, under TEFRA, there was a strong incentive to admit less costly patients into any IRF where costs exceeded the TEFRA limit. Under the IRF PPS, hospitals receive more compensation for patients who are more costly due to lower function and/or relevant comorbidities. Thus, many hospitals have a greater incentive to admit patients who will be expensive than they had under TEFRA, and may respond to this incentive by changing their admission decisions in a way that increases real case mix. Higher payments that reflect the increase in real case mix are appropriate.

2. METHODS AND DATA

ANALYTICAL STRATEGY

Case Mix Index and Volume

As discussed above, the payment for each case depends on the relative weight of the CMG to which it is assigned. In discussing how changes in coding and case mix affected Medicare payments, it is useful to define the case mix index (CMI) in each year by:

CMIy = average relative weight of a Medicare case in year y.

Then, total Medicare payments are proportional to:

VOLUMEy*CMIy.

Within both volume and CMI, short-stay transfers count as only a fraction of a case, with the fraction being the ratio of payment for the transfer to the payment for a typical case in the CMG and tier combination. In order to simplify the presentation, most of our analyses concern weight per discharge, which is adjusted downward in the usual way for short stay transfers. In the last subsections of section 3, we examine how changes in short-stay transfers affected volume and weight per discharge.

Overview

We partition changes in the CMI into real change and coding change by using information from acute hospitalizations that preceded the rehabilitation admission. To do this, we used two different approaches to obtain two sets of estimates, described below. We believe that the introduction of the IRF PPS had minimal effect on coding non-rehabilitation patients within acute care facilities.

Model-based approach. We obtain one set of estimates of real and coding change using statistical models and the following two working hypotheses:

1. Changes over time in characteristics recorded during the acute hospitalizations preceding inpatient rehabilitation are the result of real change in rehabilitation case mix.

2. Changes over time in IRF coding of patients with the same acute characteristics reflect coding change.

As discussed in the introduction, however, hospitals had an incentive to choose less expensive patients under TEFRA but not under the PPS. Thus it is reasonable to suppose that during 2002 hospitals might have selected, from among all patients with the same acute care characteristics, patients who had a higher weight than those they selected in 1999. If hospitals did in fact select in this way, the second hypothesis above will overestimate coding change and underestimate real change. Thus we present the estimates of real change and coding change from these two hypotheses only as upper bounds on coding change (the maximum possible amount) and lower bounds on real change (the minimum possible amount).

We view these model-based estimates of coding and real change as most credible when, as in the case of impairment, it is unlikely that the relationship between rehabilitation characteristics and acute care characteristics is substantially affected by unobserved case selection.

***Ad hoc* approach.** In order to get unbiased estimates of coding change in the face of selection, we use an *ad hoc* approach that varies with the characteristic being studied. For example, for tier comorbidities and motor score, we attempt to model the results of a plausible selection process. When the observed data contradict what we see as a plausible selection process, we attribute that difference to coding change and thus get our second estimate of coding change and real change.

In building these *ad hoc* estimates, we treat all change as real change except that which is not consistent with selection. Thus the biases in the *ad hoc* estimates go opposite to those of the model-based estimates. Consequently, we expect both real change and coding change to lie between their respective model-based estimate and *ad hoc* estimate.

The Nature of Our Approaches

In this subsection we will describe the approaches we use to estimate real change and coding change. Further details are found in

the results section where they are used. A mathematical description of the first approach is given in Appendix A.

In the first approach, we begin with models to predict different IRF stay characteristics: RIC, tier, motor score, and transfer status. Each of the models is based on characteristics found in the preceding acute stay. We predict RIC based on the principal diagnosis of the acute stay and on major procedures performed during the stay (e.g., joint replacement, amputations, etc.). We predict tier based on all diagnoses during the acute stay and on a small set of procedure codes (e.g., hemodialysis, tracheostomy, etc.). We predict motor score based on our predictions of RIC, predictions of tier, age, and a selected set of additional comorbidities. We predict transfer status from the presence of bills and nursing home assessments for the day of IRF discharge.

We regress weight for each discharge in 1999 on variables describing our prediction of each of these rehabilitation characteristics: predicted RIC, predicted tier, age, additional comorbidities, and predicted transfer status. We then take the acute care characteristics of each 2002 discharge and predict its weight using the coefficients from the 1999 regression. *If coding in 2002 of cases with each set of acute care characteristics was similar to coding in 1999 and if there were no selection within acute care groups*, then the difference between the model's prediction and the 1999 actual average weight per discharge is the increase in weight per discharge due to real case mix. This difference is our first estimate of real change. Further, the difference between the actual 2002 weight per discharge and the model's prediction is our first estimate of coding change. These first estimates are upper bounds on coding change and lower bounds on real change. They would be exact rather than a bound if there were no selection within acute care groups.

In preliminary analyses, we built a similar model using the 2002 data, and used its coefficients and the 1999 acute care characteristics to get a prediction of 1999 weight per discharge and another estimate of real and coding change. We found the estimates to be almost identical, and thus we present here only the 1999 regressions and their estimated real and coding change.

Although quite effective by usual statistical criteria, the models do not perfectly predict characteristics of the rehabilitation stay, but rather only predict with error. If the errors are small, such as they are with the most frequent impairments, then our model captures most of real change and coding change. If the errors are randomly distributed, then the estimates of real and coding change would be unbiased and one could use these estimates to determine how to change weights or the national payment rate to meet the BBA mandate.

It is possible, however, that the result of this estimate is biased and overestimates coding change. As discussed in the introduction, hospitals had an incentive to choose less expensive patients under TEFRA but not under the PPS. Thus it is reasonable to suppose that, during 2002, hospitals might have selected patients that had a higher weight than those they selected in 1999 from among all patients with similar acute care stays.

This selection hypothesis would mean that the CMI predicted from a model built on 1999 acute care data but using the characteristics of 2002 acute care records would underestimate the "true" CMI in 2002 if coding were the same in both years.

Consequently, we use a second approach to develop a second set of estimates of real and coding change based on *ad hoc* observations of the relationship between acute care and IRF stays. For example, when the observed data contradict what we believe is a plausible selection process, we attribute that difference to coding change and thus get our second estimate of coding change and real change. In developing the *ad hoc* estimates, we treat all change as real change except that which is not consistent with selection. Thus the biases in the *ad hoc* estimates go opposite to those of the first, model-based, set of estimates, and thus we expect both real change and coding change to lie between the two estimates of real and coding change.

Separate selection models are used for changes in tier comorbidities and for changes in motor score. A similar *ad hoc* approach was used in the initial analyses of changes in coding in the first years of the acute PPS (Ginsburg and Carter, 1986). The details of these models are found in section 3, where their plausibility can be judged in the context of their results.

Attributing CMI Change

Changes in average weight WPD arise from changes in the proportion of cases in each CMG and tier combination. We define the contribution of a subset of cases to the CMI increase as the amount by which a change in the proportion of the cases in the subset changed the average WPD. If the subset of cases has a higher than average weight, an increase in these cases results in a positive contribution to the change in the CMI, and a decrease results in a negative contribution to the CMI. If the subset of cases has a lower than average weight, we get the opposite result: an increase in such cases results in a negative contribution to the change in the CMI, and a decrease results in a positive contribution to the CMI. This method was also used in Ginsburg and Carter (1986).

For example, let's consider the contribution of a particular RIC. The contribution is the increase in the CMI that would have occurred due to an increase (or decrease) in the RIC, under the assumption that the distribution of CMG and tier within the RIC were the same in each year and typical of the average of the two years. Similarly, we can estimate the contribution of changes in the frequency of a tier by assuming that cases in the tier were found in each CMG as they were in the average of the distributions found in 1999 and 2002. Finally, we estimate the effect of changes in the CMG distribution within RIC and tier using conditional probabilities. The sum of the effects of each RIC, tier, and CMG slightly exceed the total increase in the CMI because there is a correlation between changes in RIC and changes in tier.

We approximate the contribution of changes in the distribution of subsets of cases, even those that are not defined by CMG and tier, by fixing the weight of the cases at its average across the two years. We define the contribution as how much the CMI would change due to the observed increase or decrease in the subset if all other characteristics of these cases and all other cases were distributed in both years in the amounts typical of both years' data.

By defining the subset of cases in ways related to real and coding change, we can now identify parts of the CMI change as real change or coding change using our prediction of RIC, tier, and CMG from the acute care record. For example, suppose we believe, as we do, that a change in the proportion of patients who arrive in an IRF following acute care

for a stroke represents real change in the distribution of impairment. Since this group has higher than average weights, a decline in this group contributes a negative real change in WPD.

As another example, suppose we believe, as we do, that an increase in the proportion of patients coded in the stroke RIC out of all who arrive in an IRF following a stroke represents coding change. We can use conditional probabilities (Equation (5) in Appendix A) to determine the extent to which this improved coding changed WPD.

When we add the effects of coding of different subsets of RICs, CMGs, tiers, and motor scores, we are ignoring second order effects due to the correlation, if any, of changes in coding of the different elements. We believe these to be small.

DATA

We compare change in the CMI between CY 2002 and the 1999 data that were used to develop the weights. The 2002 data are described below. The 1999 discharges in our analytic sample were bundled according to the interrupted stay rules resulting in 247,461 cases that were used to calculate weights. Further information about this sample may be found in Carter et al. (2002a).

Source Data

Our first source of data is the IRF PAI. IRFs submit each patient's IRF PAI record electronically to the national database using the Inpatient Rehabilitation Validation and Entry System (IRVEN), or vendor-purchased software. The receiving system validates the provider's identity and checks certain items on the record for valid codes. In particular, it checks that the submitted CMG and tier are consistent with information on impairment, age, functional status, and comorbidities found on the IRF PAI.

In this analysis we use the IRF PAI impairment group code at admission (item i21a), the list of up to 10 comorbidities in item 24, and the functional independence measures at admission in items 39Aa through 39Ra. We also used the demographic information, provider number, and admission, discharge, transfer, and return dates to link the IRF PAIs to bills.

Our second source of data is the inpatient bills submitted to the Fiscal Intermediaries by the IRFs. We use the bills after standard analytic file processing. These bills contain provider number, beneficiary number, age, admission date, and discharge date, which allow us to match most bills to an IRF PAI record. The bills also give discharge destination, which is used to determine whether the stay ended with a transfer or an in-hospital death. A flag on the bill is used to determine whether the hospital was paid under PPS at the time of the discharge. For cases paid under the PPS, the CMG and comorbidity tier are found on the bill. For cases paid under PPS, we use only records where the bill CMG is consistent with the IRF PAI CMG.

The bills were received in October 2003. The IRF PAI file that we used was drawn from the national file during November 2003.

Our third source of data is bills for each IRF patient's preceding acute hospitalization provided it occurred in the 30 days preceding rehabilitation admission. In both 1999 and 2002, 94 percent of IRF cases had such a preceding acute care stay. The vast majority of these acute stays (over 90 percent) were discharged on the day of admission to the IRF.

Cases are counted as transfers if the case is discharged to an acute facility, an IRF, a LTC hospital, a SNF, or a nursing home that is paid under Medicaid. We use Medicare bills for post-IRF care on the day of discharge for all Medicare paid sites and MDS records for nursing homes paid under Medicare.

Derived Variables

RIC is taken from characters 2 and 3 of the CMG found on the IRF PAI. Table 2.1 shows the meaning of each RIC number along with a short label for the RIC content that we will use in tables in this report.

The motor score is the sum of 12 items describing functional independence at admission from the IRF PAI: items 39Aa through 39Ja and 39La and 39Ma.

Table 2.1

Rehabilitation Impairment Categories and Short Labels

Rehabilitation impairment category		Label
1	Stroke	Stroke
2	Traumatic brain injury	TBI
3	Nontraumatic brain injury	NTBI
4	Traumatic spinal cord injury	TSCI
5	Nontraumatic spinal cord injury	NTSCI
6	Neurological	Neuro
7	Hip fracture	Hip FX
8	Replacement of LE joint	LE Joint
9	Other orthopedic	Other O.
10	Amputation, lower extremity	Amp LE
11	Amputation, other	Amp Other
12	Osteoarthritis	Osteo Arth
13	Rheumatoid, other arthritis	Other Arth
14	Cardiac	Cardiac
15	Pulmonary	Pulmonary
16	Pain Syndrome	Pain
17	Major multiple trauma, no brain or spinal cord injury	MMT, NBSCI
18	Major multiple trauma, with brain or spinal cord injury	MMT, WBSCI
19	Guillain-Barre	GB
20	Miscellaneous	Misc.
21	Burns	Burns
50	Atypically short stay	AtypicalSS
51	In-hospital death	Death

Conditions are defined as lists of ICD-9-CM[5] diagnostic codes that describe clinically related diseases or health states (e.g., pneumonia, amputated lower extremity). The patient is assigned to the condition if any diagnostic code in the list appears in any of the 10 IRF PAI items 24a through 24j. Most conditions used in this report are defined as shown in Table 4.10 of our implementation report (Carter et al., 2002a). However, we also use a modified definition of three conditions, dropping four diagnoses found to be not related to resource use. The modifications are that:

(1) 356.4, Idiopathic progressive polyneuropathy, is dropped from meningitis and encephalitis.

(2) 261, Nutritional marasmus, is dropped from malnutrition.

[5] Stands for "International Classification of Diseases, 9th revision, Clinical Modification."

(3) 410.91, AMI, NOS, initial, and 518.3, Pulmonary eosinophiia, are dropped from the major comorbidity condition.

The methods to determine which diagnoses are not related to resource use are the same as those found in Carter and Totten (2004). For consistency, we applied these methods to the 2002 data rather than the 2003 data used in that report.

In addition to defining the conditions from the IRF PAI diagnoses, we also determine whether the preceding acute care record contains any of the diagnoses in each condition list. As described more fully in Appendix A, we also use procedure codes from the acute stay record to predict finding four conditions during rehabilitation.

The IRF PPS contains an interrupted-stay rule. If a patient is discharged from an IRF and then returns to the same IRF in three days (the day of discharge or either of the following two calendar days), only a single payment will be made for both parts of the stay. Separate bills for each part of interrupted stays were appropriate during the pre-PPS portion of 2002 and earlier. We "bundled" multiple bills for interrupted stays into a single simulated stay described by admission date from the earliest bill, IRF PAI data from the earliest matched bill, and discharge date and discharge destination from the last discharge. We calculate LOS and cost for the bundle as the sum of the LOS and costs for all discharges in the bundle.

Transfers are defined as cases with discharge destination on the bill in any of 02 (Short term hospital), 03 (SNF), 61 (swing bed), 62 (IRF), 63 (LTC), or 64 (nursing home certified under Medicaid, but no Medicare). In-hospital deaths are defined as those with bill discharge destination of 20.

Sample Selection and Sample Size

Our bill records show that 473,645 bills for care of Medicare patients were submitted from IRFs during CY 2002.[6] As shown in Table 2.2, we eliminated 1,661 records that would not be paid under the PPS because they were part of interrupted stays. We matched 436,822 of the

[6] This number excludes two duplicate bills and 49 bills that overlapped another bill.

remaining bills to an IRF PAI where the bill data was consistent with the IRF PAI (92.5 percent).

We also eliminate records where the IRF PAI is internally inconsistent in such a way that it might distort our analyses. In particular, if the tier on the IRF PAI CMG is not consistent with the information in item 24 or inconsistent with the admission motor score or cognitive score that we calculate from item 39, we drop the case. As shown in Table 2.2, this affected only 198 cases, less than 0.05 percent.

The resulting 436,624 cases constitute the set of cases for which we calculate the 2002 case mix index, and for which we analyze change since 1999 in age and RIC. However, the comorbidities and motor score have no effect on the payment for atypical short stays or in-hospital deaths, so they are eliminated from analyses of these issues.

Table 2.2

Counts of IRF PPS Discharges During CY 2002
Excluded from Sample and Remaining Sample, by Reason for Exclusion

Reason for Exclusion	Excluded Records	Remaining Sample
Total bills	0	473,645
Bundling interrupted stays	1,661	471,984
No good match to IRF PAI	35,299	436,822
IRF PAI tier inconsistent with DX list	128	436,694
IRF PAI CMG inconsistent with item 39	70	436,624
CMI sample		436,624
In-hospital death	948	435,676
Atypical short stays	9,695	425,981
Tier, motor score sample		425,981

3. FACTORS AFFECTING CASE MIX

We begin below by presenting the change in the case mix index that occurred between the 1999 data used to normalize the weights and the 2002 data.

THE CASE MIX INDEX

The case mix index (CMI) is the average relative case weight for the IRF cases in any year. It is the sum of the relative weights assigned to each case divided by the number of equivalent full cases. Each case that is not a short-stay transfer is counted as one equivalent case. The relative weight assigned to a short-stay transfer[7] is its length of stay times the per diem relative weight for the CMG and tier plus one-half of the same per diem weight. Each short-stay transfer is counted as only a fraction of an equivalent case, where the fraction is equal to the relative weight for the short-stay transfer to the relative weight for a full case in the same CMG and tier combination.

Table 3.1 shows the case mix index in each year. The weights were calculated so that the case mix index in 1999 would be exactly 1. In 2002 the CMI was 4.55 percent higher. As the table shows, the ratio of equivalent cases to discharges declined by 1.10 percent. This could have happened only due to an increase in the number of short-stay transfers and/or a decrease in their LOS relative to average for the CMG tier. The average weight per discharge increased only 3.4 percent. Thus the changes in volume from short-stay transfers accounted for roughly one-quarter of the increase in CMI (1.10/4.55 = approximately 0.25). The change in WPD reflects the lower weight and lower payment for short-stay transfers relative to other discharges in the same CMG.

Conceptually, equivalent cases are intended to adjust discharge counts for the fact that less care is furnished to a short-stay transfer patient than to a similar patient who is discharged home, and thus it is

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[7] A transfer is a case discharged by the IRF either to a hospital (including another IRF) or to a facility paid by either Medicare or Medicaid. A short-stay transfer is a transfer that stays less than the mean length of stay (LOS) for other cases in the same CMG and tier minus one-half day.

intended to be a better measure of the volume of care delivered than simple discharge counts. The problem is that the number of equivalent cases depends on coding as well as on the volume of care delivered.

Table 3.1

Change in CMI and in Weight per Discharge Between 1999 and 2002

Year	Number of discharges after bundling	Number of equivalent cases	Case Mix Index	Equivalent cases per discharge	Average weight per discharge
1999	247461	232926	1.00000	0.94126	0.94126
2002	436624	406472	1.04546	0.93094	0.97326
% increase			4.55%	-1.10%	3.40%

Using discharge counts is much less subject to coding variation, but does not account for any real changes in the volume of care delivered because of changes in transfer rates of similar patients.

In the analysis sections that follow, we will examine how the changes in the case mix factors affected weight per discharge. We will look sequentially at age, impairment, tier comorbidities, motor score, and transfer status to see the extent to which changes in each are responsible for the change in weight per discharge. We will also examine the accuracy with which we can predict each of these factors from information on the acute care record and therefore the extent to which we can attribute the changes in the factor to real changes in case mix rather than coding. The final substantive sections below examine changes in the volume of cases from changes in transfer rates and the extent to which we can partition the remaining 1.1 percent increase in the CMI into real and coding change.

AGE

The age of the inpatient rehabilitation population may have changed during the three years from 1999 to 2002. Any effects that changes in the age distribution have on the CMI are clearly real changes.

In fact, changes in the distribution of the age of IRF patients were quite modest. The median age is 77 in both years, and the average declined only from 75.8 to 75.5. As Table 3.2 shows, there were very

small declines from 1999 to 2002 in the percent of discharges among the youngest disabled group and in the oldest old (85 and above).

The case mix index is somewhat related to age, being slightly U-shaped, with the highest weights found among the oldest and youngest and the lowest weights being in the 65 to 74 age groups.

Table 3.2

Distribution of Age, in 1999 and 2002 and Weight per Discharge

	1999		2002		
Age group	% discharges	Weight per discharge	% discharges	Weight per discharge	Contribution of change in age to change in WPD
<=44	1.55	1.0435	1.31	1.0409	-0.0002
45 to 64	6.93	0.9880	7.62	1.0113	0.0003
65 to 69	12.71	0.9339	13.27	0.9369	-0.0001
70 to 74	18.70	0.9220	18.64	0.9448	0.0000
75 to 79	23.10	0.9316	22.92	0.9691	0.0000
80 to 84	19.41	0.9410	19.95	0.9856	0.0000
85 to 89	12.33	0.9519	11.58	1.0005	-0.0001
90 to 94	4.36	0.9514	3.92	1.0058	-0.0001
>= 95	0.92	0.9687	0.77	1.0282	-0.0001
Total	100.00	0.9413	100.00	0.9733	-0.0003

How would such modest changes affect the CMI? The answer is very little. As shown in the last column, if we assume that weight per discharge within each age group were, in each year, at the average of the two years, then the weight per discharge would decline by three one-hundredths of one percent.

IMPAIRMENT

Effect of Impairment Changes on Weight per Discharge

There were some changes in the distribution of impairment between 1999 and 2002. As shown in Table 3.3, the percentage of cases in the stroke RIC 1 declined from 21.62 percent to 17.34 percent, a decline of 4.28 percentage points. This increase was offset by increases in RIC 8, the lower extremity joint replacement RIC, which increased by 3.33 percentage points and in RIC 14, the cardiac RIC, which increased by

1.36 percentage points. All other RICS maintained approximately a constant share of cases.

Table 3.3

Distribution of RIC in 1999 and 2002 and Weight per Discharge in 1999 and 2002

	1999		2002		
RIC	% discharges	Weight per discharge	% discharges	Weight per discharge	Contribution of change in RIC to change in WPD
1-Stroke	21.62	1.2859	17.34	1.3413	-0.0152
2-TBI	1.25	1.2151	1.28	1.2252	0.0001
3-NTBI	2.15	1.1828	2.01	1.2134	-0.0003
4-TSCI	0.57	1.4409	0.53	1.5002	-0.0002
5-NTSCI	3.01	1.0256	3.35	1.0857	0.0003
6-Neuro	4.76	0.9886	4.38	1.0396	-0.0002
7-Hip FX	11.40	0.9258	11.91	1.0011	0.0000
8-LE Joint	19.28	0.6216	22.61	0.6882	-0.0101
9-Other O.	4.88	0.8320	4.71	0.9170	0.0001
10-Amp LE	3.30	1.1058	2.59	1.1705	-0.0013
11-Amp Other	0.36	0.9648	0.26	1.0564	-0.0001
12-Osteo Arth	2.47	0.7851	2.30	0.8546	0.0002
13-Other Arth	1.20	0.8591	1.02	0.9422	0.0001
14-Cardiac	4.11	0.8044	5.47	0.8899	-0.0015
15-Pulmonary	2.81	0.9565	2.30	1.0142	-0.0001
16-Pain	1.48	0.7752	2.16	0.8214	-0.0011
17-MMT, NBSCI	0.91	1.0302	1.08	1.1175	0.0002
18-MMT, WBSCI	0.15	1.4157	0.20	1.5427	0.0002
19-GB	0.16	1.5129	0.13	1.6658	-0.0002
20-Misc.	11.61	0.9228	11.89	0.9862	0.0000
21-Burns	0.06	1.3390	0.05	1.5266	-0.0001
50-AtypicalSS	2.00	0.1651	2.22	0.1651	-0.0017
51-Deaths	0.47	0.9250	0.22	0.8078	0.0002
Total	100.00	0.9413	100.00	0.9733	-0.0305

Since stroke cases have much higher than average weights and joint replacement cases have much lower than average weights, we would expect that the change in RIC distribution would cause a decline in average weight per discharge. As shown in the last column, the total contribution of RIC to the change in the case mix index is to decrease the average weight per discharge by 0.0305. Almost all of this

contribution is concentrated in changes in the distribution of stroke and LE joint replacement.

Predicting Impairment

Unlike age, the change in the distribution of impairment is important. But how much of it is real change and how much is a coding change? In order to find out, we use the preceding acute care stay to predict impairment. In our implementation report (Carter et al., 2002a) we estimated the RIC from the principal diagnosis and surgery of the preceding acute stay and we use the same method here. For example, cases entering rehabilitation following acute care treatment for a stroke are predicted to be treated for a stroke impairment in rehabilitation. The RIC predicted from acute care is replaced with the correct RIC for atypical short stays and for in-hospital deaths, as these cases are assigned to RICs independent of impairment. The principal diagnosis (PDX) and procedures from the preceding acute care stay allowed estimation of the RIC in 84 percent of cases in 1999, and in 86 percent in 2002. The cases without an estimate include those with no acute hospitalization in the 30 days preceding admission to the IRF and those whose PDX and procedures are not correlated with any impairment.

Table 3.4 shows our ability to predict RIC assignment from acute care data. An assessment of the accuracy of our methods requires understanding that we are not attempting to identify the clinical reason for each individual hospitalization, but rather to identify changes in the total population of patients. Overall, we predict the correct one of the 23 RICs in 67 percent of cases in 2002 and 62 percent in 1999. We are even more likely to be correct in the two RICs (1 and 8) where there were large changes between 1999 and 2002.

The proportion of cases predicted correctly increased in almost all RICs. Since the rules used to assign predicted RIC were developed in 1999 based on our understanding of impairment coding, and not changed, the slight increase in prediction accuracy likely reflects more attention by IRF to the coding rules.

Table 3.4

Accuracy of Prediction of RIC from Acute Care Information: 1999 and 2002

	Discharges		Predicted correctly		Predicted incorrectly		No prediction	
RIC	1999	2002	1999	2002	1999	2002	1999	2002
1-Stroke	53495	75726	70.9	73.9	13.5	14.1	15.7	12.0
2-TBI	3087	5586	51.7	56.9	30.9	28.7	17.4	14.4
3-NTBI	5331	8783	33.1	37.5	44.4	38.0	22.6	24.5
4-TSCI	1415	2316	9.3	9.1	62.3	69.6	28.5	21.3
5-NTSCI	7440	14638	62.0	68.9	18.0	16.1	20.0	15.0
6-Neuro	11769	19123	31.9	34.6	43.2	45.7	24.9	19.8
7-Hip FX	28214	51995	84.7	85.9	8.5	9.2	6.8	5.0
8-LE Joint	47699	98737	86.1	93.6	10.9	4.5	3.0	2.0
9-Other O.	12072	20552	30.6	36.7	40.8	35.9	28.6	27.4
10-Amp LE	8168	11307	87.1	93.4	5.6	4.4	7.3	2.2
11-Amp Other	899	1144	54.9	78.3	37.6	19.6	7.5	2.1
12-Osteo Arth	6103	10032	2.2	4.2	66.4	63.6	31.5	32.2
13-Other Arth	2964	4442	6.0	8.5	52.5	55.4	41.5	36.2
14-Cardiac	10179	23876	64.8	63.9	22.7	24.9	12.6	11.2
15-Pulmonary	6952	10048	28.1	28.8	47.9	45.7	24.0	25.5
16-Pain	3662	9412	2.2	1.8	57.9	66.5	39.9	31.8
17-MMT, NBSCI	2250	4712	12.2	11.7	67.7	70.9	20.1	17.4
18-MMT, WBSCI	370	855	10.3	16.5	75.0	73.8	14.7	9.7
19-GB	401	566	69.8	83.8	23.2	14.8	6.9	1.4
20-Misc.	28722	51911	41.8	50.2	24.9	18.0	33.3	31.8
21-Burns	153	220	66.7	86.8	20.6	7.3	12.7	5.9
50-AtypicalSS	4953	9695	100.0	100.0	0.0	0.0	0.0	0.0
51-Deaths	1163	948	100.0	100.0	0.0	0.0	0.0	0.0
Total	247461	436624	62.1	67.0	22.0	19.4	16.0	13.6

Table 3.5

Effect on Weight per Discharge of Change in Predicted Impairment

	% discharges in case group		Weight per discharge (WPD)		Contribution of change in impairment to change in WPD		% in related RIC	
	1999	2002	1999	2002	Amount	Type	1999	2002
Cases entering IRF following								
Stroke	16.42%	13.76%	1.2726	1.3066	-0.0088	real	93.23%	93.12%
Hip fracture	12.44%	11.63%	0.9130	0.9989	0.0000	real	77.58%	87.87%
Joint replace-ment	18.65%	22.81%	0.6283	0.7004	-0.0122	real	88.91%	92.74%
Any of above	47.50%	48.21%			-0.0210	real		
All cases	100.00%	100.00%	0.9413	0.9733	-0.0253	real	62.14	66.99

Note: Cases entering IRF following joint replacement exclude those whose acute principal DX was hip fracture

Real vs. Coding Change

Let us first assume that cases were not selected on the basis of RIC within these predicted impairment groups. Then one can attribute the contribution of these predicted impairment groups to real change in case mix. The first row of Table 3.5 describes cases that entered rehabilitation following acute hospitalization for stroke. The percent of IRF cases that came after acute care for a stroke declined substantially. Since 93 percent of these cases are in the stroke RIC in both years, the decline in cases entering rehab after a stroke reduced the number of cases in the stroke RIC by a substantial amount, and thus we can be sure that much of the contribution of the stroke RIC represented a real decline in case mix. Further, the weight per discharge of all cases entering rehab following a stroke is almost identical to that for the stroke RIC cases (0.0070 higher in 1999, 0.0013 lower in 2002). The decline in the predicted RIC = stroke cases caused a real decline in weight per discharge of almost 0.01. This contribution is smaller than the total contribution of the stroke RIC because these cases constitute only 70 to 75 percent of the stroke RIC.

The next row in the table shows the percentage of cases that entered rehabilitation following an acute hospitalization with an acute diagnosis of hip fracture. The IRF PAI manual and the preceding FIM manual say that cases that had a hip replacement for a hip fracture are to be assigned to RIC 7 rather than to RIC 8, and these cases are thus counted with hip fracture. The cases hospitalized following LE joint replacement show the same substantial increase in frequency as the RIC 8 cases, so again we are led to believe that a large fraction of the increase in RIC 8 and in predicted RIC is a real increase.

The fourth line in the table merely sums the data for the three large acute care groups, while the next line summarizes information from all 23 predicted RICs. Changes in the predicted impairments of all persons admitted to rehabilitation would have decreased the average weight per discharge by 0.0253 if the average weight within each predicted impairment group were the same in each year. Stroke and joint replacement account for 84 percent of the total contribution of predicted RIC to the change in WPD. In each of these two predicted

RICs, 93 percent of 2002 cases are in the RIC group. Thus there is actually little room for selection of subsets of these patients with different impairments, and we believe the estimate of real change from predicted RIC is effectively unbiased.

The predicted acute hip fracture and joint replacement cases apparently saw some changes in coding with the percent being assigned to the appropriate RIC, increasing by 10 percent for hip fracture and 5 percent for joint replacement. These improvements are not unrelated, as there was a noticeable decline in the percent of cases that had an acute PDX of hip fracture that were incorrectly assigned to RIC 8. This affected only 1.15 percent of all cases, but is strong evidence of some impairment coding change. As we said above, we believe the increased ability of the predicted RIC function to predict RIC is due to improvements in IRF coding.

In order to quantify the effect of changes in RIC coding on WPD, Table 3.6 describes the subset of cases with each predicted RIC that are assigned by the IRF to that RIC. We present detail for the same three large RICs. So the percent of cases coded in the stroke RIC and presenting in rehab after acute hospitalization for stroke was 15.32 percent in 1999 (this can be calculated from Table 3.5: 0.1532=0.1642*0.9323). The change in the incidence of these patients contributed a -0.0087 to the change in average WPD. The next two columns partition this decline into the real part and coding part, using the method described in section 2 above. Roughly speaking, the real change is that which would have occurred if the same proportion of the acute stroke patients were coded in the stroke RIC each year, and the coding change is due to the change in the proportion of acute stroke patients who are coded with the stroke RIC. In fact, there was very little change in this fraction, so almost all change in this group was real.

On the other hand, for joint replacement and hip patients there was an improvement in coding. Since the joint replacement patients have much lower than average weights, the improvement in coding led to a decline in WPD. For all other RICs the coding improvements led to only small contributions, half negative and half positive, so the total

coding contribution is very similar to the effect of improved coding in RIC 8.

Table 3.6

Effect on Weight per Discharge of Changes in Predicted Impairment and Improved RIC Coding

Cases coded in related RIC and entering IRF following:	% discharges in case group 1999	% discharges in case group 2002	Weight per discharge (WPD) 1999	Weight per discharge (WPD) 2002	Total contribution to change WPD	Real change	Coding change
Stroke	15.32%	12.82%	1.2842	1.3238	-0.0087	-0.0086	-0.0001
Hip fracture	9.66%	10.22%	0.9300	1.0028	0.0001	-0.0001	0.0001
Joint replacement	16.59%	21.15%	0.6042	0.6833	-0.0143	-0.0116	-0.0022
All cases with predicted RIC = RIC	62.14	66.99			-0.0259	-0.0239	-0.0019
Cases with predicted RIC ne RIC	37.86	33.01			- 0.0013	-0.0013	
All cases	100	100	0.9413	0.9733	-0.0272	-0.0253	-0.0019

Note: Total contribution may not equal the sum of real and coding change due to rounding.

COMORBIDITY TIERS

Effect of Tier Changes on Weight Per Discharge

Table 3.7 shows that the proportion of cases with a tier assignment increased dramatically between 1999 and 2002. The highest increase occurred in tier 1, with the percentage of tier 1 cases almost tripling from 0.63 percent of 1999 discharges to 1.76 percent of 2002 cases. The percent of cases with any tier increased from 18.5 percent to 24.9 percent.

Because cases assigned to tiers have substantially larger relative weights, this increase in tiers is an important component of the increase in WPD. Indeed, changes in tier case mix and coding are responsible for increasing WPD by 0.0176. The contributions of increases in tier 1 and 2 are almost equal—tier 1 has a much higher weight, but the absolute increase in proportion of cases is much higher in tier 2 (2.58%=8.83-6.25) than in tier 1 (1.13%=1.76-0.63). The

contribution of tier 3, although smaller, is still substantial at 0.0037.

Table 3.7

Distribution of Tier in 1999 and 2002 and Weight per Discharge

	1999		2002		Contribution of change
Tier	% discharges	Weight per discharge	% discharges	Weight per discharge	in tier to change in WPD
Tiers as paid					
1	0.63%	1.5027	1.76%	1.4569	0.0059
2	6.25%	1.1656	8.83%	1.2073	0.0059
3	11.61%	1.0873	14.27%	1.1094	0.0037
Any tier subtotal	(18.49%)		(24.85%)		(0.0156)
No relevant comorbidity	79.04%	0.9174	72.71%	0.9316	0.0021
Atypical RICs	2.47%	0.3096	2.44%	0.2223	0.0000
Total	100.00%	0.9413	100.00%	0.9733	0.0176
Eliminate diagnoses not related to cost in 2002					
1	0.57%	1.5212	1.41%	1.4441	0.0044
2	6.24%	1.1654	8.86%	1.2090	0.0060
3	11.33%	1.0886	13.96%	1.1093	0.0037
Any tier subtotal	(18.15%)		(24.22%)		(0.0142)
No relevant comorbidity	79.38%	0.9180	73.34%	0.9334	0.0019
Atypical RICs	2.47%	0.3096	2.44%	0.2223	0.0000
Total	100.00%	0.9408	100.00%	0.9719	0.0161
Contribution of eliminated diagnoses =					0.0011

The diagnoses that define each tier correspond to a set of conditions, each defined as lists of ICD-9-CM diagnostic codes that describe clinically related diseases or health states (e.g., pneumonia, amputated lower extremity). The patient is assigned to the condition if any diagnostic code in the list appears in any of the 10 items 24a through 24j. The condition lists are given in Table 4.10 of our implementation report (Carter et al., 2002a).

Tier Comorbidities Not Associated with Resource Use

In work covered in detail elsewhere (Carter and Totten, 2004), we show that a small number of diagnoses that were assigned to tiers are not related to cost in 2003 data. We used the same methods on the 2002

data to show that a subset of 10 of these diagnoses was not related to cost in 2002 either. These 10 diagnoses[8] typically were found much more frequently in 2002 than in 1999, with increases in incidence of as much as 800 percent. Since these diagnoses are not related to cost, they cannot be viewed as real increases in case mix. Consequently, the second section of the table assigns cases in both years to tiers as if these diagnoses were not assigned to tiers. In calculating weight per discharge, the weights were multiplied by a small factor (1.00048) that maintains the average weight per discharge in 1999. As one can see from the table, if these diagnoses had not been included in tiers, the increase in the WPD would be 0.0011 smaller. We assign this part to coding.

Predicting Tier

In order to predict tier comorbidities, we use the diagnoses and procedures on the preceding acute stay. For many of the conditions the only indication from acute care of whether the patient had the condition is whether any of the diagnoses that define the condition appear on the acute care Medicare bill. However, for four of the conditions—tracheostomy, ventilator, dialysis, and lower extremity amputation—we also can and do use acute care procedure codes to determine whether the acute care predicts the condition in rehabilitation. Appendix A provides the list of procedures used for each condition. Including these procedures greatly increases the number of acute care records found to predict the condition.

The first two columns of Table 3.8 show how the relative frequency of each condition in rehabilitation changed between years. These (and all of the other columns) are percents, so the 0.06 for candidasis in 1999 indicates a frequency of six cases per 10,000. The increase in conditions varied substantially, with malnutrition and obesity having especially large increases. However, many other conditions doubled or more—including tracheostomy, cachexia, and dialysis—and a few declined in incidence.

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[8] The diagnoses are all 6 in Miscellaneous throat conditions and esophageal conditions plus diagnoses (1) 356.4, Idiopathic progressive polyneuropathy, (2) 261., Nutritional Marasmus, (3) 410.91, AMI, NOS, initial, and (4) 518.3, Pulmonary eosinophiia.

The next two columns show the percent of IRF cases that were admitted following an acute care stay with a Medicare bill that included a diagnosis from the same condition, or a procedure that predicts the condition. The increase in cases with acute care predictors is not strongly related to the increase of each condition. Many conditions that increased in rehabilitation were less frequently found in the acute care records.

The next four columns provide information about how accurately the acute care record predicts the condition in rehabilitation and how this changed over time. Higher numbers in each of these columns indicate better predictive performance. In a statistical sense, these are typically very good predictors of tier conditions. The incidence of the tier conditions among the set of cases with an acute predictor is often more than a hundred times higher than among the average case (compare the fifth column to the first and the sixth to the second). Nevertheless, the predictions typically have more error than the predictors of impairment for a variety of reasons that differentially affect different conditions, as we will discuss in detail below.

There are several reasons why the acute care record is not a completely accurate predictor of tier conditions. One reason is that the condition may not persist into the IRF stay, and thus some of the conditions coded in acute care are not present during the IRF stay. Among the conditions that one would expect to persist for almost all cases are: dialysis, amputations, non-renal complications of diabetes,[9] and obesity. Indeed, in 2002, these four conditions have the four highest rates of occurrence within the sets of those coded in acute care. Infections, on the other hand, may be less likely to persist into the rehabilitation episode. Some of the infections coded in acute care—candidasis, the infection condition, and pseudomonas—are less likely than the typical condition to be coded in rehabilitation.

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[9] Renal complications of diabetes are complicated by the coding of dialysis in IRFs.

Table 3.8

Accuracy of Acute Care Indicators of Tier Conditions

		% of cases with this condition coded in IRF		% of cases with this acute condition		% of predicted with condition		% of condition predicted correctly		% rehab coded conditions with no acute record	
Condition	**Tier**	**1999**	**2002**	**1999**	**2002**	**1999**	**2002**	**1999**	**2002**	**1999**	**2002**
Candidasis	1	0.06	0.09	0.15	0.17	16.24	22.66	38.51	41.01	4.05	2.78
Malnutrition	1	0.09	0.65	0.13	0.12	19.57	22.38	30.00	4.00	4.29	4.39
Tracheostomy	1	0.27	0.53	0.98	0.77	21.22	48.70	75.72	70.46	5.88	10.58
Vocal cord paralysis	1	0.12	0.15	0.11	0.11	30.30	43.17	26.94	30.87	7.74	6.93
Ventilator	1	0.07	0.09	3.08	2.89	1.24	1.82	57.14	57.58	4.35	8.23
Cachexia	2	0.10	0.38	0.17	0.18	13.28	23.35	22.18	10.98	11.30	8.41
Clostridium	2	0.77	1.19	0.61	0.71	33.51	50.08	26.52	29.82	3.71	5.23
Dialysis	2	0.59	1.62	2.54	2.45	18.53	53.59	79.33	80.77	6.35	5.48
Dysphagia	2	1.90	2.80	0.69	0.71	43.45	52.74	15.86	13.37	8.43	8.06
Gangrene	2	0.15	0.16	0.19	0.15	22.91	29.81	27.88	28.32	6.17	5.90
Infection	2	2.69	3.42	3.98	4.14	27.09	32.54	40.11	39.35	4.05	4.26
Meningitis & encephalitis	2	0.15	0.10	0.17	0.14	38.02	27.62	43.02	39.17	11.45	7.54
Pseudonomas	2	0.53	0.62	0.42	0.29	10.78	24.80	8.52	11.69	6.10	6.45
Amputations	3	0.62	0.56	0.52	0.34	61.80	65.12	51.91	39.29	11.59	9.06
Complications DB non-renal	3	3.87	5.53	4.33	4.11	46.06	53.71	51.54	39.96	8.85	7.78
Complications DB renal	3	1.16	0.90	1.39	1.00	38.70	34.64	46.32	38.18	7.36	6.10
Hemiplegia	3	1.07	1.01	0.63	0.48	45.85	44.18	26.84	20.83	10.18	9.09
Major comorbidities	3	5.69	6.31	12.18	12.81	26.72	29.17	57.20	59.15	4.52	4.43
Obesity	3	0.58	2.93	0.74	1.14	29.65	56.16	37.69	21.94	8.64	7.18
Pneumonia	3	2.58	3.07	4.16	4.53	31.04	34.51	50.13	50.86	3.87	3.72
Selected anemias	3	0.26	0.26	0.37	0.38	32.65	33.81	45.14	49.02	4.23	4.83
Any tier 1 condition		0.58	1.44	3.84	3.55	9.47	16.43	62.29	40.47	6.75	8.95
Any tier 2 condition		6.40	9.08	8.02	8.01	31.37	46.76	39.30	41.26	5.97	5.75
Any tier 3 condition		11.62	14.31	20.09	20.77	35.06	37.30	60.61	54.17	6.74	6.24
Any tier condition		18.60	24.83	24.41	25.07	47.56	57.49	62.40	58.04	6.47	6.22

Note: Atypical short stays and in-hospital death cases are excluded because comorbidity coding does not affect relative weights. Note: Table excludes 10 diagnoses found not to be related to costs.

The next to the last set of columns, labeled "% of condition predicted correctly," shows the percent of cases with the conditions coded in the IRF that have that condition predicted by an acute care record. These numbers are substantially higher than average for the four conditions for which we can use procedure as well as diagnosis: tracheostomy, ventilator, dialysis, and LE amputation. This suggests that a part of the problem may be undercoding of these conditions in acute care. Some of the diagnoses that are salient in rehabilitation may not be very relevant to acute care, and this may explain in part the relatively small percentage of rehabilitation patients with vocal cord paralysis, dysphagia, or hemiplegia indicated in their acute care stay. A relatively minor reason for undercoding on the acute stay is that there is room for only nine diagnoses on the Medicare bill. Patients with all diagnoses filled in their acute care record are more likely to have an IRF-coded condition that is not on the acute care record. However, the increase in likelihood is very small.

The final columns show yet another reason why we cannot always predict tier conditions—about 6 percent of cases have no preceding acute care record. This is a subset of the cases with no RIC prediction. With no information from acute care we have no way to impute any estimate of real or coding change, and thus the contribution remains uncertain after all analyses.

Real vs. Coding Change

The increase in the percent of cases with acute conditions that are coded in the IRF along with a decline or only tiny growth in the percent of cases with the condition coded in acute care suggests a substantial role for coding among those with an acute record. We have added these predictors of tier from acute records to the model used to predict the WPD from predicted RIC. The resulting model is fully interactive, so that predicted tier can have a different effect in each predicted RIC, just as tier has a different effect in each RIC. The interactions are highly significant ($p<0.0001$).

Table 3.9 shows estimated real change and coding change from these models using equations (1R) and (1C) from the Appendix. Because it is possible for hospitals to have selected more 2002 than 1999 cases with

tier comorbidities from among those with similar acute care records, these models provide only a lower bound on real change and an upper bound on coding change. Adding predicted tier does essentially nothing to the estimates of real and coding change. The decrease in the proportion of cases with an acute predictor of a tier 1 comorbidity offsets the slightly larger increase in cases with a predictor of a tier 3 comorbidity because the weights of tier 1 cases are so much larger.

Table 3.9

Lower Bound on Real Change and Upper Bound on Coding Change

Independent variables	R-Square	Estimated real change	Estimated coding change
Predicted RIC only	0.258	-0.02576	0.05777
Predicted RIC and Tier	0.275	-0.02578	0.05775

Note: Predicted tier excludes predictions of conditions not related to resource use. Estimates from Appendix A equations (1R) and (1C).

We next obtain a direct estimate of the effect of the change in tier coding. To get an estimate of tier coding change, we assume that the set of patients who could be admitted to IRF is larger in 2002 than those who are actually admitted. If this were not true, then selection would not be possible, and the estimates from Table 3.9 would in fact not be biased. Further, when there was an increase between 1999 and 2002 in persons with a specific tier comorbidity, we assume that there are still more persons with this comorbidity who could be admitted to an IRF.

We are unable to make any inferences about changes in tiers of cases without a previous acute stay record. This was 7.5 percent of our sample of 1999 records and 6.0 percent of our sample of 2002 cases. Changes in the tier assignment of these cases contributed 0.00023 to the increase in WPD, and we add this to the uncertain estimate from cases with no prediction of RIC.

We next estimate tier coding change for the remaining cases by considering the details of a plausible selection process. Table 3.10 contains information relevant to the real vs. coding issue. Unlike Table 3.8, it is restricted to the subset of cases that enter IRF

following an acute care stay for which we have a Medicare bill. The first four columns merely update the first four columns of Table 3.8 for this subset and provide an easy reference for the relative incidence of the conditions.

One would expect that increased selection of patients with tier comorbidities, if any, would occur at least proportionally from among those with tier comorbidities recorded in acute care as from among those whose acute care record does not record it.[10] Thus, if all the increase in tiers was real change, the proportion of cases with a tier comorbidity recorded in acute care out of all those with a tier comorbidity in IRF should be at least as high in 2002 as in 1999 in each condition and in those with any tier condition. As one can see in columns 5 and 6 of Table 3.10, labeled "% of condition predicted correctly," this percent declined substantially in some conditions (particularly malnutrition, cachexia, non-renal complications of diabetes, and obesity). This percent declined by one-third in cases with at least one tier 1 condition, and by more than 10 percent in any cases with at least one tier 3 condition. This is not consistent with all change being selection. Rather, it suggests an increase in coding of patients without acute care predictors beyond the increase in selection that might have occurred in both groups.

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[10] One might argue that selection of cases with comorbidities would be easier if the acute care record recorded it and thus more frequent. If true, the actual coding change is greater than the estimate of coding derived.

Table 3.10

Indicators of Coding Change Among Cases with an Acute Care Record

	% of cases with this condition coded in IRF		% of cases with acute condition coded		% of condition predicted correctly		Cases not coded in IRF but coded in acute care as a % of all non-IRF coded cases		Contribution of change in condition to change in WPD	Estimated contribution due to coding change
Condition	**1999**	**2002**	**1999**	**2002**	**1999**	**2002**	**1999**	**2002**		
Candidasis	0.06	0.10	0.16	0.18	40.14	42.19	0.13	0.14	0.0001	0.0000
Malnutrition (M)	0.09	0.66	0.14	0.12	31.34	4.18	0.12	0.10	0.0018	0.0018
Trach	0.28	0.51	1.06	0.82	80.45	78.80	0.84	0.42	0.0014	0.0013
Vocal cord paralysis	0.12	0.15	0.12	0.11	29.20	33.16	0.08	0.06	0.0001	0.0001
Ventilator	0.07	0.09	3.33	3.07	59.74	62.75	3.29	3.02	0.0001	0.0001
Cachexia	0.09	0.38	0.18	0.19	25.00	11.98	0.16	0.15	0.0005	0.0004
Clostridium	0.80	1.20	0.66	0.75	27.54	31.47	0.44	0.38	0.0012	0.0003
Dialysis	0.60	1.63	2.75	2.60	84.71	85.45	2.25	1.23	0.0020	0.0016
Dysphagia	1.88	2.74	0.75	0.76	17.32	14.55	0.43	0.37	0.0027	0.0016
Gangrene	0.16	0.16	0.20	0.16	29.71	30.09	0.16	0.11	0.0000	0.0000
Infection	2.79	3.49	4.31	4.40	41.80	41.10	3.23	3.08	0.0011	0.0005
Meningitis & encephalitis (M)	0.14	0.09	0.18	0.15	48.58	42.37	0.11	0.11	-0.0001	0.0000
Pseudonomas	0.54	0.62	0.45	0.31	9.08	12.50	0.41	0.23	0.0002	0.0001
Amputations	0.59	0.54	0.56	0.36	58.71	43.20	0.22	0.13	-0.0001	0.0000
Complications DB non-renal	3.81	5.42	4.68	4.37	56.55	43.33	2.63	2.14	0.0027	0.0023
Complications DB renal	1.16	0.90	1.50	1.06	50.00	40.66	0.93	0.70	-0.0004	0.0000
Hemiplegia	1.04	0.98	0.68	0.51	29.88	22.91	0.37	0.29	-0.0001	0.0000
Major comorbidities (M)	5.87	6.42	13.16	13.62	59.91	61.89	10.25	10.31	0.0010	0.0000
Obesity	0.57	2.89	0.80	1.22	41.25	23.64	0.56	0.55	0.0019	0.0014
Pneumonia	2.68	3.15	4.50	4.82	52.15	52.82	3.19	3.26	0.0008	0.0001
Selected anemias	0.27	0.27	0.40	0.40	47.14	51.50	0.27	0.27	0.0000	0.0000
Any tier 1	0.59	1.39	4.15	3.77	66.79	44.45	3.78	3.20	0.0036	0.0032
Any tier 2	6.51	9.10	8.67	8.52	41.79	43.78	6.36	4.99	0.0056	0.0033
Any tier 3	11.71	14.27	21.71	22.10	64.98	57.77	15.97	16.16	0.0035	0.0023
Any tier	18.81	24.77	26.38	26.66	66.72	61.89	17.04	15.06	0.0127	0.0088

Note: Table restricted to cases entering IRF after an acute care stay and not in atypical CMGs. In 1999, N=223285; in 2002 N=400485.

Note: (M) after condition name means condition has been modified to remove DX that are not related to resource use.

Note: Contribution for individual conditions not discounted for cases with multiple conditions.

Further, it seems to us to be extraordinarily unlikely that hospitals would selectively discriminate against patients without tier comorbidities on the basis that a tier comorbidity is recorded in their acute record. Thus, under the assumption that all increase in tier comorbidities was real, 2002 patients without an IRF condition should be divided into those coded and not coded in acute care in roughly the same proportion as in 1999. Here we see (Table 3.10, columns 7 and 8) sharp declines (more than 30 percent) in conditions that passed the last test, including tracheostomy, dialysis, gangrene, pseudonomas, and amputations. The decline is consistent only with an increase in IRF coding of the patients who had a tier comorbidity in acute care and also had it in IRF, but it wasn't coded in 1999.

We used the arguments above to obtain the direct estimate of coding change. First, we categorized the increase in occurrences for cases without the acute comorbidity beyond the proportionate increase for cases with acute comorbidity as due to coding. Second, the decline in the admission of cases without the tier comorbidity and with the acute care comorbidity that exceeds the proportional decline in admission of cases with the tier comorbidity and the acute comorbidity is counted as cases newly coded to the condition. The second step adds only cases with the acute comorbidity. The contribution of each tier condition to the increase in the CMI without consideration of the fact that some cases have multiple tier conditions is shown in the next to last column of Table 3.10, and the last column shows the portion of this increase that we estimate is due to coding. For many tier comorbidities, we attribute to coding almost all the increase in WPD due to increased incidence of the comorbidity. Conditions with large exceptions include many infection cases: clostridium, infection and pneumonia. Preceding acute care hospitalizations suggest these diseases were more frequent in IRFs in 2002 than in 1999.

The summary of the effect on the tier variable is shown in the bottom of the table. Over two-thirds of the change in WPD due to tier changes among cases that entered an IRF following an acute care stay is likely due to increased coding of tier conditions.

FUNCTIONAL SCORE AND RELATIVE CASE WEIGHTS

Observed Changes in Functional Scores

Table 3.11 shows that each of the 18 functional independence items decreased between 1999 and 2002. The average motor score decreased by 2.5 points, while the cognitive score decreased by 0.8 points. Lower scores mean less functional independence. CMGs are defined by intervals of motor score and occasionally cognitive score, and CMGs with lower motor score intervals (and cognitive scores, when used) have a higher weight per discharge. The average change in each of the motor items listed is -0.206, and that for the cognitive items is -0.169.

The largest item-score decrease occurred for the bladder item. As noted previously, the definitions of the bladder and bowel items changed between 1999 and 2002. In 1999 the items referred to function within 72 hours of admission, but in the IRF PAI they can be affected by frequency of accidents within the seven days preceding the assessment reference date (usually the third day of admission). Without the bladder and bowel items the average change per motor item is -0.170, which is very similar to the average change in each cognitive item of -0.169. This suggests that a substantial part of the change in the bladder and bowel items could be due to coding; since the cognitive items only help define 15 of 95 CMGs for the typical cases, the incentive to upcode cognitive scores is much less than that for motor scores. Although we do not present RIC specific detail here,[11] the cognitive score declined in all the 15 RICs where it does not affect CMG assignment.

Figure 3.1 shows the distribution of motor score for the IRF sample in 1999 and 2002. The average motor score decreased from 42.8 to 40.3, with a corresponding increase in the weights from 0.9573 to 0.9920 (excluding RICs 50 and 51, which do not use motor score to assign a weight). Figure 3.1 shows that the curve is largely shifted to the left across all values of motor score. This suggests that the shift in motor score occurred for all cases, versus occurring for only a subset.

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[11] Mean cognitive scores by RIC will be found in our forthcoming report on the first year of the IRF PPS.

Table 3.11

Change in Functional Score Items, 1999 and 2002

	1999	2002	Change
Motor items			
Eating	5.417	5.249	-0.168
Grooming	4.725	4.460	-0.266
Bathing	3.161	3.065	-0.097
Dressing upper body	4.206	3.954	-0.252
Dressing lower body	2.971	2.744	-0.227
Toileting	3.331	3.123	-0.208
Bladder	4.136	3.577	-0.559
Bowel	4.548	4.328	-0.219
Transfer to bed	3.466	3.212	-0.254
Transfer to toilet	3.331	3.237	-0.094
Transfer to tub/shower	2.231	2.152	-0.078
Walking/wheelchair	2.189	2.049	-0.140
Stairs	1.271	1.281	0.010
Cognitive items			
Comprehension	5.746	5.505	-0.241
Expression	5.851	5.680	-0.171
Social interaction	5.762	5.616	-0.145
Problem solving	5.119	4.971	-0.148
Memory	5.175	5.038	-0.137
Average change per motor item (exclude transfer to tub)			-0.206
Average change per motor item, without bladder and bowel items (exclude transfer to tub)			-0.170
Average change per cognitive item			-0.169

Note: Based on 241,345 bundled cases in 1999 and 425,981 bundled cases in 2002.

The IRF PPS provides a monetary incentive to code patients below the CMG thresholds. So a patient who would be just above a CMG threshold in our 1999 data might be coded to be below the threshold in 2002. However, in examining the distributions of motor score in each of the larger RICs, we see no evidence of coding to the threshold. In Figure 3.2 we present the motor score density for RIC 8, which exemplifies our findings of the lack of any coding related to CMG thresholds. The curve is perfectly smooth, with slightly more noise showing in the 1999 curve than in the 2002 curve.

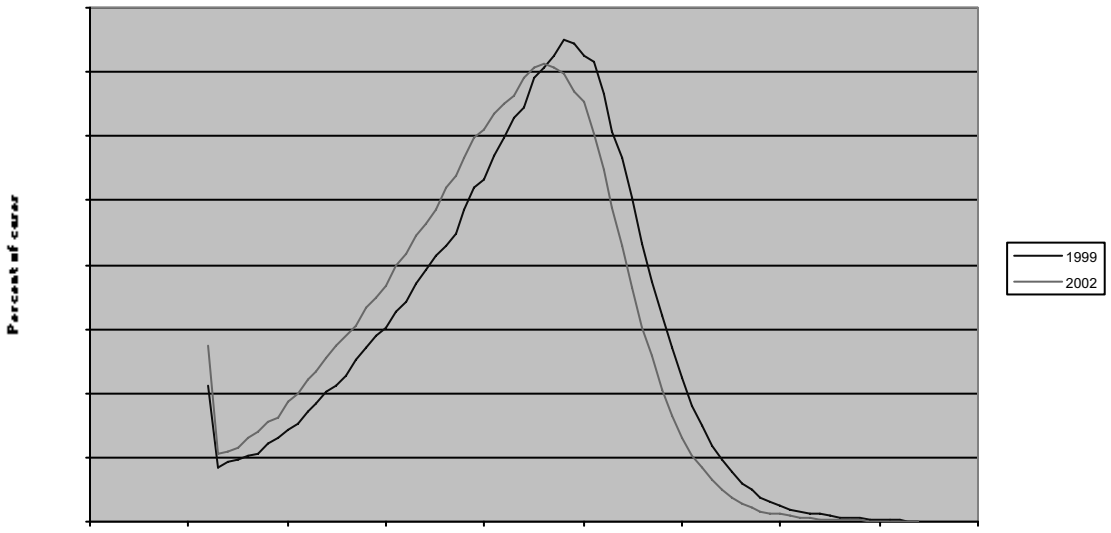

Figure 3.1 Comparison of Motor Score Density Curves in 1999 and 2002

Given that IRFs had less incentive under TEFRA in 1999 to admit higher weight cases, one might have expected to see a pattern similar to that of Figures 3.1 and 3.2 in which fewer 2002 cases were in the high range of the motor score distribution and more cases in the higher weighted lower end, which would suggest that IRFs selected more higher-weight, lower-functioning patients in 2002. Such a graph might look like Figure 3.3, in which RIC 8 cases were simulated to be redistributed from the upper 25th percentile to the lower 25th percentile in such a way that the average weight per case was similar to what was observed in 2002. The left tail of the distribution would be heavier than that for 1999, the right tail would be thinner, yet the center of the distribution would be at about the same place as before. This small simulation is only of one particular type of selection effect; the figure alone does not prove nor disprove the presence of selection, but does suggest that the motor score densities in Figures 3.1 and 3.2 are not due to this particular type of selection.

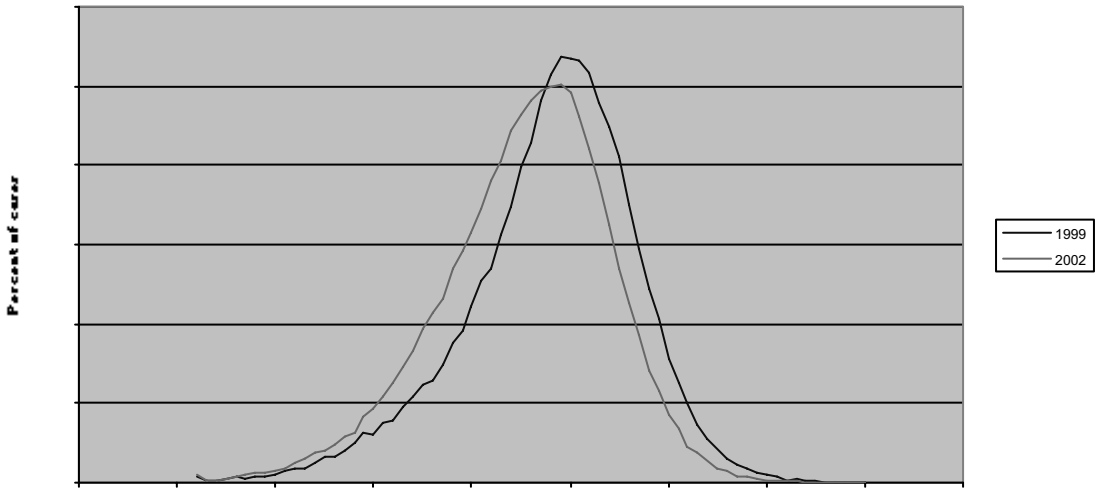

Figure 3.2 Comparison of 1999 and 2002 Motor Score Densities in RIC 8, LE Joint Replacement

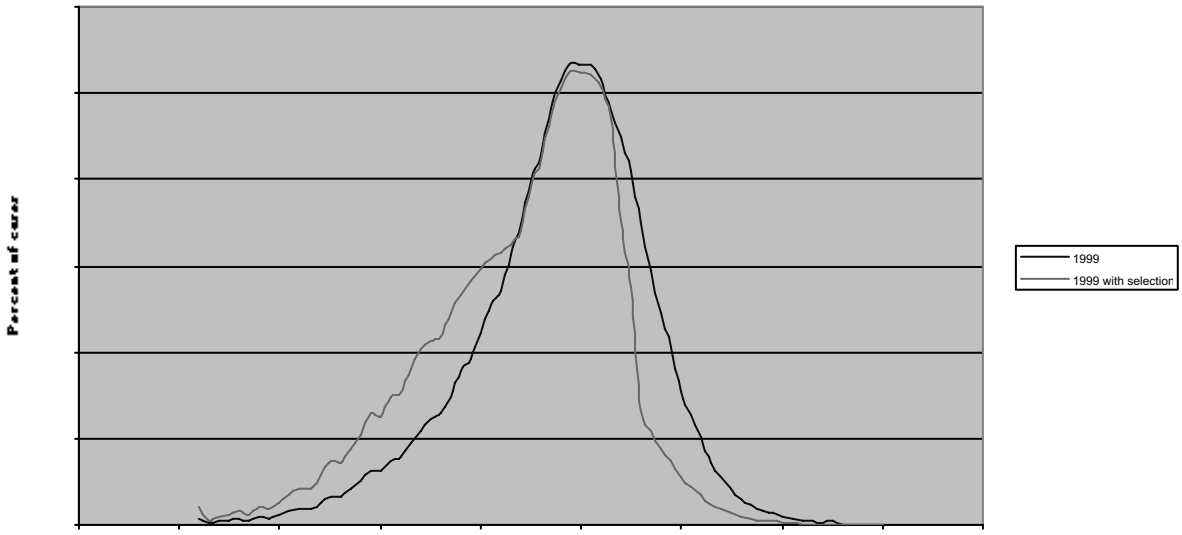

Figure 3.3 Motor Score Density in RIC 8, Modeled to Select Lower-Weighted Cases

PREDICTING MOTOR SCORE

Our analytic approach focuses on parsing the change in motor score that was observed between 1999 and 2002 into two components—the first being the amount of motor score change due to changing patient case mix, and the second being the amount due to changing coding. The change in motor scores attributable to patient case mix is determined by using the 1999 data to build a model of the relationship between patient characteristics and motor score, predicting motor score for patients in 2002 with this model, and comparing the predicted motor scores for 2002 versus 1999. To estimate the effect of coding change on motor score, the predicted motor scores for the 2002 patients are compared to the motor scores that were actually observed. Because it is possible for hospitals to have selected 2002 cases with lower motor scores from within those with similar predicted motor score, these models provide only a lower bound on real change and an upper bound on coding change.

Linear regression is used to model the 1999 motor score as a function of patient characteristics. The patient characteristics used to model motor score must be external to the implementation of the IRF PPS, since providers can change their coding behavior in response to a new prospective payment system in order to increase their payments without changing their case mix (Ellis and McGuire, 1996). We therefore rely on data from the preceding acute care stay prior to the IRF admission with the assumption that the IRF PPS implementation would not affect coding in acute care hospitals.

Demographic variables (race, gender, age) come from the MEDPAR data. Predicted RIC and the three predicted tier variables are derived from the preceding acute care stay, as described above. Each predicted tier variable is fully interacted with predicted RIC. Data on additional (i.e., non-tier) complications and comorbidities come from the preceding acute care stay. For this purpose, we looked for an acute stay any time in the six months prior to the rehabilitation stay rather than the 30 days prior used for predicted RIC and predicted tier. The comorbidities included in our model were identified by Iezzoni et al. (1994) as conditions that are nearly always present prior to hospital admission, and hence are extremely unlikely to represent complications arising during the hospitalization. These comorbidities included

primary cancer with poor prognosis, metastatic cancer, chronic pulmonary disease, coronary artery disease, congestive heart failure, peripheral vascular disease, diabetes mellitus with and without end-organ damage, chronic renal failure, nutritional deficiencies, dementia, and functional impairment. Complications that were likely to have arisen during the acute care hospital stay are also examined. To develop this list, we began with the list of complications developed by Iezzoni et al. (1994) and adapted it, keeping only those complications that were likely to have continued to affect the patient at the time of acute care discharge and therefore to have influenced whether a patient sought post-acute care; for example, we excluded from the list transient metabolic derangements and side effects of medications. We augmented the list by adding important complications for the Medicare population that had been omitted from Iezzoni's list. The complications that we used in our analyses included post-operative pulmonary compromise, post-operative gastrointestinal (GI) hemorrhage, cellulitis or decubitus ulcer, pneumonia, mechanical complications due to a device, implant, or graft, shock or arrest in the hospital, post-operative acute myocardial infarction (AMI), shock/cardiorespiratory event, venous thrombosis or pulmonary embolism, acute renal failure, delirium, stroke (for non-stroke patients only), hip fracture (for non-hip fracture patients only), iatrogenic complications, and sentinel events. We considered a few other complications, but only retained those for which at least 1 percent of cases in the 1999 universe had the complication.

RESULTS: MOTOR SCORE REGRESSIONS

The prediction model contains all of the terms described above as well as interaction terms for predicted RIC and predicted tier. Appendix B shows the motor score prediction model. The prediction model used here only explained 16.5 percent of the total variation in motor score. Thus, these results should be interpreted cautiously, given the relatively low predictive ability of the model. Table 3.12 shows the observed average motor scores by predicted RIC for 1999. The observed average motor scores for 1999 and 2002 are 42.75 and 40.28, respectively, yielding an observed decrease in average motor score of 2.47 points. The average of the predicted motor scores for the 2002

sample is 43.27, showing that a 0.5126-point *increase* in the motor score between 1999 and 2002 would have been expected due to differences in patient characteristics captured by our model. Most of this half-point difference is due to changes in the distribution of cases by predicted RIC.

Table 3.12

Change in Motor Score Attributable to Case Mix and Coding Change

	1999 observed motor score		2002 observed motor score		2002 predicted motor score		2002 (predicted) - 1999 (observed)
Predicted RIC	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	
1-Stroke	40617	37.78	60086	36.02	60086	37.84	0.0664
2-TBI	2693	38.10	4437	36.44	4437	38.50	0.3995
3-NTBI	2802	40.36	4581	37.60	4581	40.35	-0.0114
4-TSCI	244	28.48	323	26.15	323	28.92	0.4446
5-NTSCI	10033	43.04	20784	40.46	20784	43.26	0.2204
6-Neuro	5708	39.97	10069	37.15	10069	39.86	-0.1089
7-Hip FX	30779	40.75	50799	37.13	50799	40.83	0.0764
8-LE Joint	46142	48.58	99600	45.31	99600	48.66	0.0752
9-Other O.	6709	42.59	13030	39.33	13030	42.68	0.0933
10-Amp LE	8405	43.11	12330	39.65	12330	43.08	-0.0298
11-Amp Other	1095	43.75	2019	40.68	2019	43.66	-0.0853
12-Osteo Arth	588	45.54	1355	42.22	1355	45.49	-0.0505
13-Other Arth	464	43.20	844	41.44	844	43.28	0.0855
14-Cardiac	12784	45.31	25139	42.22	25139	45.61	0.2975
15-Pulmonary	3098	49.73	4508	45.09	4508	49.49	-0.2391
16-Pain	397	44.74	598	41.60	598	45.10	0.3583
17-MMT, NBSCI	797	40.23	1364	36.78	1364	40.03	-0.2036
18-MMT, WBSCI	209	35.70	391	34.41	391	35.60	-0.0993
19-GB	409	39.77	608	35.20	608	39.49	-0.2863
20-Misc.	25196	42.67	53226	39.64	53226	42.76	0.0873
21-Burns	144	38.73	243	36.05	243	38.50	-0.2328
No prediction	27559	41.98	41401	40.04	41401	42.12	0.1356
No acute hosp.	14434	42.69	18218	38.91	18218	42.70	0.0038
All	241306	42.75	425953	40.28	425953	43.27	0.5126
	Controlling for predicted RIC distribution in 1999						0.0887
	Controlling for predicted RIC distribution in 2002						0.0846

The increase in the joint replacement RIC (8) would, all other things equal, lead to an increase in the motor score since that RIC has the highest motor score in each year. In order to control for the

change in predicted RIC across years, we computed the mean difference between actual 1999 and predicted 2002 within each RIC and then weighted with a common predicted RIC distribution; the mean difference between the 2002 predictions and the 1999 observations using either the number of observations from 2002 or from 1999 to obtain mean differences is 0.0887 and 0.0846 for 1999 and 2002, respectively. Thus, there was virtually no change in motor scores attributable to changes in patient case mix within predicted RIC across 1999 and 2002.

The first row of Table 3.13 shows the estimated real and coding change in motor score from this prediction model, assuming no patient selection within acute care groups. Fitting a model to the 2002 data and using it to predict 1999 motor score, produces similar results, although we would have had estimated a slightly smaller amount of real change (0.4728 versus 0.5126).

Table 3.13

Summary of Real Change and Coding Change Effects on Motor Score

Year used for fit	Estimated real change	Estimated coding change	Estimated total change
1999	0.5126	-2.9882	-2.4756
2002	0.4728	-2.9500	-2.4772
Average	0.4927	-2.9691	-2.7327

RESULTS: CASE WEIGHT REGRESSIONS

The case weight prediction model was structured similarly to the motor score regressions, except that atypical cases are included in the fitting and prediction samples, and interaction terms are added into the model to account for the fact that cases in predicted RICs 50 and 51 have the same weight and therefore individual predictor variables of age and patient severity from the acute stay should not influence the case weight. Table 3.14 shows the average observed case weights by predicted RIC, which are 0.9412 and 0.9723 in 1999 and 2002, respectively. The model used to predict case weight explained more of the variation in weights than the motor score model (R-square = 0.308). The average predicted case weight in 2002 based on our model is 0.9130. The total change in case weight between 1999 and 2002 is 0.0311, while the real change is -0.0282, and the coding change is 0.0593. Again, most of the difference between what was observed in 1999 and predicted in 2002 is

due to changes in the distribution of cases across predicted RICs, since comparing these differences using either 1999 or 2002 predicted RIC distribution yields similar estimates of the real and coding changes. Thus, we find little evidence of change in CMG weight within predicted RIC that is attributable to changes in patient case mix across 1999 and 2002.

TRANSFERS

We next examine changes in transfer cases. A transfer is a case discharged by the IRF either to an acute hospital (including another IRF), a long-term care hospital (LTC), or to a nursing facility paid by either Medicare or Medicaid. A short-stay transfer is a transfer that stays less than the mean LOS for other cases in the same CMG and tier minus one-half day. Transfers affect the volume of cases—i.e., the number of equivalent full cases. Each case that is not a short-stay transfer is counted as one equivalent case, but each short-stay transfer is counted as only a fraction of an equivalent case, where the fraction is equal to the relative weight for the short-stay transfer to the relative weight for a full case in the same CMG and tier combination. The number of equivalent cases is the denominator of the CMI. The relative weight assigned to a short-stay transfer is its length of stay plus one-half times the per diem relative weight for the CMG and tier. The sum of the relative weights is the numerator of the CMI. In the next subsection, we look only at the volume of care delivered. In the final subsection we incorporate predictors of transfer status into our model of case weight in order to get a final lower bound on real change and upper bound on coding change.

Table 3.14

Change in CMG Weight Attributable to Case Mix and Coding Change

	1999 observed discharge weight		2002 observed discharge weight		2002 predicted motor score		2002 (predicted) - 1999 (observed)
Predicted RIC	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	
1-Stroke	40617	1.2727	60086	1.3054	60086	1.2700	-0.0027
2-TBI	2693	1.2008	4437	1.2245	4437	1.1904	-0.0104
3-NTBI	2802	1.1118	4581	1.1653	4581	1.1135	0.0017
4-TSCI	244	1.4834	323	1.5415	323	1.4769	-0.0065
5-NTSCI	10033	0.9544	20784	1.0136	20784	0.9480	-0.0064
6-Neuro	5708	1.0362	10069	1.0842	10069	1.0384	0.0022
7-Hip FX	30779	0.9130	50799	0.9982	50799	0.9119	-0.0011
8-LE Joint	46142	0.6283	99600	0.7003	99600	0.6288	0.0006
9-Other O.	6709	0.8975	13030	0.9614	13030	0.8968	-0.0006
10-Amp LE	8405	1.1120	12330	1.1758	12330	1.1133	0.0013
11-Amp Other	1095	0.9984	2019	1.0640	2019	1.0012	0.0028
12-Osteo Arth	588	0.8046	1355	0.8750	1355	0.8050	0.0004
13-Other Arth	464	0.8907	844	0.9394	844	0.8883	-0.0024
14-Cardiac	12784	0.9165	25139	0.9532	25139	0.9025	-0.0139
15-Pulmonary	3098	0.8818	4508	0.9560	4508	0.8865	0.0046
16-Pain	397	0.8669	598	0.9373	598	0.8605	-0.0064
17-MMT, NBSCI	797	0.9929	1364	1.0820	1364	0.9975	0.0046
18-MMT, WBSCI	209	1.2593	391	1.3679	391	1.2482	-0.0111
19-GB	409	1.3533	608	1.5174	608	1.3575	0.0042
20-Misc.	25196	0.9822	53226	1.0288	53226	0.9770	-0.0052
21-Burns	144	1.2804	243	1.4430	243	1.2857	0.0052
50-Atyp SS	4953	0.1651	9694	0.1651	9694	0.1653	0.0001
51-deaths	1163	0.9256	948	0.8082	948	0.9273	0.0017
No prediction	27559	0.9723	41401	1.0190	41401	0.9675	-0.0048
No acute hosp.	14434	1.0058	18218	1.0858	18218	1.0061	0.0004
All	247422	0.9412	436595	0.9723	436595	0.9130	-0.0282
			Controlling for predicted RIC distribution in 1999				-0.0025
			Controlling for predicted RIC distribution in 2002				-0.0024

Changes in the Volume of Care Delivered

Conceptually, equivalent cases are intended to adjust discharge counts for the fact that less care is furnished to a short-stay transfer patient than to a similar case that is discharged home, and thus it is intended to be a better measure of the volume of care delivered than simple discharge counts.

Table 3.15 shows how transfer cases affected the volume of equivalent cases measured in the 1999 implementation data set and in the 2002 cases. As measured here, the number of short-stay transfers increased by 9.55 percent, although the total number of transfer cases decreased by 7 percent. The number of equivalent cases per discharge declined by 1.1 percent. As discussed in the beginning of section 3, this decline caused a 1.10-percent increase in the CMI.

Table 3.15

Change in Percent of Transfers and Equivalent Cases per Discharge

	1999		2002		Percent change	
Type of case	Percent of cases	Equivalent cases per discharge	Percent of cases	Equivalent cases per discharge	Percent of cases	Equivalent cases per discharge
Short-stay transfers	13.78	0.5733	15.10	0.5423	9.55	-5.40
Other transfers	7.22	1.0000	4.42	1.0000	-38.85	0.00
(total Transfers)	21.00	0.7200	19.51	0.6459	-7.09	-10.29
Non-transfers	79.00	1.0000	80.49	1.0000	1.89	0.00
Total cases	100.00	0.9412	100.00	0.9309	0.00	-1.09

Note: In 1999, transfer status was based on the UDSmr and HealthSouth data. In 2002, transfer status was based on the discharge status found in the Medicare bill.

The number of equivalent cases depends on coding as well as on the volume of care delivered. Insofar as there are real changes across time in transfer rates of similar IRF patients, or the timing of their transfers, there are real changes in the volume of care delivered. However, if the indicator that a case is a transfer is coded differently over time, the change should be attributed to coding rather than real change. Further, if similar transfer patients are coded into different

CMGs in the two years, it will affect the count of equivalent cases and weight per discharge. If the coding change is typically into a CMG with a longer LOS, some transfer cases that used to be long stay cases would become short-stay transfers, and the number of equivalent cases would also decline.

The data used to identify transfer cases differed between the two years. In 1999 we used the discharge setting in the assessment data provided by UDSmr and HealthSouth. In 2002, we used the discharge destination field on the bill, which is the same field used by the pricer program to assign case weight. We used the assessment data in 1999 because there were known problems with discharge destination coding and we believed that the assessment data would be more accurate. The use of different sources may cause 'coding change' that is not related to changes in coding behavior but rather to the data sources used.

Predicting Transfer Status

Cases are counted as transfers if the case is discharged to an acute facility, an IRF, a LTC hospital, a SNF, or a nursing home that is paid under Medicaid. In order to get a time invariant measure of transfer cases we use Medicare bills for post-IRF care for all Medicare paid sites and MDS records for nursing homes paid under Medicare. Almost all (96 percent) IRF patients who were in a nursing home on the day of discharge were covered by a SNF bill.

Using the same terminology as we have used throughout this paper, we "predict" that a case is a transfer case if we find a post-IRF bill for the beneficiary in which the stay starts on the day of IRF discharge or if the beneficiary was in a nursing home on the day of IRF discharge. We predict that this is a short-stay transfer if the LOS plus 0.5 for the case is less than the average LOS for the case's CMG.

The first two column sets of Table 3.16 show transfer rates as calculated in the two data sets and as predicted from post-IRF information. The predictions from post-IRF information show a slightly greater increase in short-stay transfers and a small increase in total transfer rates rather than a decrease. The accuracy of the predictions is very high. We can find a bill or MDS record that verifies transfer status for 92 percent of short stay transfers, and total transfers, in

2002. This measure of accuracy is higher for transfers to nursing homes than for transfers to hospitals and noticeably higher in 2002 than in 1999.

Table 3.16

Accuracy of Prediction of Transfer Rates from Post-IRF Bills and MDS Records: 1999 and 2002

Type of transfer	Discharges of type		Predictions of type		Percent of transfers predicted correctly		Percent of predictions that are correct	
	1999	2002	1999	2002	1999	2002	1999	2002
Short stay	13.78	15.10	13.67	15.93	88.73	91.62	89.45	86.81
Any	21.00	19.51	20.66	20.87	87.56	91.96	88.99	85.98
Hospital	7.77	9.11	7.48	8.68	82.01	84.90	85.27	89.17
SNF/NH	13.23	10.40	13.19	12.18	86.89	94.34	87.27	80.57

Note: NH = nursing home.

The percentage of cases identified as transfers through their post-IRF status for which the assessment or discharge data shows a transfer is often higher in 1999 than in 2002. The only exception is transfers to hospitals. We believe this decline in accuracy indicates a continued undercoding of transfers to SNF/NH in the bill data base. In 1999, transfers were coded more accurately in the assessment data than in the bill data. Table 3.17 shows that 1999 transfers coded from bills were substantially lower than that coded either from the assessment data or indicated by the post-IRF data—even though the bill data specifically includes some (unknown) fraction of cases that are not transfers. Further, the assessment data reflect the post-IRF information much more accurately than the bills. A comparison of the bill columns of Table 3.17 with the 2002 columns of Table 3.16 (also from bills) shows that the 2002 bill data reflects the post-IRF status much more accurately than the 1999 bill data. Thus coding of transfers on the bill data has improved between 1999 and 2002 but that improved coding did not affect the CMI because CMS did not use the 1999 bill data in setting case weights.

Table 3.17

Rates of Agreement of Transfer Status from Assessment Data and from Bills with Transfer Status Predicted from Post-IRF Bills and MDS Records: 1999 Data

	Percent transfers			Percent of transfers predicted correctly		Percent of prediction that is correct	
Type of transfer	from assessment	from bills	from prediction	from assessment	from bills	from assessment	from bills
Short stay	13.78	12.74	13.67	88.73	86.70	89.45	80.70
Any	21.00	18.67	20.66	87.56	84.82	88.99	77.13
Hospital	7.77	7.72	7.48	82.01	70.96	85.27	74.05
SNF/NH	13.23	10.96	13.19	86.89	86.54	87.27	72.16

Note: Bills with a discharge destination of 2, 3, 4, or 5 are counted as transfers. Some cases with discharge destination of 4 and 5 are not transfers. If these are dropped, the transfer rate from bills would be even more biased downward than shown in this table.

If we take the post-IRF data as our best measure of actual change in transfer cases, then Table 3.18 shows that short-stay transfers increased by 16.56 percent between 1999 and 2002 rather than the 9.55 percent in Table 3.15. Further, the number of equivalent cases per discharge decreased by 1.5 percent rather than the 1.1 percent shown in Table 3.15. The differences between Table 3.18 and Table 3.15 are due to using different data elements to measure short-stay transfers in 1999 and 2002.

Table 3.18

Changes in Transfers Measured by Post-IRF Status

	1999		2002		Percent change	
Type of case	Percent of cases	Equivalent cases per discharge	Percent of cases	Equivalent cases per discharge	Percent of cases	Equivalent cases per discharge
Short stay transfers	13.67	0.6172	15.93	0.5819	16.56	-5.72
Other transfers	6.99	1.0000	4.93	1.0000	-29.44	0.00
(total Transfers)	20.66	0.7468	20.87	0.6808	0.99	-8.84
Non-transfers	79.34	1.0000	79.13	1.0000	-0.26	0.00
Total cases	100.00	0.9477	100.00	0.9334	0.00	-1.51

Note: In 1999, transfer status was based on the UDSmr and HealthSouth data. In 2002, transfer status was based on the discharge status found in the Medicare bill.

Real Change in Volume of Cases

We next regressed the number of equivalent cases provided for each discharge on variables that reflect real change in volume, namely our predictions that a case was transferred to a hospital and to a nursing home from post-IRF status information and length of stay. We used separate variables for transfers to hospitals and to nursing homes because transfers to hospitals are more likely than transfers to nursing homes to be short stay. We used a three-part variable for LOS: two spline terms[12] and a single dummy variable. The first part gives the ratio of the LOS for the case to, approximately, the median LOS in 1999 for the RIC of the case, truncated at 1 for cases beyond the median LOS. The second part gives the ratio of the LOS minus the median to the approximately 97th percentile LOS in 1999 minus the median, also truncated at 1 and set to 0 for cases with LOS less than the median. The final LOS variable is a dummy variable, which indicates an LOS greater than the 97th percentile.[13]

This regression is similar to the models we used to obtain a lower bound on real change in relative weights. As in that case, we first regress the 1999 data and use the relating equation and 2002 LOS and post-IRF data to predict the equivalent cases in the 2002 data. Since the explanatory variables are not affected by either the coding of discharge destination or the coding of CMGs, the prediction found in the 2002 data minus the actual 1999 data give an estimate of real change. There is no reason to believe that a hospital would deliberately select patients who are more likely to be short-stay transfers. Therefore we believe this estimate is an unbiased estimate of the real change in volume per discharge. The full regression model is shown in Table B.2

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[12] A linear spline function is a continuous function that is linear in each of multiple segments (two in our case).

[13] We use actual RIC rather than predicted RIC for two reasons. First, as we show earlier in this section, almost all change in RIC is real rather than coding. Second, this allows us to better estimate the LOS in the smaller RICs, where our prediction of RIC is often less accurate. Although a limited dependent variable model is formally more correct than a regression because the dependent variable cannot exceed 1, our formulation is close to equivalent as the prediction from the model never exceeded 1.0078 in 1999 or 1.0054 in 2002.

in Appendix B. In a similar manner, we fit a model on the 2002 data and used it to predict the 1999 equivalent cases.

Table 3.19 shows that the real change in equivalent cases per discharge is a decline of -0.0098, or 1.04 percent, which is 95.5 percent of the 1.09 percent total decline in equivalent cases measured in the analysis data sets, and about 65 percent of the decline in equivalent cases measured consistently across time using the post-IRF information. Since the measured change in the CMI is from only the analysis data sets, we can attribute a 1.1 (=0.95.5*1.15)-percent increase in the CMI from the decline in equivalent cases to real change. However, if coding of discharge destination continues to improve when all hospitals are on the PPS throughout the year, we would expect that we would find an even larger increase in the CMI from a decline in the equivalent cases and part of that could be attributed to coding change as transfer cases are placed in CMGs and tiers with longer expected LOS.

Table 3.19

Estimated Real Change in Volume Per Case Due to Change in Short Stay Transfers and Estimated Coding Effects

Year used for fit	R-Square	Estimated real change	Estimated coding change from payment data	Estimated coding change from post-IRF data
1999	0.7416	-0.0098	0.0005	-0.0045
2002	0.7636	-0.0099	0.0004	-0.0044
Average		-0.0098	0.0005	-0.0045

FINAL LOWER BOUND ON REAL CHANGE IN WEIGHT PER DISCHARGE AND CMI

Since short-stay transfers have lower than average case weight, the increase in the percent of cases that are short-stay transfers lowered the weight per discharge by -0.003 beyond what it would be if the percent of short-stay transfers had remained the same. The decline in the equivalent cases per short-stay transfer case further lowered the average weight per discharge.

Since much of the change in equivalent cases is real change, it is likely that much of the decline in case weight from the increase in equivalent cases is also real. Thus, we need to add the post-IRF status information into our regression model, which produces a lower bound on

the total real change. Although we used the case's LOS in our model of equivalent cases, it is not appropriate to use it in predicting discharge weight, since decreased LOS may be due to increases in efficiency rather than to changes in patient characteristics. Consequently, we add only the two indicators of post-IRF location (one each for hospital and SNF/NH), each interacted with predicted RIC, since the proportion of short-stay transfers varies by RIC. The full regression model is in Table B.3 in Appendix B.

Table 3.20 shows that after accounting for all known predictors of real change, we can say that real weight per discharge was no less than -0.0325 less than in 1999. The majority of the decline is due to by the change in the distribution of RIC.

Table 3.20

Lower Bound on Real Change and Upper Bound on Coding Change

Independent variables	R-Square of model	Estimated real change	Estimated coding change
Predicted RIC only	0.258	-0.0258	0.0578
Predicted RIC and Tier	0.275	-0.0258	0.0577
Predicted RIC, Tier, and predictors of motor score	0.308	-0.0282	0.0601
Predicted RIC, Tier, predictors of motor score, predicted transfer	0.342	-0.0325	0.0644

Note: Estimates from equations (1R) and (1C) of Appendix A.

4. DISCUSSION AND IMPLICATIONS

The case mix index increased by 4.55 percent between 1999 and 2002, the first year of the IRF PPS. The LOS of transfer cases decreased relative to their CMG, thus accounting for approximately 1.15 percentage points of the CMI increase. Weight per discharge increased by 3.40 percent. In this paper we have examined the acute care records for the hospitalizations that preceded the IRF stay and those that followed the IRF stay in an attempt to determine the extent to which this increase is due to a real change in the resource requirements of the patients and the extent to which it is due to coding change.

SUMMARY OF FINDINGS ON REAL CASE MIX CHANGE

We find little evidence that the patients admitted to IRF in 2002 had higher resource needs than the patients admitted in 1999. Indeed, most of the changes in case mix that we have documented from the acute records imply a lower case mix in 2002 than in 1999. These changes include:

(1) a 16-percent decrease in the proportion of IRF patients who come following acute hospitalization for stroke (from 16.42 percent in 1999 to 13.76 percent in 2002). These patients have much higher than average weights in both years, so, all other things equal, this decrease will cause an decrease in WPD.

(2) a 22-percent increase in the proportion of IRF cases who come following a lower extremity joint replacement (from 18.65 percent in 1999 to 22.81 percent in 2002). These patients have much lower than average weights in both years, so, all other things equal, this increase will cause an decrease in WPD.

(3) a 9-percent decrease in the percentage of cases with an acute care record that indicates a tier 1 comorbidity (from 3.84 percent of cases to 3.55 percent of cases).

(4) an increase of 1 percent in the motor score predicted from acute care characteristics, including predicted RIC.

Further, there was an increase in the number of cases whose post-IRF information indicated that they were transferred and whose LOS was

less than the mean LOS for their CMG. This caused a further small decrease in the WPD. However, it also increased the CMI because the denominator of the CMI was smaller than it would have been if these cases had not been transferred.

The only sign of real change consistent with an increase in WPD that we found was an increase in the number of cases whose acute care record predicts a tier 3 comorbidity. This number increased by 3.5 percent, from 20.09 to 20.77. However, because the weight of cases with a tier 3 comorbidity is so much smaller than the weight of cases with a tier 1 comorbidity, the total effect on WPD of tier conditions found in acute care is essentially 0.

Using a model that includes predictions of motor score, tier, RIC, and transfer status, we estimated that the real weight per discharge declined by 0.0325, a decline of 3.45 percent. If we take this as the true measure of real change, it implies that coding increased weight per discharge by 0.0644, or 6.84 percent. However, these estimates assume that hospitals did not select patients with higher weighted characteristics from among cases with similar acute characteristics. In order to explore more directly how coding changed, we were able to obtain the following estimates of coding change.

SUMMARY OF DIRECT ESTIMATES OF CODING CHANGE

Although most of the change in assignment of RIC was true change, there was also a small amount of coding change. Our predictions of RIC based on the principal diagnoses and major procedures in the preceding acute stay and our understanding of the rules were correct for about 5 percent more cases in 2002 than in 1999. The net effect of these corrections was a lowering of weight per discharge.

A set of 10 tier diagnoses were found not to cause greater case cost. These diagnoses increased in frequency much more than average. This increase did not affect real resource use and thus should not affect future payments. Therefore we count the increase as coding.

Although we cannot test the hypothesis that hospitals might have selected cases with active tier comorbidities from among those with and without indicators of tier comorbidities on their acute record, we believe that a reasonable selection process would have two properties.

Increased selection of patients with tier comorbidities should occur at least proportionally from among those with tier comorbidities recorded in acute care as from among those whose acute care record does not record it. Second, hospitals would not discriminate against cases with a tier comorbidity on their acute record. Using these assumptions, we estimate that coding was responsible for the majority of the increase in tier incidence.

Finally, we believe that hospitals would not differentially select cases with greater bowel and bladder dysfunction than other functional areas, and that the greater coding of these two motor items reflects changes in the rules rather than an increase in real case mix. If the bowel and bladder items had declined only at the rate of other items, the total motor score decline would have been only 80 percent as large as observed. Thus we attribute 20 percent of the increase in the CMI from the decrease in the motor score to coding.

The total amount of coding that occurred increased the WPD by at least 0.0177, or 1.88 percent.

IMPLICATIONS FOR FUTURE PPS PAYMENTS

We estimate that weight per discharge was between 1.9 percent and 6.8 percent higher in 2002 than in the 1999 database used to norm the weights for reasons unrelated to resource use, largely coding changes. Correspondingly, we estimate that the real change in WPD was between a 3.45-percent decline and an increase of 1.5 percent. Because the measured increase in the CMI from the decline in volume of cases per discharge is almost entirely real, this translates into a real increase in the CMI of between -2.4 percent and +2.6 percent, and a coding increase in the CMI of between 1.9 percent and 6.9 percent.

The FY 2002 conversion factor was not based on our case sample alone. The office of the actuary (OACT) projected TEFRA payments to obtain the budget neutral conversion factor. OACT also used a behavioral offset of 1.16 percent to decrease the conversion factor. This offset was designed to adjust payment because decreased TEFRA payment would result from shorter stays under the IRFPPS. LOS has indeed decreased and would have reduced TEFRA payments. Thus this behavioral offset does not appear relevant to the current issue.

However, part of the conversion factor calculation involved using a RIC prediction formula similar to the one used here. It was applied to the entire universe of 1999 IRF cases and showed that, even in 1999, the population had a distribution of predicted RIC with lower weights than our sample. In response to this finding, CMI used a conversion factor that was 1 percent higher than the conversion factor that would have matched cost just within our sample. Thus, one-third of the observed 3-percent decline in real case mix from impairment was already taken into account in setting the 2002 rates. This affects our lower bound of coding change and upper bound of real change. Thus, our final bounds on the causes of the increase in the CMI are:

- Coding change between 1.9 percent and 5.9 percent
- Real change between a 1.4-percent decline and a 2.4-percent increase

We recommend that CMS either reduce weights by at least 1.9 percent or reduce the conversion factor by at least 1.9 percent less than the market basket update in order to ensure that future payments reflect only real changes in resource needs. Further, since in 2002 many hospitals were on the PPS for only part of the year, we believe that this analysis should be repeated using more recent data in order to gauge the full impact of the PPS on case mix change.

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APPENDIX A: METHODOLOGICAL DETAILS

THEORETICAL FRAMEWORK

We use the following notation. Let x denote a vector of the rehabilitation characteristics that determine case weight: namely RIC, CMG, and tier. Each element of x is discrete and not all combinations are possible. Let z denote a vector of demographics and characteristics of the acute hospitalization that preceded the rehabilitation admission. The elements of z are also discrete. Define the functions:

Fy(x/z) = probability(x during y given z),

Ry(x) = unconditional probability of x during year y, and

Ay(z) = unconditional probability of z during year y.

So:

$$Ry(x) = \sum\{Fy(x/z)*Ay(z)\},$$

where the sum is over all values of the vector z. The CMI in year y is a direct function of Ry(x):

CMI = FCMI(Ry(x)).

Further, we can use the relationship between x and z during 1999 and the values of z during 2002 to predict what the CMI would be in 2002 *if coding in 2002 of cases with the same value of z was similar to coding in 1999*. In particular, the prediction based on relationship between x and z observed during 1999 but using the values of z found in 2002:

pred_cmi(1999,2002) = FCMI(SUM{F1999(x/z)*A2002(z)})

gives a prediction of the CMI in 2002 assuming coding was the same as in 1999. Thus, we can estimate that:

real change = pred_cmi(1999, 2002)- pred_cmi(1999,1999)

= predcmi(1999, 2002)- CMI(1999). (1R)

And

coding change = actual(2002)-pred(1999,2002)

= predcmi(2002, 2002)- pred_cmi(1999,2002) (1C)

Equation (1C) follows from the fact that total change in the CMI (= actual (2002) - actual(1999)) is the sum of real change and coding change.

We can also use the relationship between x and z during 2002 to estimate what the CMI would have been in 1999 if coding in 1999 had been the same as current standards. Thus

pred_cmi(2002,1999) = FCMI(SUM{f2002(x/z)*A1999(z)})

gives a prediction of the CMI in 1999 assuming current coding. We can get a second estimate of real change as:

real change = pred_cmi(2002, 2002)- pred_cmi(2002,1999) (2R).

Then another estimate of coding change is:

coding change = pred_cmi(2002,1999) – CMI(1999) (2C).

The success of this strategy depends on the accuracy of the function Fy:

Fy(x/z) = probability(x during y given z).

We developed different models to predict different determinants of x: dummies for each RIC, dummies for each tier, and motor score (and thus CMG). Although quite effective by usual statistical criteria, the models do not perfectly predict the elements of x, but rather predict only with error. If the errors are small, such as they are with the most frequent impairments, then our model captures most of real change and coding change. If the errors were randomly distributed, then the estimates of real and coding change would be unbiased; if errors for the mean of the population (rather than for each case) are also sufficiently accurate, then one could use these estimates to determine how to change weights or the national payment rate to meet the BBA mandate.

One reason for believing at least some of the errors in estimating rehabilitation characteristics (F1999(x/z)) are random is that we believe the 1999 coding was subject to error which is likely to be random. In section 3, we show that impairment coding has greater correspondence to the preceding acute event in 2002 than it had in 1999, and we believe that the change in the CMI due to this increased accuracy is coding change. Another example is the subset of tier comorbidities indicated by the acute care record that are likely to persist from acute care into rehabilitation are more frequently coded in 2002 than in 1999. For changes in x that are caused by coding improvements, it is likely that the estimates of coding change and real change are unbiased.

As discussed in the introduction, however, hospitals had an incentive to choose less expensive patients under TEFRA but not under

the PPS. Thus it is reasonable to suppose that hospitals might have selected patients during 2002 that had a higher weight from among all patients with the same value z than were selected in 1999.

This selection hypothesis would mean that the CMI predicted from a model built on 1999 acute care data but using the characteristics of 2002 acute care records would underestimate the 'true' CMI in 2002 if coding were the same in both years. Similarly, the CMI predicted from a model built on 2002 data and using characteristics of 1999 acute care would overestimate the 'true' CMI in 1999 if coding in 1999 were the same as coding in 2002.

Thus:

pred_cmi(1999, 2002) < same coding cmi(2002)

and

pred_cmi(1999, 2002) – actual(1999) < real change

and

actual(2002)- pred_cmi(1999,2002) > coding change.

Both models offer similar bounds:

pred_cmi(2002,1999) > same coding cmi(1999)

actual(2002) – predcmi(2002,1999) < real change

pred_cmi(2002,1999) – actual(1999) > coding change.

Because the selection process may vary for different elements of x, the bias in our estimates also varies for different values of x. We view the estimates of coding change as credible only when we believe it very likely that the difference between the functions F2002(x/z) and F1999(x/z) is not substantially affected by unobserved case selection. This in turn implies that, rather than hoping for an unbiased estimate of coding and case mix change, we must be satisfied to bound the amount of real and coding change though separate estimates for some of the elements of x, rather than for the entire vector.

ATTRIBUTING CMI CHANGE

Let xij denote CMG i and tier j, then define the contribution of this combination of tier and CMG to the increase in the weight per discharge as:

cij = (wij – 0.5*(wbar99+wbar02))*(R2002(xij)-R1999(xij)), (3)

where wij is the relative weight of a case in CMG i and tier j.[14] It is easy to see that the contribution from ij sum across all i and j to the actual change in the CMI. The contribution has the property that if wij is larger than the typical weight, an increase in incidence will result in a positive contribution to the change in the CMI and a decrease in incidence will result in a negative contribution to the CMI.

We approximate the contribution of changes in the distribution of any subset of cases by fixing the weight of the cases at its average across the two years. Let w(s) denote the average weight of a case in subset s across the two years—i.e., one-half the average weight in the subset in 99 plus one-half the average weight in the subset in 2002. Then the effect of the change in the distribution of s is estimated as:

c(s) = (w(s)- 0.5*(wbar99+wbar02))*(Pr(s/2002)-Pr(s/1999)). (4)

Thus the contribution is how much the CMI would change due to the change in s if all other characteristics of the cases were distributed in ways typical of both year's data.

For example, let s denote a particular RIC. Then c(s) is the increase in the CMI that would have occurred due to a change in the distribution of s, under the assumption that the distribution of CMG and tier within RIC s, were the same in each year and typical of the average of the two years. Similarly, we can estimate the contribution of changes in the frequency of tier j by assuming that cases with tier j were found in each CMG as they were in the average of the distributions found in 1999 and 2002. The sum of the effects of each RIC, tier, and CMG slightly exceed the total increase in the CMI because there is a correlation between changes in RIC and changes in tier and CMG.

By defining s in certain ways, we can now identify parts of the CMI change as real change or coding change using our prediction of ij and s from the acute care record. For example, suppose we believe, as we do, that a change in the proportion of patients who arrive in an IRF following acute care for a stroke represents real change in the distribution of impairment. By defining this group as s we can use equation (4) to estimate the effect of this real change on the CMI.

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[14] The relative weight per discharge varies very slightly across years due to differences in equivalent cases per discharge. The relative weight per equivalent case is the same in the two years.

As another example, suppose we believe, as we do, that an increase in the proportion of patients coded in the stroke RIC out of all who arrive in rehab following a stroke represents coding change. We can begin by defining s as patients in the stroke RIC who arrive following an acute stroke, and thus calculate c(s). But the entire increase in this group is not real—part is due to the better coding of RIC. Let delta(real) = pr2002(acute stroke)-pr1999(acute stroke) and

delta(coding) = pr2002(stroke ric/acute stroke)-pr1999(stroke ric/acute stroke). Since:

pry(s) = pry(acute stroke)* pry(stroke ric/acute stroke), and

pr2002(s)-pr1999(s) = pr1999(acute stroke)*delta(coding) +
pr1999(stroke ric/acute stroke)*delta(real) +
delta(real)*delta(coding).

We apportion the second order term (which is very small in the case of RIC coding) in proportion to each of the two major components. Thus the part of the contribution of s due to coding is

code(s) = (w(s)- 0.5*(wbar99+wbar02))*
(pr1999(acute stroke)*delta(coding)
+delta(real)*delta(coding)/
[pr1999(acute stroke)*delta(coding)
+ pr1999(stroke ric/acute stroke)*delta(real)]) (5)

Note that if we consider the sum of the contribution of all possible states in a vector variable that describes acute care, say z, we would get exactly the same result as if we modeled CMI on z as a class variable and then averaged the estimates of real change from equations (1R) and (2R). Equation (4) adds to the statistical model an ability to examine the effect of changes in only subsets of cases rather than having to consider the complete distribution of z at one time as we would in equations (1R) and (2R).

However, when we add the effects of coding in RICs, tiers, and motor scores we are ignoring second order effects due to the correlation, if any, of changes in coding of the different elements. We believe these to be small.

PROCEDURES USED TO PREDICT TIER CONDITIONS

Four of the tier conditions, viz., dialysis, tracheostomy, ventilator dependence, dialysis, and lower extremity amputation, are often recorded by procedures in acute care rather than just by the V-code that is used in IRFs to indicate the condition. Table A.1 shows all the ICD-9-CM procedure codes that we use for prediction. If one of these codes appears in the acute care record for the hospitalization that preceded IRF admission, then we predict that the patient will have the condition shown in the last column coded in their IRF stay.

Table A.1

Procedure Codes Used to Predict Tier Conditions

Code	Label	Condition
31.1	TEMPORARY TRACHEOSTOMY	Tracheostomy
31.21	MEDIASTINAL TRACHEOSTOMY	Tracheostomy
31.29	OTHER PERM TRACHEOSTOMY	Tracheostomy
30.3	COMPLETE LARYNGECTOMY	Tracheostomy
30.4	RADICAL LARYNGECTOMY	Tracheostomy
96.72	CONT MECH VENT 96+ HRS	Ventilator
96.71	CONT MECH VENT < 96 HRS	Ventilator
96.70	CONT MECH VENT UNSPEC DUR	Ventilator
39.95	HEMODIALYSIS	Dialysis
39.42	REVIS REN DIALYSIS SHUNT	Dialysis
54.98	PERITONEAL DIALYSIS	Dialysis
38.95	VEN CATH RENAL DIALYSIS	Dialysis
39.27	DIALYSIS ARTERIOVENOSTOM	Dialysis
84.15	BELOW KNEE AMPUTAT NEC	LE amputation
84.16	DISARTICULATION OF KNEE	LE amputation
84.17	ABOVE KNEE AMPUTATION	LE amputation
84.18	DISARTICULATION OF HIP	LE amputation
84.19	HINDQUARTER AMPUTATION	LE amputation
84.3	AMPUTATION STUMP REVIS	LE amputation
84.45	FIT ABOVE KNEE PROSTHESIS	LE amputation
84.46	FIT BELOW KNEE PROSTHESIS	LE amputation
84.47	FIT LEG PROSTHESIS NOS	LE amputation
84.48	IMPLANT LEG PROSTHESIS	LE amputation

APPENDIX B: REGRESSION MODELS

Table B.1

Regression of Motor Score

Parameter	COEFFICIENT	t Value	F statistic (where appropriate)
Intercept	35.629	57.62	
race=white	1.935	28.42	
female	0.364	7.54	
age	0.322	18.7	
age squared	-0.003	-24.7	
Number of acute care stays in 6 months prior to IRF admission			189.13
0	-0.760	-4.68	
1	0.000		
2	-1.310	-21.53	
3	-1.251	-14.86	
4 or more	-1.781	-18.93	
Predicted RIC			522.75
1-Stroke	-2.151	-14.02	
2-TBI	-1.388	-4.75	
3-NTBI	-0.463	-1.64	
4-TSCI	-12.461	-15.13	
5-NTSCI	1.055	5.71	
6-Neuro	-2.601	-13.16	
7-Hip FX	-1.561	-10.04	
8-LE Joint	4.608	30.53	
9-Other O.	0.173	0.86	
10-Amp LE	2.552	11.51	
11-Amp Other	1.758	2.94	
12-Osteo Arth	2.743	5.44	
13-Other Arth	0.286	0.47	
14-Cardiac	6.211	32.04	
15-Pulmonary	8.361	31.72	
16-Pain	2.800	4.56	
17-MMT, NBSCI	-2.226	-5.1	
18-MMT, WBSCI	-6.293	-7.16	
19-GB	-2.252	-3.4	
20-Misc.	2.477	14.42	
21-Burns	-1.211	-1	
No prediction	1.663	10.35	
No hospitalization within 30 days (C.G.)	0.000		

(TABLE B.1 CONTINUED)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Predicted tier 1	-2.145	-7.44	
Predicted tier 2	-1.150	-6.08	
Predicted tier 3	-1.421	-8.82	
Predicted tier 1 interacted with predicted RIC			13.85
1-Stroke	-4.505	-10.45	
2-TBI	-5.348	-7.77	
3-NTBI	-4.024	-4.04	
4-TSCI	-7.029	-2.66	
5-NTSCI	-6.026	-8.4	
6-Neuro	-0.856	0.86	
7-Hip FX	-0.968	-1.41	
8-LE Joint	-0.693	-0.82	
9-Other O.	0.750	0.67	
10-Amp LE	0.727	0.78	
11-Amp Other	-2.006	-0.87	
12-Osteo Arth	-4.198	-0.75	
13-Other Arth	-3.903	-1.09	
14-Cardiac	-0.465	-1.07	
15-Pulmonary	-1.673	-1.6	
16-Pain	-7.396	-1.1	
17-MMT, NBSCI	0.652	0.37	
18-MMT, WBSCI	-1.610	-0.65	
19-GB	-1.002	-0.46	
20-Misc.	0.347	0.94	
21-Burns	-6.830	-2.48	
No prediction	0.000	.	
Predicted tier 2 interacted with predicted RIC			3.64
1-Stroke	-0.319	-0.91	
2-TBI	-1.594	-1.88	
3-NTBI	-1.558	-1.79	
4-TSCI	-6.570	-2.16	
5-NTSCI	-2.957	-5.77	
6-Neuro	-1.094	-1.95	
7-Hip FX	-0.472	-1.18	
8-LE Joint	0.133	0.27	
9-Other O.	-0.679	-0.96	
10-Amp LE	-0.730	-2.08	
11-Amp Other	0.684	0.94	
12-Osteo Arth	1.227	0.51	
13-Other Arth	3.133	2.23	
14-Cardiac	-0.720	-1.8	
15-Pulmonary	-1.436	-1.88	

(Table B.1 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
16-Pain	-3.500	-1.26	
17-MMT, NBSCI	-5.336	-2.23	
18-MMT, WBSCI	-6.187	-1.58	
19-GB	2.207	1.35	
20-Misc.	0.087	0.35	
21-Burns	0.598	0.26	
No prediction (C.G.)	0.000	.	
Predicted tier 3 interacted with predicted RIC			7.49
1-Stroke	-0.051	-0.23	
2-TBI	-0.522	-0.93	
3-NTBI	0.543	1.02	
4-TSCI	3.500	1.8	
5-NTSCI	-1.848	-4.88	
6-Neuro	3.017	6.46	
7-Hip FX	0.138	0.5	
8-LE Joint	-0.320	-1.15	
9-Other O.	-0.646	-1.29	
10-Amp LE	-0.946	-3.17	
11-Amp Other	1.663	2.26	
12-Osteo Arth	-1.420	-0.86	
13-Other Arth	1.594	1.05	
14-Cardiac	-1.102	-4.25	
15-Pulmonary	-1.305	-2.14	
16-Pain	2.635	1.47	
17-MMT, NBSCI	0.133	0.1	
18-MMT, WBSCI	1.959	0.69	
19-GB	-0.565	-0.37	
20-Misc.	0.602	2.81	
21-Burns	-0.052	-0.02	
No prediction (C.G.)	0.000	.	
Comorbidities			
Cancer with poor prognosis	0.203	0.88	
Metastatic cancer	-0.531	-2.7	
Chronic renal failure	-0.250	-1.3	
Nutritional deficiencies	-2.665	-17.66	
Dementia	-4.850	-40.59	
Diabetes with organ damage	0.737	5.54	
Peripheral vascular disease	0.586	5.61	
Functional impairment	-5.873	-79.82	
Venous thrombosis or pulmonary embolism (not applicable for PREDRIC 15)	0.295	4.33	
Congestive heart failure	-0.941	-14.07	
Diabetes without organ damage	-0.938	-15.17	

(Table B.1 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Coronary artery disease (not applicable for PREDRIC 14)	0.552	9.05	s
Complications			
Shock or cardiorespiratory arrest	-0.635	-2.67	
Post-op heart attack (AMI)	0.166	0.81	
Venous thrombosis or pulmonary embolism	-1.681	-7.82	
Hip fracture (not applicable for PREDRIC 7)	-2.876	-11.85	
Latrogenic complications	-0.381	-3.17	
Post-op pulmonary compromise	-1.851	-13.1	
Post-op GI hemorrhage or ulceration	-1.475	-6.89	
Celluitis or decubitus ulcer	-2.827	-20.36	
Pneumonia	-2.698	-21.56	
Mechanical complications due to device or implant	-1.889	-10.62	
Acute renal failure	-1.428	-8.36	
Sentinel event	-1.425	-6.27	
Delirium	-1.272	-7.17	
Stroke (not applicable for PREDRIC 1)	-6.918	-40.9	

Note: Based on 241,306 cases in 1999. R-Square = 0.165

Table B.2

Regression of Equivalent Cases

Parameter	COEFFICIENT	t Value
Intercept	0.9921	4826.93
Predicted transfer to hospital	-0.9290	-562.25
Predicted transfer to SNF/NH	-0.8170	-303.84
Predicted transfer to hospital interacted with LOS relative to RIC statistics		
Min(1,LOS/ median)	0.7872	295.20
Min(1, (LOS-median)/(LOS - 97th percentile))	0.1341	36.13
Indicator that LOS > 97th percentile	0.0018	0.50

(**Table B.2 continued)**

Parameter	COEFFICIENT	t Value
Predicted transfer to SNF/NH interacted with LOS relative to RIC statistics		
Min(1,LOS/ median)	0.6211	187.83
Min(1, (LOS-median)/(LOS - 97th percentile))	0.2116	100.05
Indicator that LOS > 97th percentile	-0.0141	-7.76

Note: Based on 241,343 cases in 1999. R-Square = 0.739.

Table B.3

Regression of Case Weight

Parameter	Coefficient	t Value	F statistic (where appropriate)
Intercept	1.1333	55.40	
Race (white)	-0.0575	-25.84	
Female	-0.0258	-16.45	
Age	-0.0020	-3.53	
Age squared	0.0000	2.91	
Number of acute care stays in 6 months prior to IRF admission			2.05
0	0.0018	0.33	
1 (Comparison Group (C.G.)	0.0000	.	
2	0.0415	20.67	
3	0.0313	11.24	
4 or more	0.0523	16.82	
Predicted RIC			1707.65
1-Stroke	0.1775	35.03	
2-TBI	0.0871	9.01	
3-NTBI	0.0410	4.39	
4-TSCI	0.4007	14.74	
5-NTSCI	-0.1026	-16.81	
6-Neuro	0.0057	0.88	
7-Hip FX	-0.0911	-17.74	
8-LE Joint	-0.3659	-73.33	
9-Other Orthopedic	-0.1170	-17.62	
10-Amp LE	0.0412	5.63	
11-Amp Other	-0.0157	-0.80	
12-Osteo Arth	-0.2086	-12.55	
13-Other Arth	-0.1400	-6.95	

(Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
14-Cardiac	-0.1927	-30.10	
15-Pulmonary	-0.1501	-17.26	
16-Pain	-0.1465	-7.23	
17-MMT, NBSCI	-0.0311	-2.16	
18-MMT, WBSCI	0.1733	5.99	
19-GB	0.2458	11.26	
20-Misc.	-0.0813	-14.34	
21-Burns	0.1752	4.39	
50-Short stay (<= 3 days)	-0.9371	-7.04	
51-In-hospital death	-1.1097	-2.61	
No prediction	-0.0978	-18.43	
No hospitalization within 30 days (C.G.)	0.0000	.	
Predicted tier 1	0.0846	8.87	
Predicted tier 2	0.0496	7.94	
Predicted tier 3	0.0406	7.63	
Predicted tier 1 interacted with predicted RIC			21.28
1-Stroke	0.1391	9.76	
2-TBI	0.2019	8.86	
3-NTBI	0.1336	4.08	
4-TSCI	0.5213	5.93	
5-NTSCI	0.2649	11.18	
6-Neuro	0.0320	0.97	
7-Hip FX	0.0046	0.20	
8-LE Joint	0.0043	0.16	
9-Other O.	0.0911	2.46	
10-Amp LE	-0.0618	-2.00	
11-Amp Other	0.0753	0.99	
12-Osteo Arth	0.1219	0.66	
13-Other Arth	-0.0421	-0.36	
14-Cardiac	-0.0051	-0.35	
15-Pulmonary	-0.0400	-1.16	
16-Pain	0.0679	0.31	
17-MMT, NBSCI	0.0143	0.25	
18-MMT, WBSCI	0.2543	3.04	
19-GB	0.0929	1.29	
20-Misc.	-0.0362	-2.96	
21-Burns	0.2135	2.36	
No prediction (C.G.)	0.0000	.	

(Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Predicted tier 2 interacted with predicted RIC			6.67
1-Stroke	0.0074	0.64	
2-TBI	0.0501	1.80	
3-NTBI	0.0105	0.37	
4-TSCI	0.5775	5.60	
5-NTSCI	0.1444	8.53	
6-Neuro	-0.0058	-0.32	
7-Hip FX	0.0127	0.96	
8-LE Joint	0.0101	0.62	
9-Other O.	0.0459	1.96	
10-Amp LE	0.0031	0.27	
11-Amp Other	-0.0448	-1.87	
12-Osteo Arth	0.0197	0.25	
13-Other Arth	-0.0021	-0.04	
14-Cardiac	0.0141	1.07	
15-Pulmonary	0.0527	2.09	
16-Pain	-0.0180	-0.20	
17-MMT, NBSCI	0.2703	3.43	
18-MMT, WBSCI	-0.0318	-0.24	
19-GB	0.0432	0.80	
20-Misc.	-0.0048	-0.58	
21-Burns	0.0728	0.97	
No prediction (C.G.)	0.0000	.	
Predicted tier 3 interacted with predicted RIC			11.45
1-Stroke	-0.0421	-5.81	
2-TBI	0.0219	1.18	
3-NTBI	-0.0084	-0.48	
4-TSCI	-0.3172	-4.87	
5-NTSCI	0.0849	6.79	
6-Neuro	-0.0587	-3.81	
7-Hip FX	-0.0200	-2.21	
8-LE Joint	0.0219	2.38	
9-Other O.	0.0126	0.77	
10-Amp LE	-0.0038	-0.38	
11-Amp Other	-0.0668	-2.74	
12-Osteo Arth	0.0890	1.64	
13-Other Arth	-0.0313	-0.62	
14-Cardiac	0.0250	2.92	
15-Pulmonary	-0.0330	-1.64	
16-Pain	-0.1021	-1.71	

(Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
17-MMT, NBSCI	-0.0098	-0.21	
18-MMT, WBSCI	-0.0075	-0.08	
19-GB	0.1555	3.09	
20-Misc.	-0.0310	-4.39	
21-Burns	-0.0564	-0.77	
No prediction (C.G.)	0.0000	.	
SNF/NH on day of discharge	0.0439	19.37	
Acute, LTC, or IRF on day of discharge	-0.3077	-107.60	
Comorbidities			
Cancer with poor prognosis	-0.0126	-1.65	
Metastatic cancer	-0.0029	-0.45	
Delirium	0.0338	5.78	
Chronic renal failure	-0.0014	-0.22	
Nutritional deficiencies	0.0572	11.49	
Dementia	0.0582	14.75	
Diabetes with organ damage	0.0109	2.48	
Peripheral vascular disease	-0.0151	-4.38	
Functional impairment	0.1839	75.55	
Chronic Pulmonary Disease	-0.0210	-9.35	
Congestive heart failure	0.0142	6.45	
Diabetes without organ damage	0.0286	14.03	
Coronary artery disease (not applicable for PREDRIC 14)	-0.0117	-5.81	
Complications			
Shock or cardiorespiratory arrest	0.0251	3.19	
Sentinel event	0.0369	4.91	
Venous thrombosis or pulmonary embolism	0.0410	5.78	
Post-operative GI	0.0356	5.03	
Stroke (not applicable for PREDRIC 1)	0.2949	52.69	
Acute mycardial infarction	0.0035	0.52	
Mechanical complications due to device or implant	0.0416	7.07	
Hip fracture (not applicable for PREDRIC 7)	0.0470	5.87	
Acute renal failure	0.0273	4.84	
Cellulitis or decubitus ulcer	0.0627	13.67	
Iatrogenic complications	0.0021	0.53	
Post-operative pulmonary compromise	0.0684	14.66	
Pneumonia	0.0909	22.00	

(Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Age interacted			3.16
Predicted RIC 50	0.0024	0.61	
Predicted RIC 51	0.0278	2.44	
Other (C.G.)	0.0000	.	
Age squared interacted with			2.87
Predicted RIC 50	0.0000	-0.30	
Predicted RIC 51	-0.0002	-2.38	
Other (C.G.)	0.0000	.	
Number of acute care stays in 6 months prior to IRF admission interacted			1.89
4 or more			
Predicted RIC 50	-0.0404	-1.61	
Predicted RIC 51	-0.0779	-2.17	
Other (C.G.)	0.0000	.	
3 or more			
Predicted RIC 50	-0.0224	-1.00	
Predicted RIC 51	-0.0439	-1.25	
Other (C.G.)	0.0000	.	
2 or more			
Predicted RIC 50	-0.0326	-2.18	
Predicted RIC 51	-0.0102	-0.38	
Other (C.G.)	0.0000	.	
1 or more (C.G.)			
Predicted RIC 50	0.0000	.	
Predicted RIC 51	0.0000	.	
Other	0.0000	.	
none			
Predicted RIC 50	0.0000	0.00	
Predicted RIC 51	0.0971	1.44	
Other (C.G.)	0.0000	.	
Comorbidities interacted			
Cancer with poor prognosis			1.33
Predicted RIC 50	0.0027	0.04	
Predicted RIC 51	0.1041	1.63	
Other (C.G.)	0.0000	.	
Metastatic cancer			4.56
Predicted RIC 50	0.0014	0.03	
Predicted RIC 51	0.1551	3.02	
Other (C.G.)	0.0000	.	

(Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Delirium			1.23
Predicted RIC 50	-0.0492	-1.04	
Predicted RIC 51	0.0881	1.16	
Other (C.G.)	0.0000	.	
Chronic renal failure			2.75
Predicted RIC 50	0.0184	0.36	
Predicted RIC 51	0.1226	2.32	
Other (C.G.)	0.0000	.	
Nutritional deficiencies			0.09
Predicted RIC 50	-0.0158	-0.35	
Predicted RIC 51	0.0103	0.25	
Other (C.G.)	0.0000	.	
Dementia			2.00
Predicted RIC 50	-0.0601	-1.65	
Predicted RIC 51	-0.0607	-1.15	
Other (C.G.)	0.0000	.	
Diabetes with organ damage			1.00
Predicted RIC 50	-0.0090	-0.28	
Predicted RIC 51	0.0618	1.39	
Other (C.G.)	0.0000	.	
Peripheral vascular disease			0.27
Predicted RIC 50	0.0144	0.54	
Predicted RIC 51	-0.0199	-0.48	
Other (C.G.)	0.0000	.	
Functional impairment			51.88
Predicted RIC 50	-0.1810	-8.86	
Predicted RIC 51	-0.1557	-5.11	
Other (C.G.)	0.0000	.	
Chronic Pulmonary Disease			3.02
Predicted RIC 50	0.0229	1.48	
Predicted RIC 51	0.0528	1.98	
Other (C.G.)	0.0000	.	
Congestive heart failure			3.96
Predicted RIC 50	0.0007	0.04	
Predicted RIC 51	-0.0704	-2.81	
Other (C.G.)	0.0000	.	
Diabetes without organ damage			3.97
Predicted RIC 50	-0.0264	-1.70	
Predicted RIC 51	-0.0675	-2.26	
Other (C.G.)	0.0000	.	

(Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Coronary artery disease (not applicable for PREDRIC 14)			0.27
Predicted RIC 50	0.0095	0.70	
Predicted RIC 51	0.0053	0.21	
Other (C.G.)	0.0000	.	
Complications interacted			
Shock or cardiorespiratory arrest interacted			0.28
Predicted RIC 50	-0.0440	-0.70	
Predicted RIC 51	-0.0183	-0.26	
Other (C.G.)	0.0000	.	
Sentinel event interacted			0.68
Predicted RIC 50	-0.0516	-0.99	
Predicted RIC 51	-0.0723	-0.64	
Other (C.G.)	0.0000	.	
Venous thrombosis or pulmonary embolism interacted			0.47
Predicted RIC 50	-0.0371	-0.61	
Predicted RIC 51	-0.0540	-0.76	
Other (C.G.)	0.0000	.	
Post-operative GI interacted			1.12
Predicted RIC 50	0.0052	0.08	
Predicted RIC 51	-0.1123	-1.50	
Other (C.G.)	0.0000	.	
Stroke (not applicable for PREDRIC 1) interacted			49.23
Predicted RIC 50	-0.2901	-6.34	
Predicted RIC 51	-0.4250	-7.71	
Other (C.G.)	0.0000	.	
Acute mycardial infarction interacted			0.98
Predicted RIC 50	-0.0003	-0.01	
Predicted RIC 51	0.0975	1.40	
Other (C.G.)	0.0000	.	
Mechanical complications due to device or implant			0.21
Predicted RIC 50	-0.0318	-0.64	
Predicted RIC 51	-0.0065	-0.09	
Other (C.G.)	0.0000	.	
Hip fracture (not applicable for PREDRIC 7) interacted			2.96
Predicted RIC 50	-0.0331	-0.60	
Predicted RIC 51	-0.1811	-2.37	
Other (C.G.)	0.0000	.	

Table B.3 continued)

Parameter	Coefficient	t Value	F statistic (where appropriate)
Acute renal failure interacted			1.04
Predicted RIC 50	0.0029	0.07	
Predicted RIC 51	-0.0780	-1.44	
Other (C.G.)	0.0000	.	
Cellulitis or decubitus ulcer interacted			1.21
Predicted RIC 50	-0.0614	-1.54	
Predicted RIC 51	-0.0108	-0.23	
Other (C.G.)	0.0000	.	
Iatrogenic complications interacted			1.23
Predicted RIC 50	-0.0058	-0.22	
Predicted RIC 51	-0.0940	-1.55	
Other (C.G.)	0.0000	.	
Post-operative pulmonary compromise interacted			4.85
Predicted RIC 50	-0.0490	-1.36	
Predicted RIC 51	0.1111	2.78	
Other (C.G.)	0.0000	.	
Pneumonia interacted			3.57
Predicted RIC 50	-0.0778	-2.43	
Predicted RIC 51	-0.0423	-1.14	
Other (C.G.)	0.0000	.	

Note: Based on 245,963 cases in 1999. R-Square = 0.342.